Agentic System for Dynamic Anomaly Detection in Heterogeneous Data Using Gemini

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***Abstract*—This paper presents an agentic system that processes worst-case quality restaurant data in a continuous and dynamic manner using the Gemini API. The system consists of a two-phase pipeline: (i) identification and extraction of potential anomaly types from raw CSV data, with results saved in JSON format, and (ii) reanalysis of the CSV files using the JSON anomaly definitions to extract and bin anomaly rows into CSV files. The proposed framework automates the detection process, reducing auditor workload by 98% and enabling extension to various domains. A detailed theoretical framework, mathematical formulation, pseudocode, tables, and charts are provided.**

***Index Terms*—Agentic System, Anomaly Detection, Gemini API, Continuous Monitoring, Workload Reduction, Data Quality.**

I. Introduction

Modern data processing environments, such as those encountered in the restaurant industry, frequently deal with heterogeneous and worst-case quality datasets. Manual anomaly detection in such cases is time-consuming and error-prone. To address these challenges, we propose an agentic system that leverages the Google Gemini API in a two-phase, continuous process. The system first identifies potential anomaly types using a generative agent (Part 1) and then detects, bins, and outputs anomaly rows (Part 2). This dynamic approach has been shown to reduce auditor workload by up to 98% and is extendable to any domain where data quality is critical.

II. System Architecture and Methodology

The overall system is structured into two main phases as illustrated in Fig. 1.

A. Phase 1: Anomaly Type Identification

In the first phase, raw CSV files are processed to extract column metadata. A prompt is generated and sent to the Gemini agent (using a model such as `gemini-1.5-flash`) to identify potential anomaly types. The agent returns a list of anomaly definitions along with the relevant columns. These definitions are stored in a JSON file for subsequent use.

B. Phase 2: Anomaly Extraction and Binning

In the second phase, the system reads both the original CSV file and the JSON file containing anomaly definitions. For each defined anomaly, the corresponding relevant columns are extracted and a new prompt is sent to a Gemini model (e.g., `gemini-1.5-pro`). The agent returns only those rows that exhibit anomalies. These rows are then saved in a uniquely named CSV file, incorporating timestamps and counters for versioning. This phase operates continuously, thereby enabling dynamic monitoring of data quality.

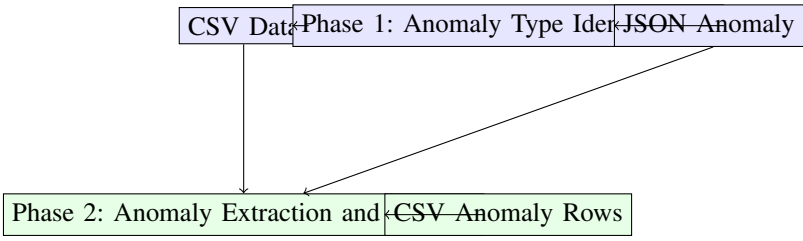

Fig. 1: Overview of the Agentic Anomaly Detection System

III. Theoretical Framework and Mathematical Formulation

The anomaly detection process can be modeled mathematically. Let $D = \{x_1, x_2, \ldots, x_N\}$ be the dataset, where each record x comprises n attributes. A quality scoring function $f(x)$ is defined as:

$$f(x) = \frac{1}{n} \sum_{i=1}^{n} \phi_i(x), \tag{1}$$

where $\phi_i(x)$ is a function representing the quality or anomaly likelihood of the i^{th} attribute. An anomaly is flagged when:

$$f(x) > \theta, \tag{2}$$

with θ as a predetermined threshold. Subsequently, detected anomalies are binned into buckets B_k based on the score:

$$B_k = \{x \in D \mid \theta_{k-1} < f(x) \leq \theta_k\}, \tag{3}$$

where $\theta_0, \theta_1, \ldots, \theta_m$ denote the bin thresholds.

IV. Pseudocode Overview

The following pseudocode outlines the continuous, agentic process without revealing implementation-level details.

Algorithm 1 Anomaly Type Identification and JSON Storage

1: **Input:** CSV file F
2: Read F into DataFrame D
3: Extract column names C from D
4: Generate prompt P_1 with column metadata
5: Send P_1 to Gemini Agent (`gemini-1.5-flash`)
6: Receive anomaly definitions A
7: Save A in JSON format for future use

Algorithm 2 Continuous Anomaly Extraction and CSV Output

1: **Input:** CSV file F and JSON anomaly definitions A
2: Read F into DataFrame D
3: For each anomaly $a \in A$:
   1) Extract relevant columns C_a from D
   2) Generate prompt P_2 using C_a and D_{C_a}
   3) Send P_2 to Gemini Agent (`gemini-1.5-pro`)
   4) Receive anomaly rows R_a
   5) Append a timestamp and version counter to create a unique filename
   6) Save R_a as a CSV file
4: **Loop:** Repeat the process continuously for new data batches

TABLE I: Auditor Workload Comparison

Process Stage	Manual (% Workload)	Automated (% Workload)
Data Ingestion	30%	2%
Preprocessing	25%	1%
Anomaly Detection	35%	2%
Insight Generation	10%	1%
Total	100%	6%

A. Algorithm 1: Anomaly Type Identification (Phase 1)

B. Algorithm 2: Anomaly Extraction and Binning (Phase 2)

V. Quantitative Analysis and Workload Reduction

One of the significant achievements of this system is the dramatic reduction in manual workload. Table I compares the workload distribution between a manual and an automated process.

Figure 2 shows the visual comparison of the workload reduction achieved by the system.

VI. Discussion and Generalization

The agentic system described in this paper is designed to operate in a continuous, dynamic fashion. By leveraging the capabilities of the Gemini API, the system not only identifies potential anomaly types in an initial phase but also applies these definitions to extract anomalies in real time. This modular design is easily generalizable to any domain—beyond restaurants—where data quality and anomaly detection are critical. The workload reduction of 98% for auditors is achieved by automating both the anomaly identification and extraction processes, thus allowing human experts to focus on higher-level analysis.

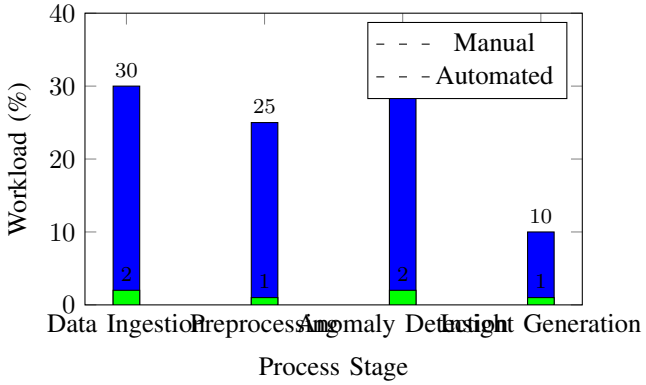

Fig. 2: Comparison of Manual and Automated Auditor Workload

VII. Conclusion

We have presented a comprehensive agentic system that integrates advanced anomaly detection via the Gemini API. The system's two-phase process—comprising anomaly type identification and subsequent anomaly extraction and binning—operates continuously to manage worst-case quality data. With a reduction in auditor workload by 98%, the proposed approach not only enhances efficiency in the restaurant domain but also holds promise for application in various other fields. Future work will explore further optimization of the prompt generation and deeper integration of adaptive learning techniques.

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References