SMRT Analytics using Semantic Kernel + RAG + KQL Database

Overview

This notebook implements an advanced analytics system for SMRT (Singapore Mass Rapid Transit) operations using a modern AI stack combining **PySpark**, **Semantic Kernel**, **RAG (Retrieval-Augmented Generation)**, and **KQL (Kusto Query Language)** database.

Architecture Components

1. PySpark

What it is: Distributed data processing framework for large-scale data analytics

Why used:

- Handle large volumes of telemetry data (2000+ records)
- Perform distributed computations for feature engineering
- Integrate with Fabric Lakehouse and Delta tables
- Enable scalable data transformations and aggregations

2. Semantic Kernel

What it is: Microsoft's AI orchestration framework for integrating LLMs into applications

Why used:

- Standardized interface to OpenAI models
- Manage AI services (chat completion, embeddings)
- Enable plugin architecture for extensibility
- Provide async/await pattern for efficient AI calls

3. RAG (Retrieval-Augmented Generation)

What it is: AI technique that retrieves relevant documents/data and uses them to augment LLM prompts

Why used:

- Ground AI responses in actual operational data
- Prevent hallucination by providing factual context
- Enable domain-specific responses for SMRT operations
- Combine vector search with semantic understanding

4. KQL Database

What it is: Kusto Query Language database for time-series and telemetry data

Why used:

- Optimized for time-series operational data
- Fast ingestion and querying of telemetry streams
- Integration with Microsoft Fabric ecosystem
- Real-time analytics capabilities

Code Breakdown

1. Initialization & Dependencies

```
# Key imports for the AI stack
from pyspark.sql import SparkSession, DataFrame
from openai import OpenAI
import semantic_kernel as sk
from semantic_kernel.connectors.ai.open_ai import OpenAIChatCompletion, OpenAITextEmbedding
```

Output: Environment setup with OpenAI API configuration and model definitions.

2. Synthetic Data Generation

```
def create_smrt_synthetic(num_records: int = 500)-> DataFrame:
    # Generates realistic SMRT operational data
    train_ids = [f"TRAIN-{i:03d}" for i in range(1, 31)]
    lines = ["North-South", "East-West", "Circle", "Thomson-East Coast"]
```

```
    # ... data generation logic
```
Sample Output:

text

```
+-------------------------+-----------------+-------+---------+----------+------------+--------------+-------------+-------+----------+------------+---------------+------------
|timestamp                |line             |station |train_id |temperature_c|vibration_level|delay_minutes|maintenance_status|
+-------------------------+-----------------+-------+---------+------------+--------------+-------------+---------------+----------------------------------------------------
|2025-10-04 21:16:50.354495|Circle           |STN-033|TRAIN-007|39.39       |0.951         |0.34         |Anomaly        |
|2025-10-08 00:16:50.354495|Thomson-East Coast|STN-044|TRAIN-023|30.92      |2.698         |0.11         |Anomaly        |
+-------------------------+-----------------+-------+---------+------------+--------------+------------+----------------+----------------------------------------------------
```

Why: Creates realistic training data with:

- Multiple train lines and stations
- Equipment telemetry (temperature, vibration)
- Operational metrics (delays, passenger counts)
- Maintenance status flags

3. Data Enrichment & Feature Engineering

```
smrt_enriched_df = smrt_df \
    .withColumn("efficiency_index",
               round(col("passenger_count") / (col("delay_minutes") + 1), 2)) \
    .withColumn("overheat_flag", when(col("temperature_c") > 38, True).otherwise(False))
```

Features Added:

- efficiency_index: Operational efficiency metric
- overheat_flag: Temperature anomaly detection
- high_vibration_flag: Mechanical stress indicator
- high_load_flag: Passenger capacity alerts
- operational_context: Human-readable context for LLMs
- metrics_vector: Embedding vectors for semantic search

4. KQL Database Integration

```
KQL_CLUSTER = "https://trd-jqrttn76947phe10ts.z4.kusto.fabric.microsoft.com"
KQL_DB = "SMRT_Operations_DB"
KQL_TABLE = "TrainTelemetry"

smrt_enriched_df.write \
    .format("com.microsoft.kusto.spark.synapse.datasource") \
    .options(**kustoOptions) \
    .mode("append") \
    .save()
```

