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Fraudulent Claim Detection

VAISHALI MAKWANA
PRAVEENKUMAR PERIYASWAMY

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PROBLEM STATEMENT

Global Insure, a leading insurance company, processes thousands of claims annually. However, a significant portion of these claims are fraudulent, leading to substantial financial losses.

The current approach to fraud detection primarily involves manual inspections, which are:

- Time-consuming
- Inefficient
- Often too late — fraud is detected after the claim has been paid

KEY OBJECTIVES

Global Insure seeks to leverage data-driven models to identify potential fraud early in the claims approval process, enabling the company to:

- Reduce financial losses
- Speed up claim processing for legitimate claims
- Enhance operational efficiency

DATA UNDERSTANDING & MODELING APPROACH

- Data includes customer demographics, policy details, incident and claim info.
- Target variable: Whether the claim is Fraudulent (1) or Legitimate (0).

ths_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_deductable	policy_annual_premium	umbrella_limit	insured_zip	insured_s
328	48	521585	2014-10-17	OH	250/500	1000	1,406.91	0	466132	MA
228	42	342868	2006-06-27	IN	250/500	2000	1,197.22	5000000	468176	MA
134	29	687698	2000-09-06	OH	100/300	2000	1,413.14	5000000	430632	FEMA
256	41	227811	1990-05-25	IL	250/500	2000	1,415.74	6000000	608117	FEMA
228	44	367455	2014-06-06	IL	500/1000	1000	1,583.91	6000000	610706	MA

```
# Inspect the features in the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 40 columns):
```

DATA CLEANING

Handling Null Values

- Detection: Identified columns with missing data using df.isnull(). Found nulls in collision_type, authorities_contacted, property_damage, police_report_available, and a completely empty column _c39.
- Treatment:
- Dropped _c39 (all values null).
- Replaced missing values with reasonable defaults:
- collision_type: 'General Collision'
- authorities_contacted: 'None'
- property_damage & police_report_available: 'NO'

Handling Redundant or Invalid Data

- Redundant Columns:
- Removed columns with only one unique value or all unique values (e.g., policy_number, incident_location, insured_zip).
- Invalid Values:
- Detected negative values in umbrella_limit — dropped affected row.
- Empty Columns:
- Confirmed no columns were completely empty after initial drop.
- Low Predictive Power Columns:
- Dropped high-uniqueness columns (e.g., policy_number) unlikely to help in pattern recognition.

Fixing Data Types

- Identified and converted date-related columns (e.g., policy_bind_date) to appropriate datetime types.
- Categorical features were converted to category data type to optimize memory and allow efficient analysis.
- Binary columns (e.g., insured_sex, fraud_reported) were handled distinctly for value count validation.

FEATURE ENGINEERING

- **Initial Features:** ~50 mixed data types.
- **Technique Used:**
  - **L1**-penalized logistic regression (SAGA) with SelectFromModel (mean-threshold) for feature selection.
- **Result:**
  - Reduced to ~20 top predictors based on their importance scores.
  - The selected features are now ready for use in downstream models.

This feature selection process streamlines the model, focusing on the most important predictors for better performance.

MODELING APPROACH

- **Baseline Model:** Logistic Regression with optimized decision cutoff (accuracy, sensitivity, specificity).
- **Advanced Model:** Random Forest with feature selection (top ~12 features) and 5-fold GridSearchCV for hyperparameter tuning.
- **Hyperparameters Tuned:** n_estimators, max_depth, min_samples_split/leaf, max_features.

🔍 **Key Point:** By extracting feature importances and retraining on the top features, the random forest model was optimized for performance. Hyperparameter tuning further ensured that the model was well-adjusted to the data.

