UNVEILING DECEIT: FRAUD DETECTION THROUGH THE ART OF MACHINE LEARNING

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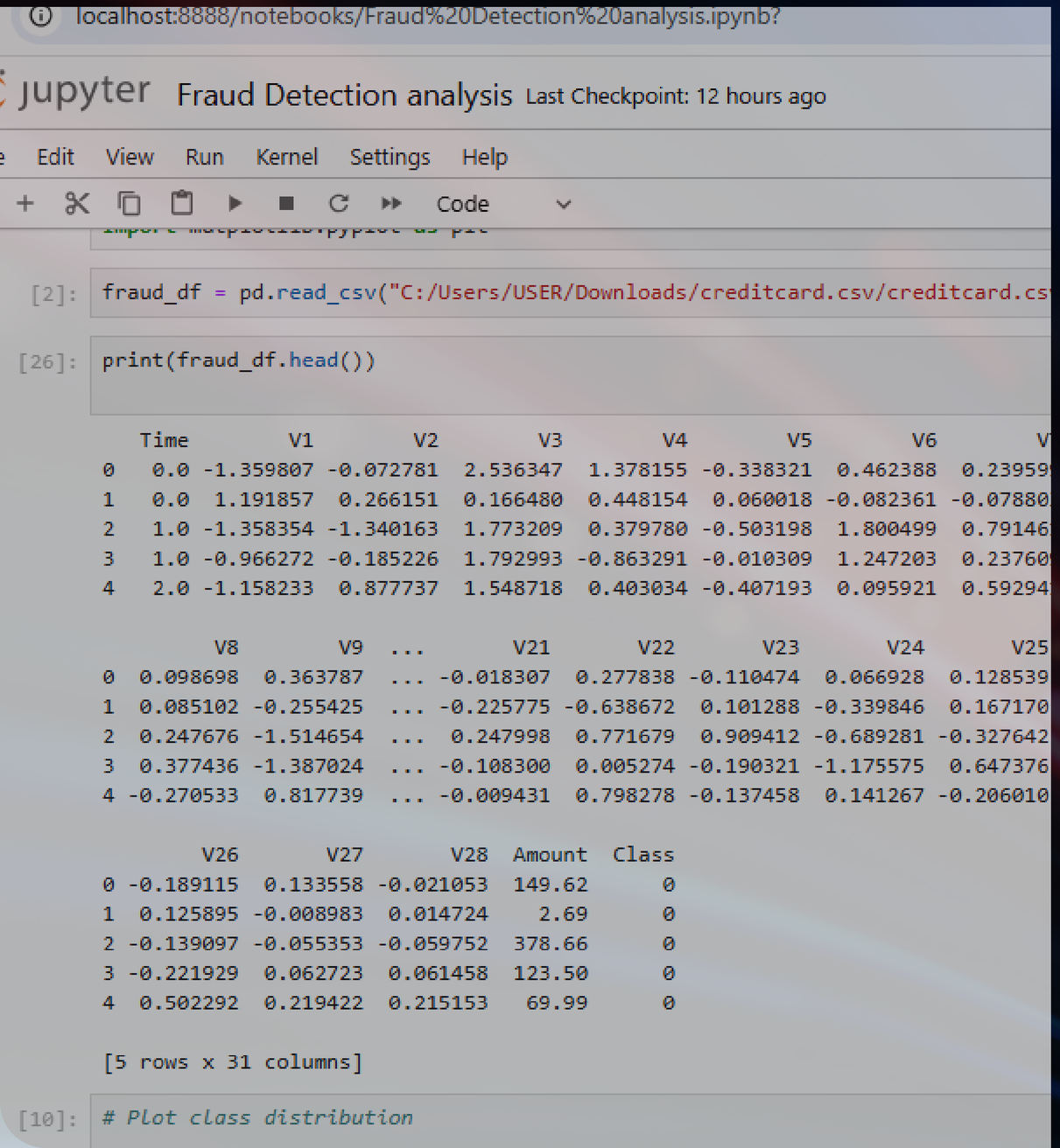
PROJECT OBJECTIVE

The goal is to detect fraudulent credit card transactions by building a machine learning model that accurately identifies fraud while minimizing false positives that could affect real customers.

