

Gen AI agent for data engineering

**GenAI-Powered Data Engineering Agent**

**Project Overview**

In real-world data engineering workflows, data is often stored in **multiple formats and schemas**, making interoperability a challenge. This project will explore how **Generative AI (GenAI) can automate data format detection, schema inference, and serialization/deserialization** by generating Python code dynamically.

The goal is to build an **autonomous data engineering agent** that:

1. **Scans an S3 prefix (or a local folder for simplicity)** to identify files and their formats (e.g., JSON, CSV, Avro, XML, Parquet, etc.).
2. **Infers schemas** and groups files into distinct schema categories.
3. **Dynamically generates Python classes** that handle serialization and deserialization for each schema.
4. **Converts data into standardized formats** (e.g., Parquet for analytics, Avro for streaming).
5. **Performs data cleaning and transformation** before storage.
6. **Writes transformed data** to an S3 prefix (or a local folder for simplicity), partitioned by schema type.

This project integrates **LLM-based code generation, data engineering, and automation**, creating a pipeline that **writes and executes its own serialization/deserialization logic** based on the data it encounters.

**Why Synthetic Data?**

To **test and evaluate** the data engineering agent without relying on sensitive or proprietary datasets, we will use **synthetic data**—artificially generated datasets that mimic real-world data structures. Synthetic data allows us to:

- * **Control complexity** (e.g., structured vs. semi-structured data).
- * **Test edge cases** (e.g., nested JSON, inconsistent schemas, missing values).
- * **Benchmark performance** under different scenarios.

**Example Synthetic Data Files**

The project will generate synthetic data files in various formats, such as:

1\. JSON Files (Nested & Flat)

```
📄 `nested_data.json`  
  
json  
CopyEdit  
{  
  "user": {"id": 123, "name": "Alice", "email": "alice@example.com"},  
  "transactions": [  
    {"id": 1, "amount": 50.75, "timestamp": "2024-01-01T10:00:00Z"},  
    {"id": 2, "amount": 20.00, "timestamp": "2024-01-02T12:30:00Z"}  
  ]  
}
```

2\. CSV Files (Simple & Messy)

```
📄 `users.csv`  
  
csv  
CopyEdit  
`id,name,email,age`  
`1,John Doe,john@example.com,25`  
`2,Jane Smith,jane@example.com,`  
`3,Bob,,30`
```

3\. XML Data

```
📄 `products.xml`  
  
xml  
CopyEdit  
<products>  
  <product>  
    <id>101</id>  
    <name>Smartphone</name>  
    <price>699.99</price>  
  </product>  
  <product>  
    <id>102</id>  
    <name>Laptop</name>  
    <price>1299.99</price>  
  </product>
```

`</products>`

4\. Avro & Parquet Files

Binary files containing structured data, which the agent will generate and process dynamically.

Technical Components & Implementation

1. **Generative AI for Code Generation**

- * Use an **LLM (e.g., Llama 3.3, Nova, Claude 3.5 Haiku) to generate Python code** to write code for determining the schema of a file, write code for serialization/deserialization.
 - * Prompt engineering: "Write a Python class that reads XML and converts it to Parquet."
 - * Self-correction & validation using LLM-based evaluation.
 - * Have the LLM write all code as per PEP8, use PyDantic, and the usual good programming practices.

2. **Schema Inference & Transformation**

- * Extract schema from JSON, CSV, XML, and other formats.
- * Identify **duplicate fields, nested structures, and missing values**.
- * Standardize data into a **clean, structured format**.

3. **Execution & Automation**

- * **Write & execute** the LLM-generated Python code dynamically.
- * Automate the pipeline for **schema-based partitioning and storage** in S3.

Evaluation & Success Metrics

- * **Accuracy of schema detection** (comparison with ground truth).
- * **Correctness of generated serialization/deserialization code**.
- * **Efficiency of format conversion** (latency, data size reduction).
- * **Scalability tests** with large datasets.

Why This Project Matters?

This project demonstrates the potential of **GenAI in automating complex data engineering workflows**, reducing manual effort, and enabling AI-driven **data pipeline orchestration**.