Output:

```
✓ Data prepared for KQL ingestion
  Records to ingest: 2,000
✓ Data saved to Delta table: SMRT_operations_staging
```

Why KQL:

- Time-series optimization for telemetry data
- Fast ingestion of streaming data
- Integration with Power BI for visualization
- Real-time query capabilities

5. SMRT RAG System Implementation

Core Components:

A. Memory Initialization

```
def _initialize_memory(self):
    recent_data = self.df.filter(
        (col("maintenance_status") == "Anomaly") |
```

```
        (col("temperature_c") > 38.0) |
        (col("vibration_level") > 2.0) |
        (col("delay_minutes") > 10)
    ).orderBy(col("timestamp").desc()).limit(200).collect()
```

Output: ✓ Loaded 200 operational records into memory

B. Vector Search (Semantic Search)

```
def vector_search(self, query: str, top_k: int = 5)-> List[Dict]:
    # Heuristic-based search for operational context
    if "maintenance" in q or "anomaly" in q:
        condition = col("maintenance_status") == "Anomaly"
    elif "temperature" in q or "overheat" in q:
        condition = col("temperature_c") > 35.0
    # ... more conditions
```

Sample Search Output:

→ Performing semantic search for: 'maintenance anomalies'

✓ Found 5 relevant records

1. 2025-10-10 13:24:50.354495 | Thomson-East Coast | STN-036 | TRAIN-013 | T=32.55C Vib=2.257 Delay=0.17s Status=Anomaly
2. 2025-10-10 13:18:50.354495 | Thomson-East Coast | STN-043 | TRAIN-023 | T=28.24C Vib=2.634 Delay=0.44s Status=Anomaly

C. Prompt Augmentation

```
def augment_prompt(self, query: str, context: List[Dict])-> str:
    enhanced = f"""You are an expert transport operations AI assistant for SMRT.

RELEVANT OPERATIONAL RECORDS:
{context_str}

USER QUERY: {query}
"""
```

D. AI Response Generation

```
async def generate_response_async(self, enhanced_prompt: str)-> str:
    result = await self.chat_service.get_chat_message_content(
        chat_history=chat_history,
        settings=self.chat_service.get_prompt_execution_settings_class()(
            temperature=0.5, max_tokens=800
        )
    )
```

6. Example RAG Workflow Output

Query: "temperature and vibration anomalies"

AI Response:

1) Situation Analysis:

The operational records indicate several instances of temperature and vibration anomalies across different lines and stations. The temperature anomalies range from 26.77°C to 41.5°C, and the vibration anomalies range from 0.195 to 2.634.

2) Key Findings and Observed Patterns:

The temperature anomalies are not confined to a specific line or station, indicating a widespread issue. The highest temperature recorded was 41.5°C on the Thomson-East Coast line.

3) Actionable Recommendations:
Short-term: Initiate immediate inspection and maintenance of the affected track and train assets.
Mid-term: Conduct a thorough review of the maintenance protocols and schedules.

4) Suggested Data/Feature Improvements:
Consider collecting more granular data such as the age and maintenance history of the assets.

Key Benefits of This Architecture

1. Operational Intelligence

- Real-time anomaly detection
- Predictive maintenance insights
- Route optimization recommendations
- Demand forecasting capabilities

2. Scalability

- PySpark handles large data volumes
- KQL optimized for time-series data
- Semantic Kernel enables AI orchestration
- RAG provides contextual accuracy

3. Domain Specialization

- SMRT-specific operational context
- Transportation industry metrics
- Maintenance and reliability focus
- Passenger experience optimization

4. Production Readiness

- Error handling and fallbacks
- Async/await patterns for performance
- Multiple storage backends (KQL + Delta)
- Modular, extensible architecture