DATASET OVERVIEW



- Source: creditcard.csv (~285,000 rows)
- Features: PCA-transformed V1–V28, Time, Amount, Class
- Class distribution:
- Non-Fraud: 99.83%
- Fraud: 0.17% (492 cases)

KEY CHALLENGES

Severe Class Imbalance

- In the dataset, fraud cases represent only 0.17% of all transactions.
- This extreme imbalance means that if a model simply predicts "non-fraud" for every transaction, it would still achieve over 99% accuracy, but fail at its true purpose: detecting fraud.
- Therefore, accuracy alone is misleading — more advanced evaluation metrics like precision, recall, and F1-score must be prioritized.

Fraud is Rare but High-Impact

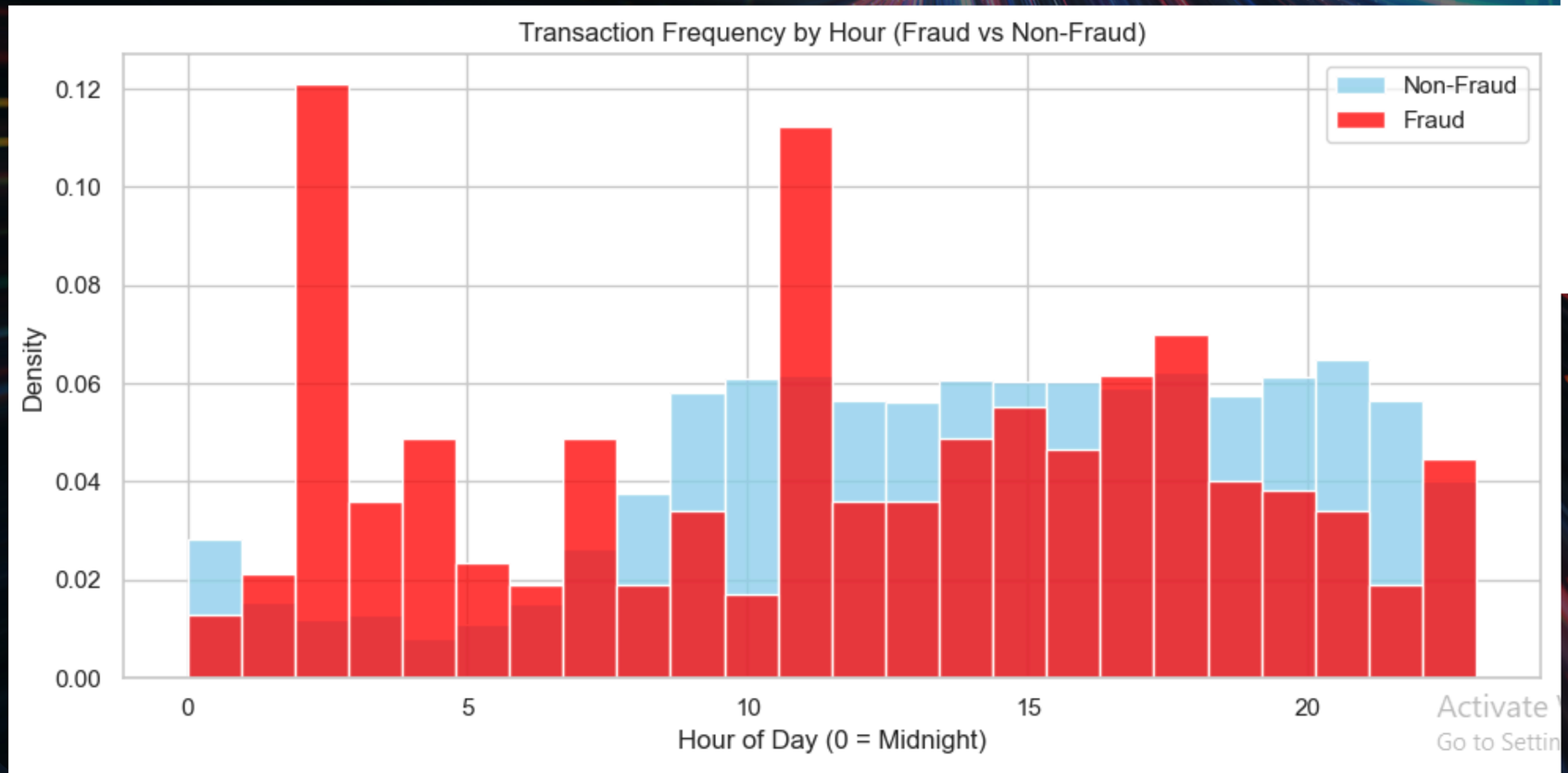
- Although fraud is rare, the financial and reputational impact of missing fraudulent transactions is enormous.
- Even a single undetected fraud can cause serious losses to customers and businesses.
- The cost of missing a fraud is much higher than the cost of wrongly flagging a legitimate transaction.

