

Current progress and limitations of GenAI in the field of Data Management

Evaluating GenAI using Willibald



Sebastian Bruns
Hamburg, April 12th 2024



We prompted ...

“Draw a picture of a Data vault driven by Artificial intelligence”

Your speaker

Sebastian Bruns
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Eraneos Analytics

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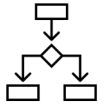


The speaker is a **technology enthusiast** and loves to discuss DevOps and CI/CD topics

Sebastian's background is **Computer Science** with focus on **Data Engineering**

- 2007 Oracle
- 2010 SAP Business Warehouse
- 2014 SQL Analysis Services
- 2015 NoSQL Databases
- 2016 "Big Data" / ELT
- 2019 Cloud Engineering

Agenda



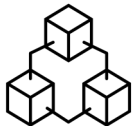
The power of Generative AI (GenAI) in automation

How we use Large Language Models (LLMs) to tackle complex automation tasks



GenAI applications in Data Warehouse Automation (DWA)

Taking on the Willibald challenge: Evaluation of LLMs in the realm of the DWA benchmark dataset



Looking Ahead

What we expect from the development in the field of GenAI in 2024 and beyond

We were experts in Machine Learning long before the rise of GenAI. Now we see the opportunity to solve many problems in a faster and more cost efficient way.

150+
Data & AI Top Experts

500+
Data & AI Projects

150+
Customers in various industries

Electricity Price Forecasting Energy Supplier

Lightblue Project - Electricity Price Forecasting

Electricity Price forecasting for European day-ahead markets

Industry: Energy	Year: 2023
Country: Germany	

Customer

One of Germany's largest electricity providers, clients in various sectors need their electricity use in the forthcoming period of forecasting. However, especially in winter, the power plants and gas turbine capacity are limited.

Initial Situation

- Power plant facilities need to constantly decide on the optimal generation capacity to be made available for the next period. The decision depends on forecast accuracy and the current market situation.
- Forecast accuracy is crucial due to the high energy prices and associated costs.

Approach and Solution

- Development of machine learning and deep learning models to predict future electricity demand.
- Use of advanced optimization techniques to determine the optimal generation capacity.
- Integration of real-time data and weather forecasts into the forecasting model.
- Regular model retraining and validation to ensure accuracy.

Impact

- Power plants can adjust their output and generate more revenue.
- Forecasting accuracy can be improved and costs reduced.
- CO₂ emissions are potentially reduced.



Predictive Maintenance MRO Service Provider

Lightblue Project - Predictive Maintenance

State-of-the-art predictive maintenance for aircraft sensor data

Industry: Industry/MRO	Year: 2018 - 2023
Country: Germany	

Customer

A leading airline service provider developed an aircraft sensor platform.

General customers are sending full flight sensor data. The Customer's Monitoring tool is required to provide live maintenance to define the correct demand.

Initial Situation

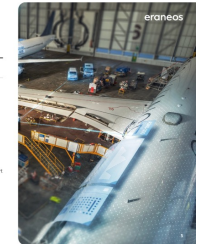
- Customers' flight sensor data is too large to be processed in real-time.
- The data volume is too high for the current computing power of the MRO category.

Approach and Solution

- On-premises cluster was migrated fully to cloud-based infrastructure using AWS.
- Implementation of machine learning models for predictive maintenance.
- Integration of real-time data streams and AI-powered analytics for predictive maintenance.
- Implementation of edge computing for data processing.
- Full integration with external systems.

Impact

- Implementation provided real-time data of the actual sensor data.
- Reduction of maintenance costs and improved aircraft availability.
- Improved safety and operational performance.
- Cost reduction for the MRO category.



AI in Train Disposition Railway

Lightblue Project - AI in Train Disposition

Train dispatching is optimized by a digital twin and machine learning

Industry: Industry	Year: 2020 - 2023
Country: Germany	

Customer

A railway company currently faces significant challenges in train dispatching and scheduling. Responses for the railway are of high complexity. The customer is looking for a solution to optimize train dispatching and scheduling. Best operational efficiency and cost reduction in the railway industry are the main goals.

Initial Situation

In a highly complex network, numerous real-time operational decisions are made. The complexity of these decisions is high. The customer is looking for a solution to optimize train dispatching and scheduling. Best operational efficiency and cost reduction in the railway industry are the main goals.

Approach and Solution

- Creating a digital twin to integrate real-time data and optimize train dispatching and scheduling.
- Implementation of machine learning models for predictive maintenance and scheduling optimization.
- Integration of real-time data and AI-powered analytics for predictive maintenance.
- Full integration with external systems.

Impact

- Significant reduction in train delays and operational costs.
- Improved safety and operational performance.
- Cost reduction for the railway industry.



Legacy DWH Migration Global Shipping Company

Transport & Logistics - Data Hub

Migration from a monolithic IT landscape to a data mesh architecture with a modern tech stack

Industry: Transport & Logistics	Year: 2023
Country: Germany	

The Client

A leading international logistics company, committed to innovation and digital transformation. The company is looking for a solution to optimize its data management and analytics capabilities. The customer is looking for a solution to optimize its data management and analytics capabilities. The customer is looking for a solution to optimize its data management and analytics capabilities.