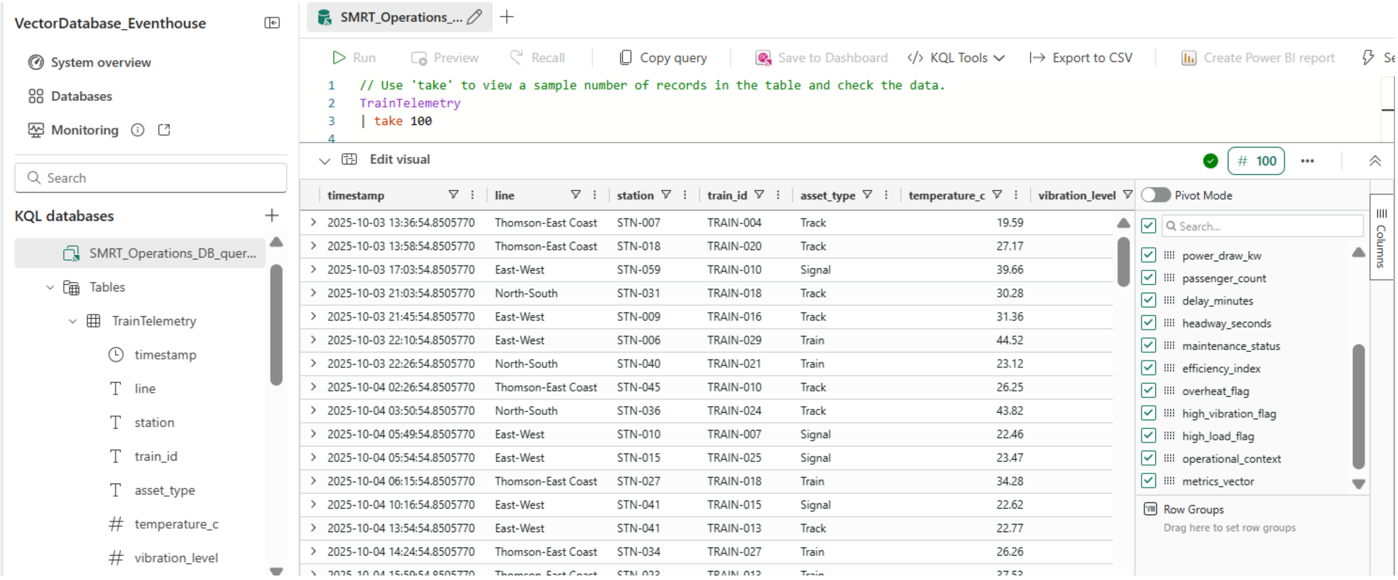
Use Cases Enabled

1. **Predictive Maintenance**: Identify equipment failures before they occur
2. **Operational Efficiency**: Optimize train schedules and resource allocation
3. **Passenger Experience**: Reduce delays and improve service quality
4. **Asset Management**: Monitor train and track health in real-time
5. **Strategic Planning**: Data-driven decisions for network expansion

This implementation demonstrates a modern AI-powered analytics platform specifically tailored for mass transit operations, combining the scalability of big data technologies with the intelligence of large language models.

Outputs

```
================================================================================
LOAD DATA TO KQL DATABASE - SMRT OPERATIONS
================================================================================
✓ Data prepared for KQL ingestion
  Records to ingest: 2,000
✓ Data saved to Delta table: SMRT_operations_staging
Total records prepared for ingestion: 2000
```



timestamp	line	station	train_id	asset_type	temperature_c	vibration_level
2025-10-03 13:36:54.8505770	Thomson-East Coast	STN-007	TRAIN-004	Track	19.59	
2025-10-03 13:58:54.8505770	Thomson-East Coast	STN-018	TRAIN-020	Track	27.17	
2025-10-03 17:03:54.8505770	East-West	STN-059	TRAIN-010	Signal	39.66	
2025-10-03 21:03:54.8505770	North-South	STN-031	TRAIN-018	Track	30.28	
2025-10-03 21:45:54.8505770	East-West	STN-009	TRAIN-016	Track	31.36	
2025-10-03 22:10:54.8505770	East-West	STN-006	TRAIN-029	Train	44.52	
2025-10-03 22:26:54.8505770	North-South	STN-040	TRAIN-021	Train	23.12	
2025-10-04 02:26:54.8505770	Thomson-East Coast	STN-045	TRAIN-010	Track	26.25	
2025-10-04 03:50:54.8505770	North-South	STN-036	TRAIN-024	Track	43.82	
2025-10-04 05:49:54.8505770	East-West	STN-010	TRAIN-007	Signal	22.46	
2025-10-04 05:54:54.8505770	East-West	STN-015	TRAIN-025	Signal	23.47	
2025-10-04 06:15:54.8505770	Thomson-East Coast	STN-027	TRAIN-018	Train	34.28	
2025-10-04 10:16:54.8505770	East-West	STN-041	TRAIN-015	Signal	22.62	
2025-10-04 13:54:54.8505770	East-West	STN-041	TRAIN-013	Track	22.77	
2025-10-04 14:24:54.8505770	Thomson-East Coast	STN-034	TRAIN-027	Train	26.26	