Balancing Detection vs. Customer Experience

- It's not enough to just detect fraud — we must also avoid too many false positives.
- Wrongly flagging legitimate transactions can:
- Frustrate loyal customers
- Increase operational costs (manual review teams)
- Damage brand trust
- Therefore, our model must carefully balance sensitivity (catching fraud) with specificity (not bothering real customers).

EDA INSIGHTS

- Fraud spikes around 2AM and 11AM
- Amount of fraud transactions is inconsistent (not always high-value)
- Features V10, V12, V14 showed strong correlation with fraud
- Class distribution visual confirmed imbalance



PREPROCESSING STEPS

- Scaled Amount and Time using StandardScaler
- Created train/test split (stratified)
- Applied SMOTE to balance fraud class in training set
- Ensured test set remains untouched for real-world evaluation

Feature Scaling (to standardize)

Some models (like Logistic Regression and Neural Networks) are sensitive to the scale of numbers. Features like:

Amount → can range from 0 to 25,000+ Time → can go up to 170,000+

Other features (V1 to V28) are already standardized.

So we only need to scale Amount and maybe Time to bring everything to a similar scale.

[22]:
```
from sklearn.preprocessing import StandardScaler
```

[24]:
```
# this create a copy to keep original data safe
scaled_df = fraud_df.copy()

# Columns to scale
cols_to_scale = ['Amount', 'Time']

# activating SCaler
scaler = StandardScaler()

# Apply scaler
scaled_df[cols_to_scale] = scaler.fit_transform(scaled_df[cols_to_scale])
```

jupyter Fraud Detection analysis Last Checkpoint: 2 days ago

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Code

[22]:
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from sklearn.preprocessing import StandardScaler
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# Apply scaler
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# Preview scaled data
print(scaled_df[['Amount', 'Time']].head())
```

```
     Amount      Time
0  0.244964 -1.996583
1 -0.342475 -1.996583
2  1.160686 -1.996562
3  0.140534 -1.996562
4 -0.073403 -1.996541
```

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Code

Prepare for Modeling

Define features (X) and labels (y) Split into training & testing sets

[26]:
```
from sklearn.model_selection import train_test_split
```

[28]:
```
# Define features
X = scaled_df.drop(['Class'], axis=1)
y = scaled_df['Class']

# Split the data with stratification
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)
```

[30]:
```
print("Training set:", X_train.shape)
print("Testing set:", X_test.shape)
print("Fraud in train:", sum(y_train))
print("Fraud in test:", sum(y_test))
```

```
Training set: (227845, 31)
Testing set: (56962, 31)
Fraud in train: 394
Fraud in test: 98
```

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Code

My model will learn from 394 real fraud examples and 227,451 non-fraud

It'll be tested on 98 fraud cases, which is enough to get a reliable measure of R

[32]:
```
# let use Logistic Regression to Detect Fraud

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix,
```

[34]:
```
#activating the model
log_reg = LogisticRegression(max_iter=1000)

#this train the model
log_reg.fit(X_train, y_train)