The Challenge

- Legacy IT landscape based on mainframe and relational databases.
- Complex data integration and data silos.
- High operational costs and slow time-to-market.
- Need for real-time data processing and analytics.

The Solution

- Migration to a modern cloud-based data mesh architecture.
- Implementation of a modern data stack including data lakes, data warehouses, and data marts.
- Integration of real-time data and AI-powered analytics for predictive maintenance.
- Full integration with external systems.

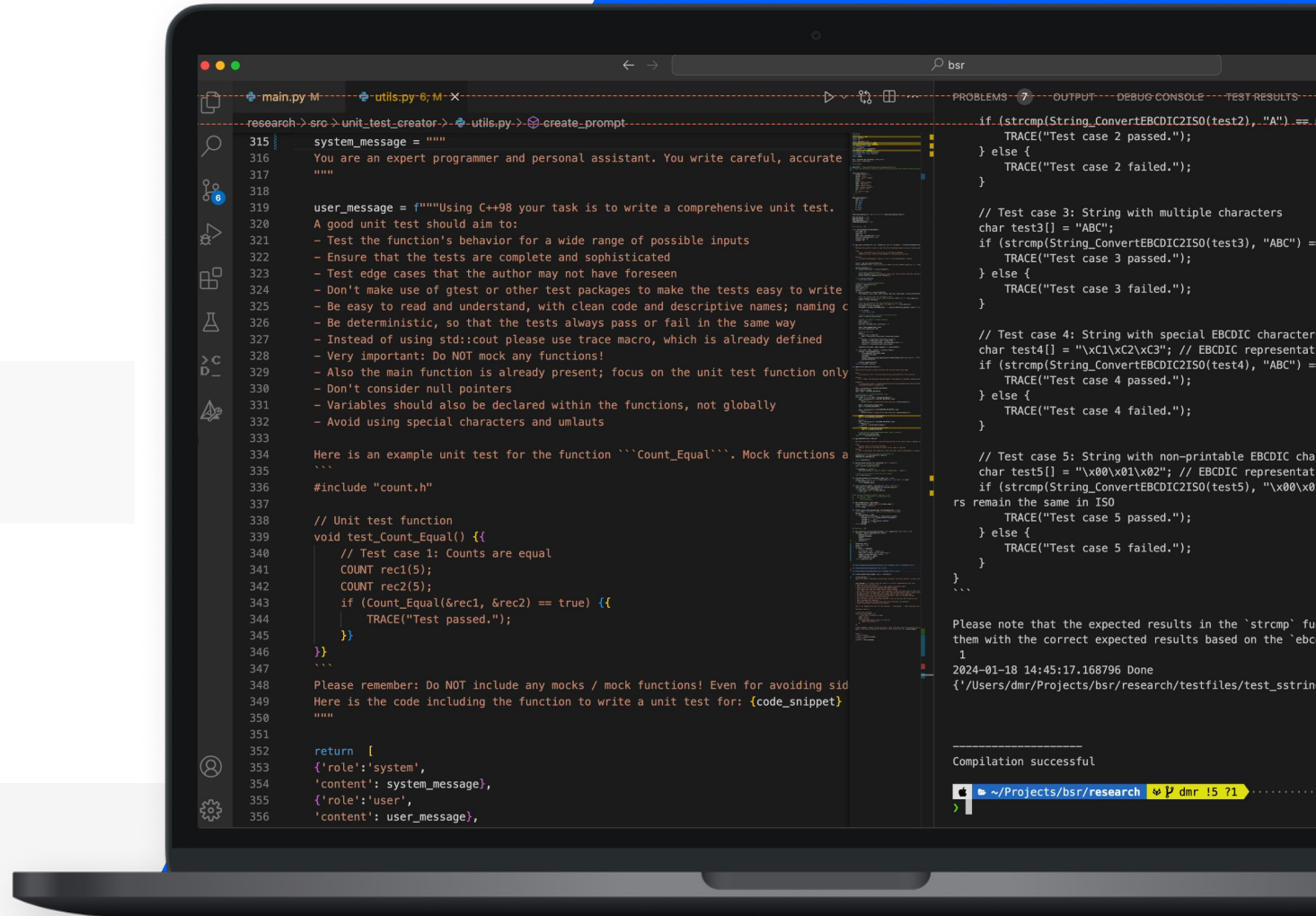
The Effect

- Significant reduction in operational costs and improved data management.
- Improved safety and operational performance.
- Cost reduction for the shipping industry.