LOGISTIC REGRESSION MODEL

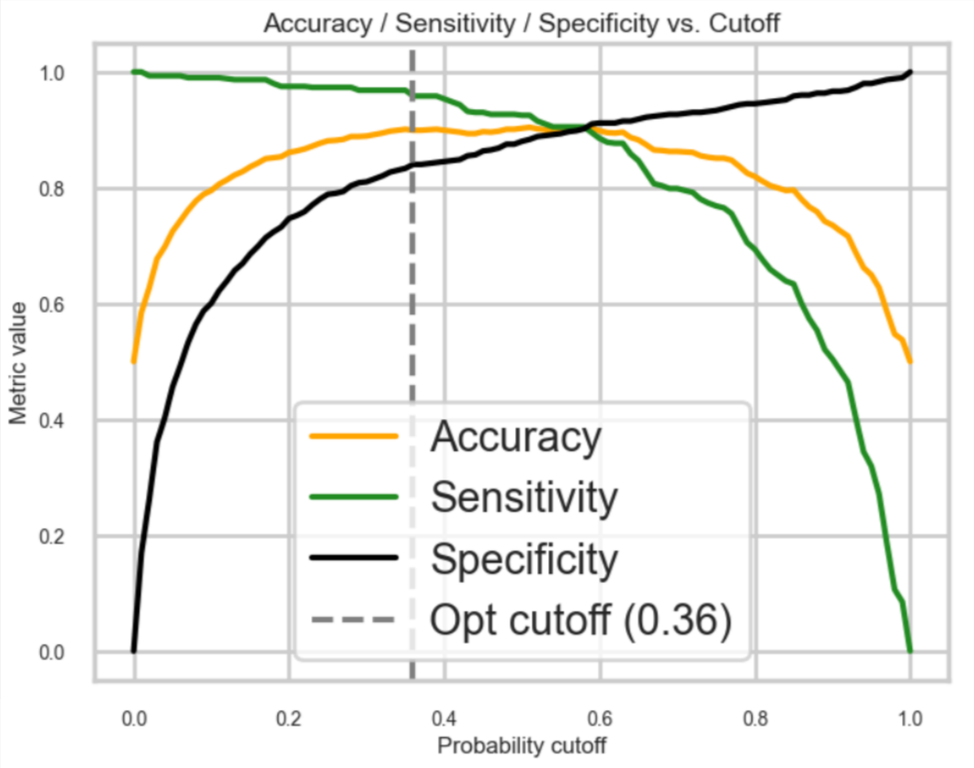
- **The Logistic Regression model** performed well, with strong accuracy (85%) and solid recall (82%) during training, indicating good generalization to the positive class.

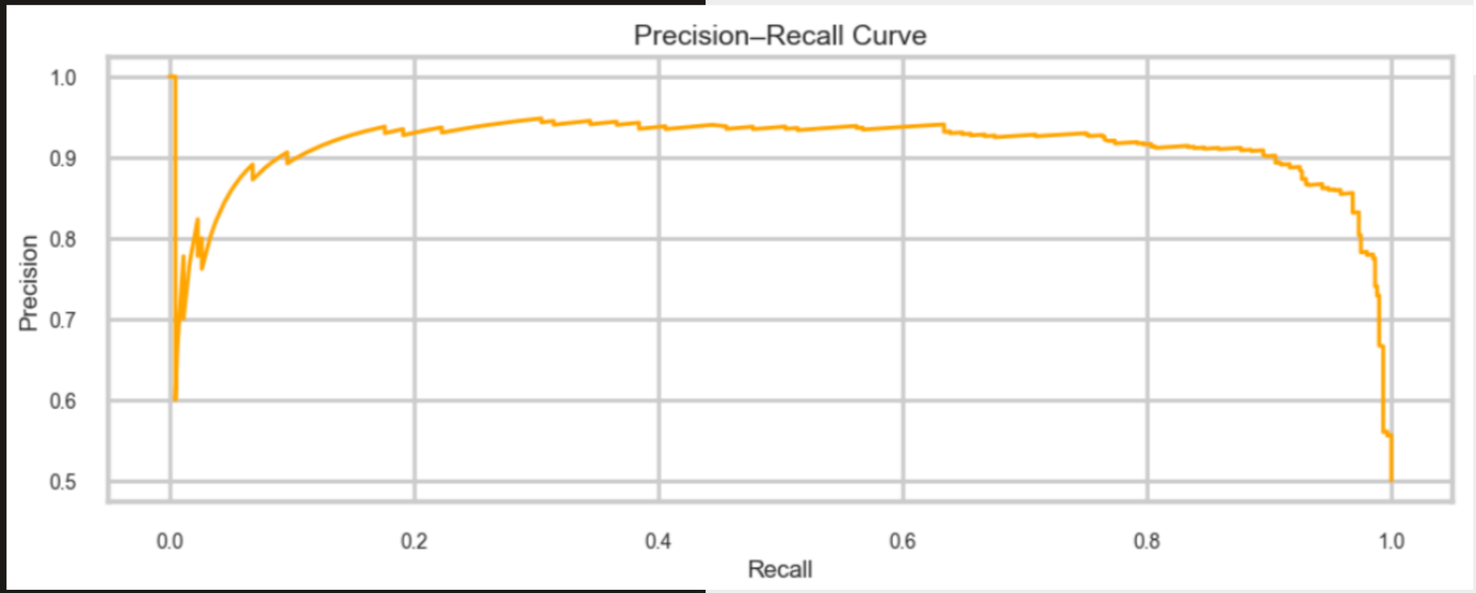
- **Precision** (80%) reflects a reasonable trade-off, ensuring that false positives were kept in check.