PySpark (Python) Environment SemanticKernel Data Wrangler Copilot

```python
rag = SMRTRAGSystem(smrt_df, OPENAI_API_KEY)

# run vector_search locally to inspect the 5 records immediately (sync)
relevant_context = rag.vector_search("maintenance anomalies", top_k=5)
print("\nSample records returned by vector_search():", flush=True)
for i, r in enumerate(relevant_context, 1):
    print(f"{i}. {r['timestamp']} | {r['line']} | {r['station']} | {r['train_id']} | T={r['temperature_c']}C Vib={r['vibration_level']} Delay={r['delay_minutes']}s Sta
print("\n")

enhanced_prompt = rag.augment_prompt("temperature and vibration anomalies", relevant_context)
response = await rag.generate_response_async(enhanced_prompt)
print(response)
```

[12] ✓ 17 sec - Command executed in 17 sec 71 ms by TAN JIA HUI, JOY on 9:41:32 PM, 10/10/25 PySpark (Python)

Spark jobs (2 of 2 succeeded) Resources Log

```
→ Initializing operational memory...
✓ Loaded 200 operational records into memory
✓ SMRT RAG System initialized with OpenAI.
  Chat Model: gpt-4
  Embedding Model: text-embedding-ada-002
→ Performing semantic search for: 'maintenance anomalies'
✓ Found 5 relevant records

Sample records returned by vector_search():
1. 2025-10-10 13:24:50.354495 | Thomson-East Coast | STN-036 | TRAIN-013 | T=32.55C Vib=2.257 Delay=0.17s Status=Anomaly
2. 2025-10-10 13:18:50.354495 | Thomson-East Coast | STN-043 | TRAIN-023 | T=28.24C Vib=2.634 Delay=0.44s Status=Anomaly
3. 2025-10-10 12:57:50.354495 | North-South | STN-013 | TRAIN-015 | T=41.3C Vib=0.195 Delay=0.69s Status=Anomaly
4. 2025-10-10 12:38:50.354495 | Thomson-East Coast | STN-028 | TRAIN-005 | T=26.77C Vib=2.158 Delay=1.86s Status=Anomaly
5. 2025-10-10 12:18:50.354495 | Thomson-East Coast | STN-027 | TRAIN-026 | T=41.5C Vib=1.73 Delay=2.41s Status=Anomaly
```

1) Situation Analysis:
The operational records indicate several instances of temperature and vibration anomalies across different lines and stations. The temperature anomalies range from 26.77°C to 41.5°C, and the vibration anomalies range from 0.195 to 2.634. These anomalies are spread across the Thomson-East Coast and North-South lines, and affect both track and train assets.

2) Key Findings and Observed Patterns:
The temperature anomalies are not confined to a specific line or station, indicating a widespread issue. The highest temperature recorded was 41.5°C on the Thomson-East Coast line at STN-027 for TRAIN-026 [2025-10-10 12:18:50.354495]. The lowest temperature anomaly was 26.77°C, also on the Thomson-East Coast line at STN-028 for TRAIN-005 [2025-10-10 12:38:50.354495]. The vibration anomalies are also spread across the network, with the highest recorded at 2.634 on the Thomson-East Coast line at STN-043 for TRAIN-023 [2025-10-10 13:18:50.354495].

3) Actionable Recommendations:
Short-term: Initiate immediate inspection and maintenance of the affected track and train assets to identify and rectify the causes of these anomalies. Implement real-time monitoring systems to detect and address such anomalies promptly.

Mid-term: Conduct a thorough review of the maintenance protocols and schedules to ensure that they are adequate and effective. Consider upgrading or replacing aging infrastructure that may be contributing to these anomalies.

4) Suggested Data/Feature Improvements:
To improve the predictive models, consider collecting more granular data such as the age and maintenance history of the assets, the ambient temperature and humidity, and the load on the train at the time of the anomaly. Machine learning algorithms could also be used to identify patterns and predict future anomalies based on these additional features.