The power of Generative AI (GenAI) in automation

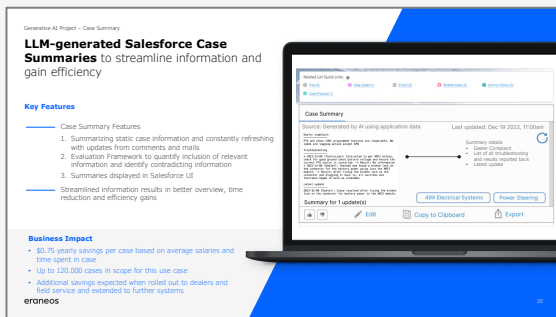
How we use Large Language Models (LLMs) to tackle complex automation tasks



Eraneos has successfully **leveraged GenAI to automate migration and evaluation tasks** across multiple problem domains and industries

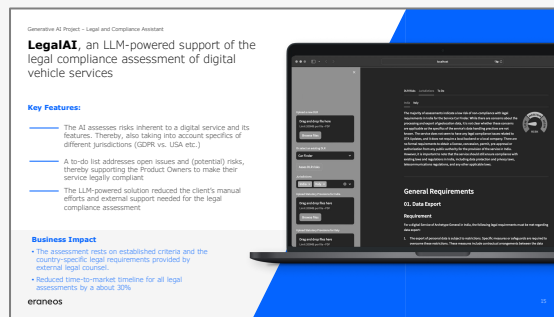
+10 more GenAI projects

LLM-generated Case Summaries Commercial Vehicles OEM



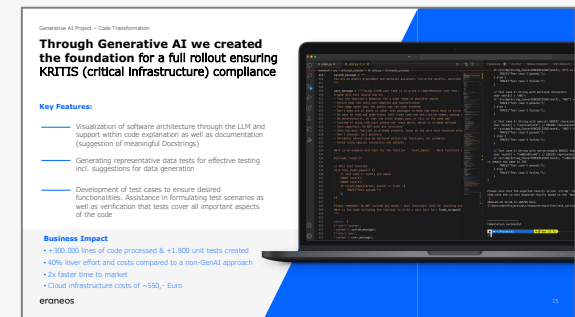
Identifying closed tickets that should not have been closed by the service desk

Legal and Compliance Assistant Automotive



Highlight legal regulations for global rollout of products

Code Transformation Public Sector



We have auto-created 1800 Unit Tests on a legacy C++ codebase with >300 K lines of code

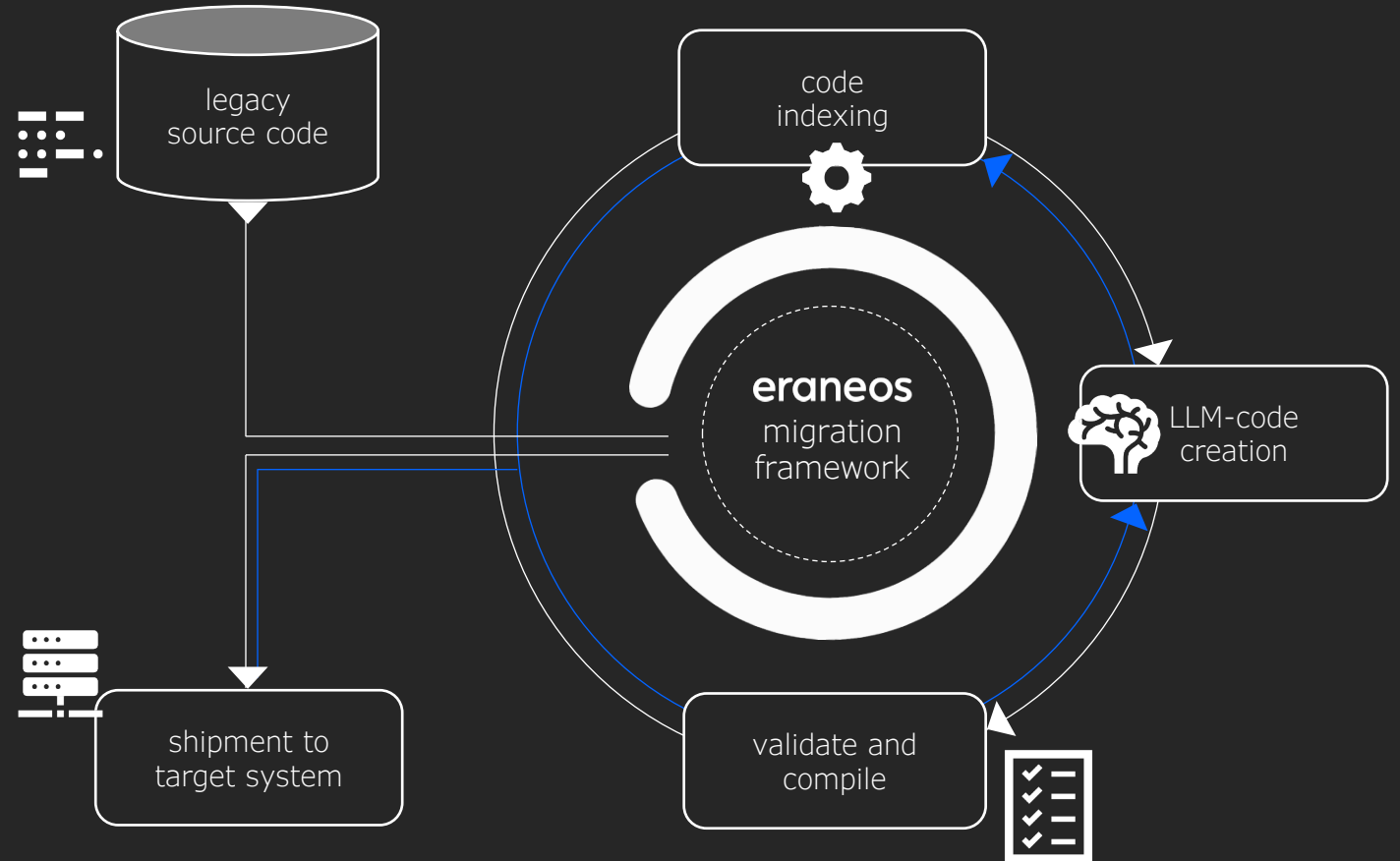
Eraneos Code Migration Framework as the core building block for a scalable, reliable and cost-efficient automation around LLMs