- **Validation** results showed slight performance degradation, particularly in Recall (78%), but overall, the model remains robust with an accuracy of 83%.

- **The optimal cutoff of ~0.40** helped to improve performance across key metrics in both training and validation.

LOGISTIC REGRESSION MODEL





RANDOM FOREST MODEL

Best Hyperparameters (via 5-fold GridSearchCV)

- n_estimators: 200
- max_depth: 20
- min_samples_split: 5
- min_samples_leaf: 2
- max_features: 'sqrt'

Performance Metrics

Training Set:

- Accuracy: **0.90**
- Recall: **0.88**
- Precision: **0.89**
- F1 Score: **0.89**

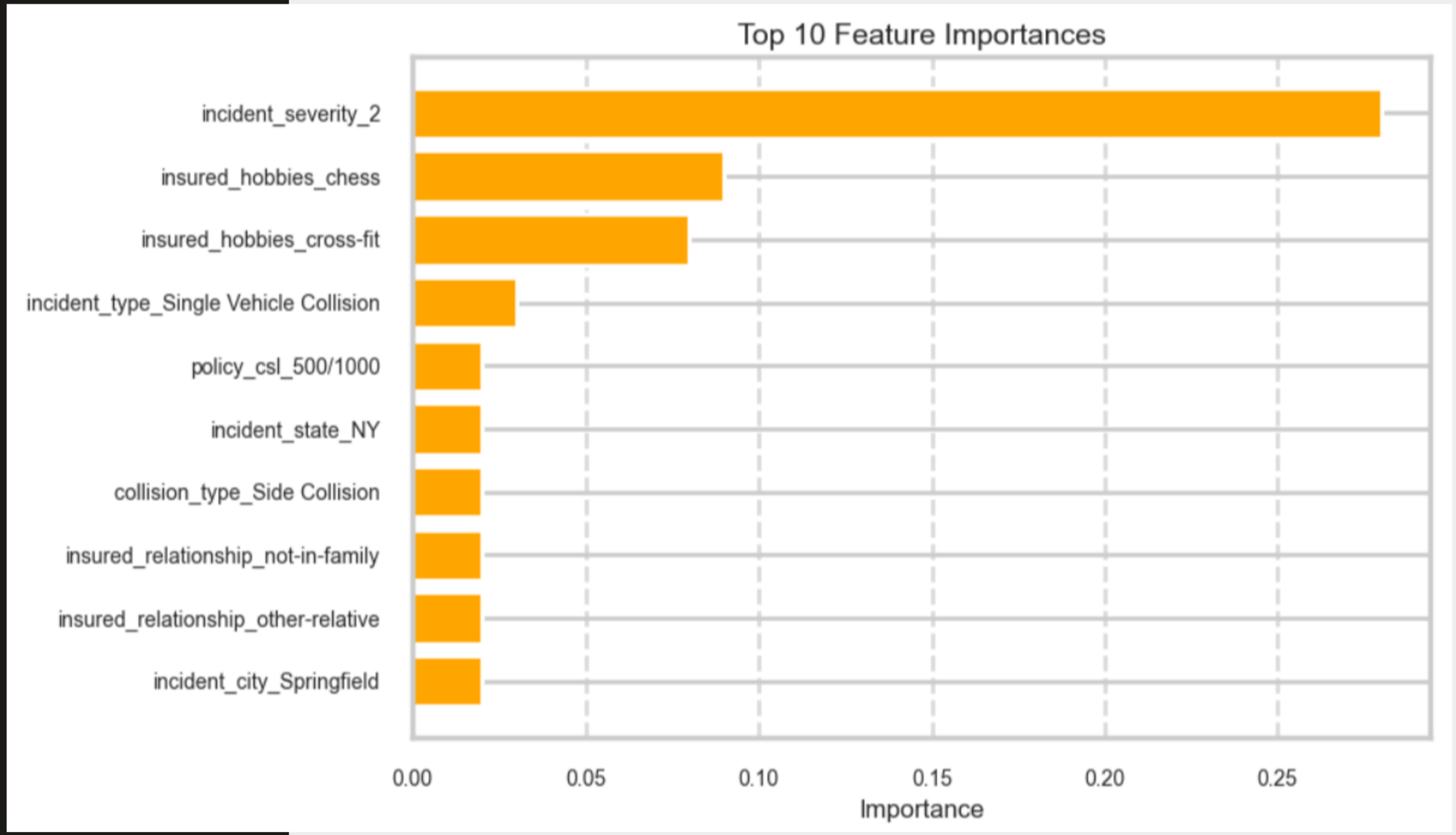
Cross-Validation (5-fold):

