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## **Project Report: Detecting Anomalies in Credit Card Transactions**

### **1. Understanding the CUSUM Principle**

This project focused on using the **CUSUM (Cumulative Sum) algorithm**, which is a clever statistical method, to detect suspicious credit card transactions in real-time.

Unlike simpler monitoring tools that only look at one transaction at a time, CUSUM is powerful because it **keeps a running total** of how much transactions deviate from the normal average, or baseline ( $\mu_0$ ). This makes it really good at spotting small, consistent shifts that might be missed otherwise.

Essentially, CUSUM answers the question: "Has the typical transaction behavior changed enough to worry about?"

#### **The Core Idea**

CUSUM tracks two scores as each new transaction ( $x_t$ ) arrives:

1. **Positive CUSUM ( $S_t^+$ ):** This score goes up when transactions are consistently *too high* (looking for sudden spending increases).
2. **Negative CUSUM ( $S_t^-$ ):** This score goes up when transactions are consistently *too low* (looking for sudden spending decreases).

The score only increases if the transaction is outside a small margin defined by the **Tolerance Constant** ( $k$ ). If either score passes the **Decision Threshold** ( $h$ ), we get an alert. After an alert, the score is reset to zero, and we start tracking again.

### **2. The Data We Used**

We ran this analysis on a file called `transactions_100k_clean.csv`, which contains 100,000 simulated credit card transactions.

- **Normal Transactions:** Most transactions naturally hover around the expected average, which we set as  $\mu_0 = \$50.0$ .
- **Anomalous Transactions:** The data includes some transactions that were deliberately designed to be outliers—either much higher or much lower than normal—to simulate fraudulent activity.

### **3. Implementation and Key Findings**

Our Python program `cusum_detector.py` worked like a stream-processing tool, analyzing the data one transaction after another.

CUSUM Settings:

| Parameter                  | Value | What it Means   |
|----------------------------|-------|---|
| Reference Mean ( $\mu_0$ ) | 50.0  | The expected average transaction in dollars.                |
| Tolerance Constant ( $k$ ) | 5.0   | We ignore deviations of less than $k$ per transaction.      |
| Decision Threshold ( $h$ ) | 20.0  | The total accumulated deviation needed to trigger an alarm. |

Summary of Results

| Metric                                  | Result  |
|---|---------|
| Total Transactions Examined             | 100,000 |
| Total Anomalies Spotted by CUSUM        | 6,151   |
| Average Absolute Deviation of Anomalies | \$40.71 |

With our current settings, the system flagged 6,151 anomalies. Since the average deviation is over \$40, it confirms that the CUSUM successfully flagged transactions that were significantly different from the baseline of \$50.

A Few Examples of Anomalies Found:

| ID | Timestamp           | Amount | Deviation $S_t^+ / S_t^-$ | Type            |
|----|---------------------|--------|---------------------------|-----------------|
| 55 | 2025-01-01T00:00:54 | 296.98 | 246.98 241.98 ( $S_t^+$ ) | Positive (High) |
| 64 | 2025-01-01T00:01:03 | 26.81  | -23.19 32.64 ( $S_t^-$ )  | Negative (Low)  |

4. Discussion on How to Tune the CUSUM Detector

The performance of a CUSUM system depends heavily on how we set  $k$  and  $h$ . This is crucial for balancing speed and accuracy in a real system.

A. Tuning the Tolerance Constant ( $k$ )

$k$  dictates how much small variations are allowed before they even start to add up.

- **If you use a high  $k$  (e.g.,  $k=15$ ):** The system becomes less sensitive. It's great for reducing **False Alarms (FAR)**, but it will take longer to catch a genuine problem.
- **If you use a low  $k$  (e.g.,  $k=1$ ):** The system becomes hyper-sensitive, adding up even tiny deviations quickly. You'll catch issues faster (lower **Average Run Length, or ARL**), but you'll get many more alerts for normal process noise.

B. Tuning the Decision Threshold ( $h$ )

$h$  is the final alarm limit—how high the total cumulative score can go before we raise an alert.

- **If you use a high  $h$  (e.g.,  $h=50$ ):** The detector is very cautious. Only really large, persistent shifts will trigger an alarm. This is useful if you only care about critical changes.
- **If you use a low  $h$  (e.g.,  $h=5$ ):** The detector is much more aggressive. Even a short burst of suspicious activity will set it off. This is preferred when the cost of missing fraud is extremely high.

## 5. Summary

The CUSUM algorithm is a really effective solution for monitoring continuous data streams like financial transactions. It's efficient because it only requires keeping track of two numbers ( $S^+$  and  $S^-$ ), saving memory. Most importantly, it's designed to catch the subtle, gradual fraud schemes that would easily bypass simpler detection methods. By carefully tuning  $k$  and  $h$ , financial institutions can fine-tune the system to meet their specific security needs.