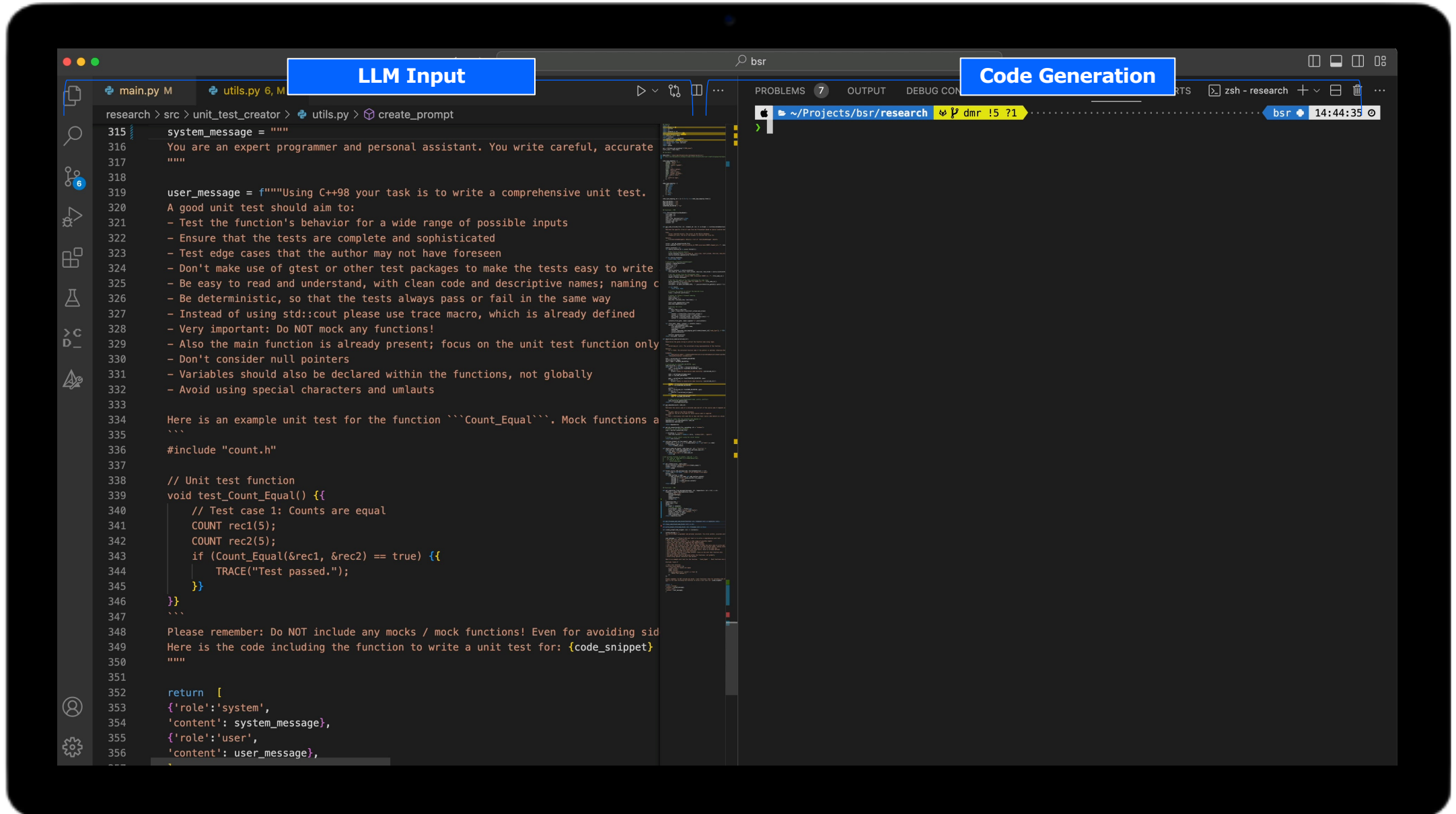
1800+
Unit Test generated

550€
GenAI Bill

80%
Cost & Time Saving

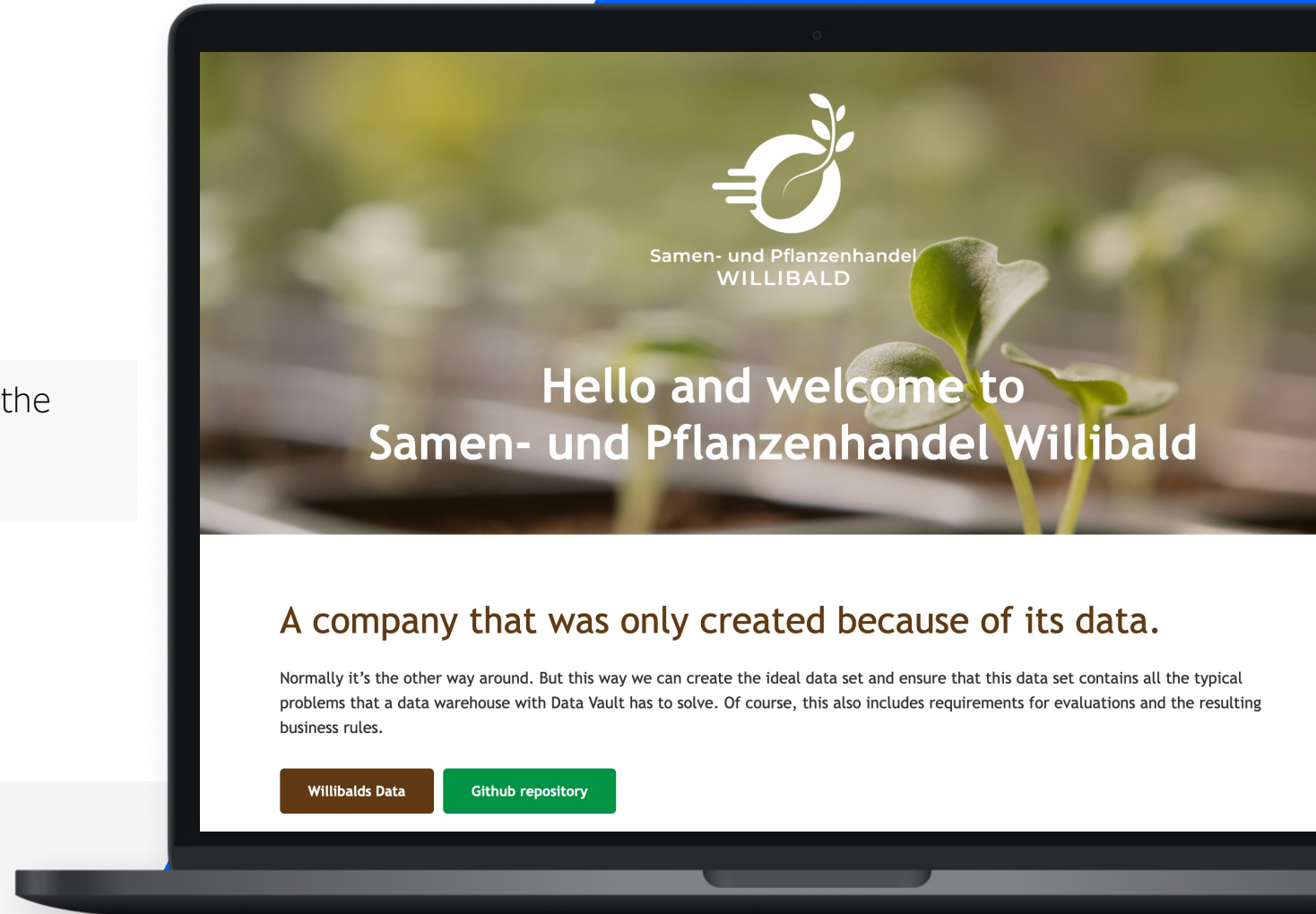
eraneos





GenAI applications in Data Warehouse Automation (DWA)

Taking on the Willibald challenge: Evaluation of LLMs in the realm of the DWA benchmark dataset



The **strength of general-purpose LLMs** is their knowledge and universal applicability to a wide variety of problem statements



Explain & Understand

- Write comments and documentation

DEMO

Create field mappings

DEMO

Explain the content data and scripts

- Outline data lineage in legacy systems



Assess & Monitor

- Evaluate the functionality of the data model (potentially from business analysts)
- Assess the quality of the data in the database
- Automatically detect anomalies and fraud



Generate & Propose

DEMO

Create data model from raw data

- Generation of test data (synthetic data)

DEMO

Create data model from an ERD

- Recommend refactorings (indexes and constraints and performance improvements)



Optimize & Migration

DEMO

Migrate the data modeling

- Write data migrate scripts
- Modernize the code base
- Resolve dependencies between (e.g. normalized stacked views)

Creating a basic setup using the markup file and **deducting information about the business context** to build an **initial data vault model**



Using the [**readme en.md**] markup file as initial starting point

The initial data

The company Willibald is a traditional house and trades with seeds and plants via the internet. In the past, the company sold exclusively via a catalogue. The catalogue was quickly terminated in 2000, a full 4 years after the webshop was opened. Willibald was the first plant supply shop on the internet and is still proud of it today.

