Comprehensive Credit Card Fraud Detection Report

1. **Legit vs Fraudulent Transactions Shape:**

- Legitimate transactions: 284,315
- Fraudulent transactions: 492
- **Inference**: This large imbalance (less than 0.2% fraud) in the data can lead to a model biased toward predicting legitimate transactions. Careful handling of the imbalance is necessary to avoid misclassifications.

2. **Statistical Summary of Legitimate Transactions:**

- Mean transaction amount: $88.29
- Median (50%) transaction amount: $22.00
- Max transaction amount: $25,691.16
- **Inference**: Most legitimate transactions have small amounts, with a few high-value outliers. The spread of the amounts (observed through standard deviation) shows some high variability, but typical transactions are concentrated around a lower range (as shown by 25% at $5.65).

3. **Statistical Summary of Fraudulent Transactions:**

- Mean transaction amount: $122.21
- Median (50%) transaction amount: $9.25
- Max transaction amount: $2,125.87
- **Inference**: Fraudulent transactions tend to be smaller on average than legitimate ones. The 75th percentile is $105.89, indicating that most frauds involve relatively low amounts. However, the spread (standard deviation) is also high, meaning there are some higher-amount fraudulent transactions, but they are rare.

4. **Impact of Class Imbalance:**

- **Resampling Technique**: The code applies RandomUnderSampling to balance the dataset. This reduces the majority class (legitimate transactions) to match the fraud class size (492 instances).
- **Inference**: Balancing the dataset using undersampling is essential for ensuring that the logistic regression model has equal focus on both fraud and legitimate transactions. Without this, the model would likely favor legitimate transactions, given the original data’s imbalance.

Based on the **confusion matrix**, here are the key inferences:

1. **Confusion Matrix Analysis:**

- **True Positives (TP)**: 93 (fraudulent transactions correctly identified)
- **True Negatives (TN):** 97 (legitimate transactions correctly identified)
- **False Positives (FP):** 2 (legitimate transactions incorrectly identified as fraud)
- **False Negatives (FN):** 5 (fraudulent transactions incorrectly classified as legitimate)

Inference: The model performs well in identifying both fraud and legitimate transactions, with only a few misclassifications (2 false positives and 5 false negatives).

2. **Precision:**

- Precision for class 0 (legitimate transactions): 0.95
- Precision for class 1 (fraudulent transactions): 0.98

Inference: The model is very precise in detecting fraudulent transactions (98%). This means that when the model flags a transaction as fraudulent, it is correct 98% of the time. However, there is a slightly lower precision for legitimate transactions (95%), indicating a small number of false positives.

3. **Recall:**

- Recall for class 0 (legitimate transactions): 0.98
- Recall for class 1 (fraudulent transactions): 0.95

Inference: The model captures 95% of fraudulent transactions, which is good but leaves room for improvement. However, 98% of legitimate transactions are correctly identified, suggesting the model is more effective at identifying legitimate transactions than fraud.

4. **F1-Score:**

- F1-score for **class 0: 0.97**
- F1-score for **class 1: 0.96**

Inference: The F1-scores indicate strong overall performance for both classes, with the model striking a good balance between precision and recall.

5**. Accuracy:**

- Overall accuracy: 96%

Inference: The model achieves a high accuracy of 96%, which is a good result considering the typical challenge in fraud detection (class imbalance). The balanced nature of the resampled data helps the model achieve this high accuracy.

6. **Macro and Weighted Averages:**

- Macro avg precision, recall, and F1-score: 0.96
- Weighted avg precision, recall, and F1-score: 0.96

Inference: Both the macro and weighted averages are consistent across precision, recall, and F1-score, which indicates that the model handles both classes (fraud and legitimate) equally well after balancing the dataset.

Conclusion:

The model performs excellently, with high precision, recall, and F1-scores, particularly in detecting fraudulent transactions. However, the few false negatives (5) indicate that there are still some fraudulent transactions that go undetected. Further model tuning or incorporating more complex models could improve these results.

The outputs from the notebook highlight that fraudulent transactions are typically of smaller value, and undersampling is used to combat class imbalance. Logistic regression provides a baseline model, but further enhancements could be made with more advanced models like random forests or neural networks. The confusion matrix and performance metrics emphasize the trade-off between catching fraud and avoiding false positives, which is critical for fraud detection systems.