#telling the model to make prediction

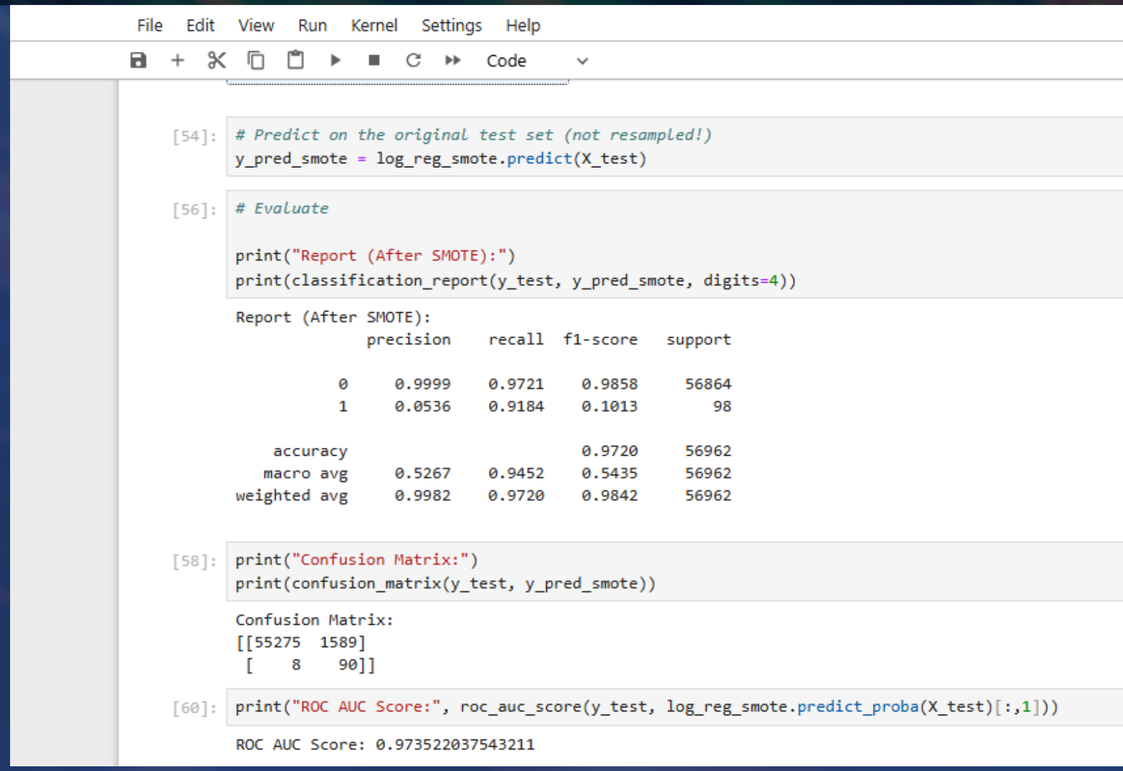
y_pred = log_reg.predict(X_test)
```

[36]:
```
print("Report:")
print(classification_report(y_test, y_pred, digits=4))
```