When ordering via the v simple process, the cus

The evaluation

The desired report for Willibald includes the following key figures on a granular level:

- Quantity The quantity of ordered products per product. This key figure is taken directly from the order item.
- Revenue The amount of money to be paid for the ordered product quantity. For this purpose, the quantity and price from the order item are multiplied and then the discount is deducted.
- Open order A 1 to indicate briefly whether this order is still open.
- Completely delivered order A 1 to indicate briefly whether this order has already been delivered in full.
- Difference between request date and delivery date in days If each item has been delivered, the deviation is calculated from the order.requestdate and the last delivery.deliverydate. If the delivery was made before the requested date, the deviation is negative. Willibald wants to deliver on time, because too early deliveries also cause problems for the customer (care of seedlings).



Text Input: If we were having larger text input (e.g. documents) we would exceed the token limit at some point and go for RAGs

We prompted ...

"Give me in brief explanation what Willibald is about"

"Create a Data Vault model reflecting Willibaldds business processes"

"What challenges do you see modeling the Willibald data?"
"What customers have no phone number?"

This file provides information about the data and data model for a fictitious company called 'Samen und Pflanzenhandel Willibald' that trades seeds and plants online. It explains the company's history, its ordering and delivery process, and its data model. It also details the company's data model. Creating a Data Vault model based on the information provided would involve the following steps:

1. **Hubs:** These are the core business keys in your system. In this case, the hubs would likely be `Customer`, `Product`, `Order`, `ClubPartner`, and `Delivery`.
2. **Links:** These represent the relationships between business keys. Possible links in this scenario could be `Customer-Order`, `Order-Product`, `Customer-ClubPartner`, `Order-Delivery`, and `Customer-Delivery`.
3. **Satellites:** These hold descriptive data (attributes) about the business keys and their relationships. For example, a `Customer` satellite might hold data like `CreditCard`, `ValidTo`, and `CreditCard Company`. An `Order` satellite could hold `Quantity`, `Price`, `Discount`, `RequestDate`, `DeliveryDate`, and `DeliveryStatus`.
4. **Business Vault:** This layer would handle the necessary transformations and business rules mentioned, such as unifying the orders of the association partners and assigning roadshow orders to the customers.

"Incomplete Data" and "Data Quality: There are some fields that appear to have missing"

We want to know **how knowledgeable general-purpose LLMs are about modeling techniques** and how they implement them



The [Lieferung] Data from Willibald's "Webshop Testdata 1" contains references to other tables (e.g. [Bestellung]) as well as actual data (e.g. [LieferDatum])

BestellungID	PosID	LieferAdrID	LieferDienstID	LieferDatum
1	1	1	1	06.03.2022
1	2	2	1	07.03.2022
1	3	1	3	08.03.2022
2	4	120	8	07.03.2022
2	5	1	10	09.03.2022
2	6	120	12	05.03.2022

This is new: LLMs understands the *meaning* of the data fields and model them accordingly.

Non-deterministic: Column names are often, but not always deduced correctly.

We prompted ...

"Model this dataset as **star schema** with fact and dimension tables."

"Model this dataset as **Data Vault** with hubs, links and satellites."

"Model this dataset as **3rd Normal Form**."

RESULT

1. Fact Table:

- Fact_Lieferung (Keys: Lieferung_ID, Produkt_ID, Kunde_ID, Datum_ID, Attributes: Menge)

2. Dimension Tables:

- Dim_Produkt (Key: Produkt_ID)
- Dim_Kunde (Key: Kunde_ID)
- Dim_Datum (Key: Datum_ID, Attributes: Day, Month, Year)

Based on the provided data, here's how it could be modeled in Data Vault

1. Hubs:

- Hub_Lieferung (Key: Lieferung_ID)
- Hub_Produkt (Key: Produkt_ID)
- Hub_Kunde (Key: Kunde_ID)
- Hub_Datum (Key: Datum)

2. Links:

- Link_Lieferung_Produkt (Keys: Lieferung_ID, Produkt_ID)
- Link_Lieferung_Kunde (Keys: Lieferung_ID, Kunde_ID)
- Link_Lieferung_Datum (Keys: Lieferung_ID, Datum)

3. Satellites:

- Satellite_Lieferung (Parent: Hub_Lieferung, Attributes: Menge)
- Satellite_Produkt (Parent: Hub_Produkt, Attributes: None in this case)