- Mean Train Accuracy: **0.90**
- Mean Validation Accuracy: **0.87**
- Interpretation: **Minimal overfitting observed**

Validation Set:

- Accuracy: **0.88**
- Recall: **0.85**
- Precision: **0.87**

RANDOM FOREST MODEL



FEATURE IMPORTANCE

- **incident_severity_2 (0.28) –** Most impactful; indicates severity is a key predictor.
- **insured_hobbies_chess (0.09) –** Suggests hobbies affect risk profile.
- **insured_hobbies_cross-fit (0.08) –** Physical activity may correlate with claim patterns.
- **incident_type_Single Vehicle Collision (0.03) –** Indicates different fraud or risk behavior.
- **policy_csl_500/1000 (0.02) –** Coverage level influences outcomes.

🔍 **Key Insight:**
Incident-level attributes — specifically **type, severity, and reported damage** — are the strongest indicators of potential fraud. These contextual features significantly outweigh demographic or historical factors in predictive power.

INVESTIGATIVE TAKEAWAYS

- **How can we analyse historical claim data to detect patterns that indicate fraudulent claims?**
  Historical data analysis reveals patterns such as:
- Claim severity
- Claim-to-premium ratio
- Policyholder hobbies (e.g., cross-fit, chess)

By using machine learning models like Logistic Regression and Random Forest, patterns indicative of fraud are extracted by analyzing how certain features correlate with known fraudulent cases.

- **Which features are most predictive of fraudulent behaviour?**
  The key features identified as most predictive include:
- incident_severity_2 (0.28)
- insured_hobbies_chess (0.09)
- insured_hobbies_cross-fit (0.08)
- incident_type_Single Vehicle Collision (0.03)
- policy_csl_500/1000 (0.02)

These features likely show higher importance in the Random Forest model, which inherently ranks feature importance based on splits and impurity reduction.

INVESTIGATIVE TAKEAWAYS

- **Can we predict the likelihood of fraud for an incoming claim, based on past data?**

Yes. Both models — Logistic Regression and Random Forest — are trained on historical labeled data (fraudulent vs. legitimate claims), allowing them to:

- Predict the probability of fraud for new incoming claims.
- Flag high-risk cases early in the claim approval pipeline.

Random Forest, with higher recall (0.7551), is particularly effective at catching more actual frauds, even if it occasionally mislabels legitimate claims.

INVESTIGATIVE TAKEAWAYS

- **What insights can be drawn from the model that can help in improving the fraud detection process?**

  - **Random Forest** is more sensitive to detecting fraud (higher recall), but **Logistic Regression** offers better **interpretability.**

  - Combining both models **(hybrid model approach)** could offer a balance of power and transparency.

  - **Model deployment** can significantly reduce financial losses by flagging claims early.

  - **Continuous monitoring and periodic retraining** are essential due to evolving fraud tactics.

  - **Implementing a dashboard** to monitor performance ensures ongoing effectiveness.

  - **Precision-Recall trade-offs** should be carefully managed depending on **business risk tolerance.**

IMPLICATIONS & FUTURE RECOMMENDATIONS

- **Early Fraud Detection:**

Deploying the model helps flag high-risk claims early, reducing financial losses and operational overhead.

- **Model of Choice – Random Forest:**

Due to its high recall (75.5%), it is better suited for catching more fraudulent cases in real-world use.

- **Hybrid Approach:**

Combine Random Forest for detection power and Logistic Regression for transparency and auditability.

- **Ongoing Monitoring:**

Set up a dashboard to monitor precision-recall trade-offs and retrain models regularly to stay ahead of evolving fraud trends.

- **Operational Efficiency:**

Automating fraud scoring streamlines claim processing, enabling faster resolutions for legitimate claims.

Thank you !

Team:

Vaishali Makwana
Praveenkumar Periyaswamy