```
Report:
              precision    recall  f1-score   support
```

MODELS TESTED

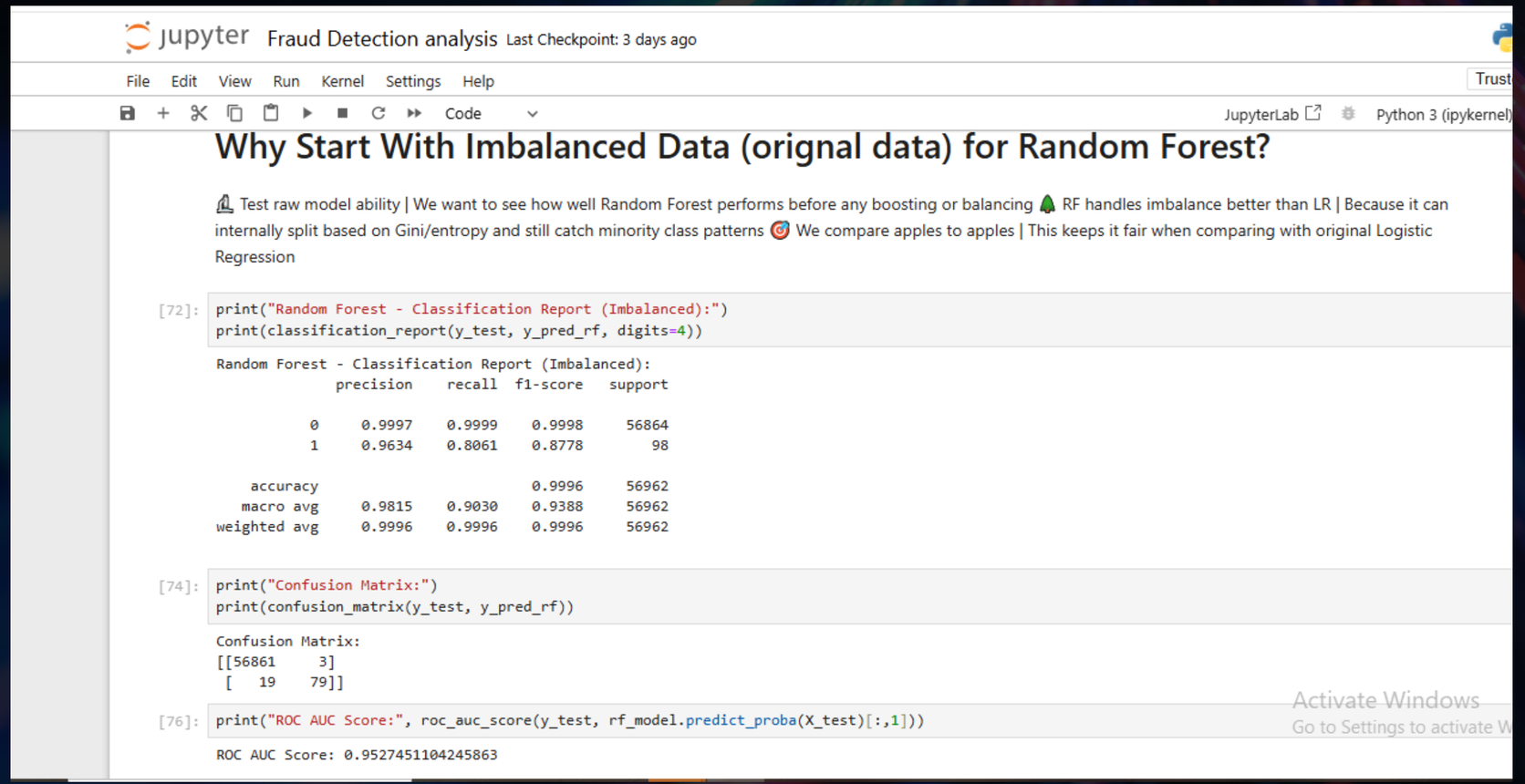
Model	Precision	Recall	F1-Score
Logistic Regression (raw)	82.9%	64%	72.4%
Logistic Regression + SMOTE	9.5%	91%	17.3%
Random Forest (raw)	96.3%	80.6%	87.8%
Random Forest + SMOTE	85.1%	81.6%	83.3%



This table highlights the performance trade-offs across different models. While Logistic Regression with SMOTE improved recall, it significantly reduced precision, leading to many false positives. Random Forest, even without any oversampling, achieved the best balance — combining high precision (96.3%) and strong recall (80.6%), resulting in the highest F1-score. These results support Random Forest (trained on imbalanced data) as the most reliable model for real-world fraud detection.

FINAL MODEL SELECTION

RANDOM FOREST (TRAINED ON ORIGINAL IMBALANCED DATA)



- BEST BALANCE OF RECALL AND PRECISION
- VERY FEW FALSE ALARMS (ONLY 3)
- STRONG F1-SCORE AND ROC AUC
- NO NEED FOR EXTRA OVERSAMPLING STEPS

BUSINESS IMPACT

- Catches majority of frauds
- Reduces false alarms — smoother experience for real customers
- Scalable and explainable model for real-world deployment
- Supports security teams in early fraud detection

The selected Random Forest model achieves a strong balance between catching fraudulent activity and minimizing false alarms. With over 80% fraud recall and only a few false positives, it ensures that suspicious transactions are flagged early without negatively impacting genuine users. This reduces financial risk, protects customer trust, and supports fraud investigation teams with accurate, scalable, and explainable predictions — making it suitable for both real-time systems and batch processing environments.

Thank You

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Data Analyst | Psychology Meets Data Science