1. Data Warehouse:

- Lieferung (Attributes: Lieferung_ID, Produkt_ID, Kunde_ID, Datum, Menge)
- Produkt (Attributes: Produkt_ID)
- Kunde (Attributes: Kunde_ID)
- Datum (Attributes: Datum_ID, Day, Month, Year)

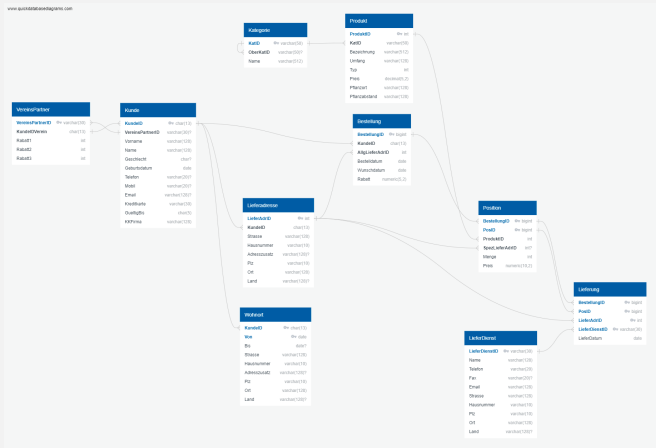
2. Data Marts:

- Lieferung Data Mart (Attributes: Lieferung_ID, Produkt_Name, Kunde_Name, Datum, Menge)
- Produkt Data Mart (Attributes: Produkt_ID, Produkt_Name)
- Kunde Data Mart (Attributes: Kunde_ID, Kunde_Name)
- Datum Data Mart (Attributes: Datum_ID, Day, Month, Year)

We have been provided the **source table UML diagram** and wish to create the data vault model including build scripts and field mappings

TASK → PROMPT → RESULT

We provide the LLM the file [webshop-willibald.png] without providing any more information than the prompt



Only two years back, this kind of image recognition task would have taken us a full project!

We prompted ...
 "Create a data vault model from this UML diagram"

"Create the SQL statements that generate the data vault"

"Draw me a mapping of the fields between the source and the target model"

Hube on the core business concepts in the model. In this diagram, these would correspond to the "Kunde" (Customer), "Produkt" (Product), "Bestellung" (Order), "Lieferadresse" (Delivery Address), "Kategorie" (Category), "WarenPartner" (Club Partner) and "Lieferadresse" (Delivery Address).

Satellites contain the descriptive details (attributes) of each Hub. For example, for the "Kunde" Hub, there would be a Satellite containing "Vorname" (First Name), "Name" (Last Name), "Geschlecht" (Gender), etc.

Links connect Hubs together and represent transactions or interactions. In this schema, you might have links such as between "Kunde" and "Bestellung" to represent an order being placed by a customer, or between "WarenPartner" and "Bestellung" to represent which products were in an order.

To illustrate, I'll outline what some of the Data Vault components could look like based on the UML diagram:

- Hub_Kunde with a Satellite containing Vorname, Name, Geschlecht, etc.
- Hub_Produkt with a Satellite containing Bezeichnung, Umfang, etc.
- Hub_Bestellung with a Satellite containing Bestelldatum, Warenpartner, Rabatt, etc.
- Hub_Lieferung with a Satellite containing Lieferdatum.
- Hub_Kategorie with a Satellite containing Name.
- Link_Kunde_Bestellung to relate the "Kunde" with their "Bestellung"
- Link_Bestellung_Produkt which would also include the "Warenpartner" entity to relate "Bestellung" with "Produkt" and to capture quantity and price details.

```

CREATE TABLE Hub_Kunde (
    KundeID INT PRIMARY KEY, -- Assuming KundeID is the business key
    Load_Date TIMESTAMP,
    Record_Source VARCHAR(255)
);

CREATE TABLE Hub_Produkt (
    ProduktID INT PRIMARY KEY, -- Assuming ProduktID is the business key
    Load_Date TIMESTAMP,
    Record_Source VARCHAR(255)
);

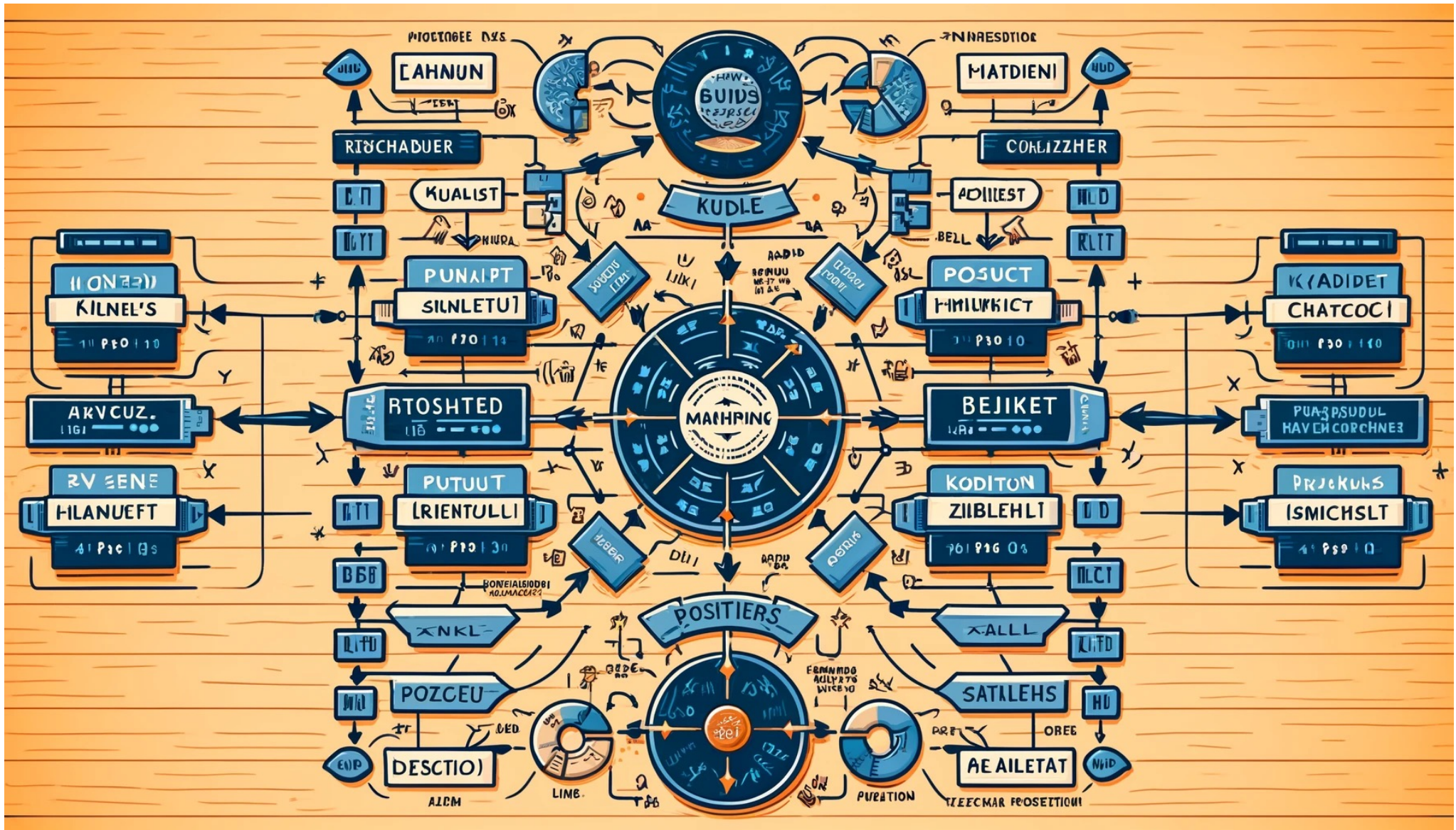
CREATE TABLE Hub_Bestellung (
    BestellID INT PRIMARY KEY,
    KundeID INT,
    Load_Date TIMESTAMP,
    Record_Source VARCHAR(255)
);
                
```

```

-- Load data into Hub_Kunde from Kunde
INSERT INTO Hub_Kunde (KundeID, Load_Date, Record_Source)
SELECT KundeID, CURRENT_TIMESTAMP, 'source_system_name' -- Replace with actual source
FROM Kunde;

-- Load data into Sat_Kunde from Kunde
INSERT INTO Sat_Kunde (KundeID, Load_Date, Record_Source, Vorname, Name, Geschlecht,
SELECT KundeID, CURRENT_TIMESTAMP, 'source_system_name', Vorname, Name, Geschlecht,
FROM Kunde;
                
```

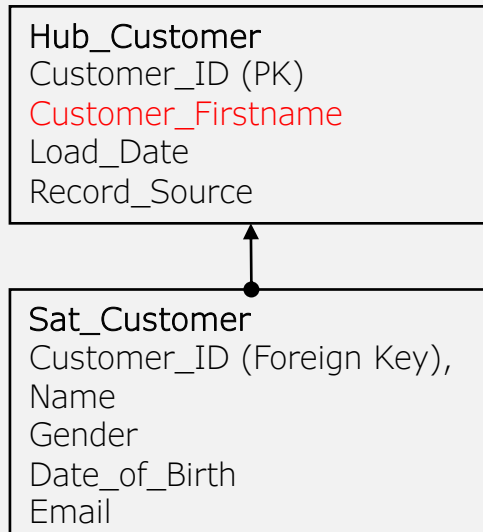
Original UML Field	Data Vault Entity	Data Vault Attribute
KundeID	Hub_Kunde	KundeID
Name	Sat_Kunde_Details	
Vorname	Sat_Kunde_Details	
Geschlecht	Sat_Kunde_Details	
Geburtsdatum	Sat_Kunde_Details	
...	...	
ProduktID	Hub_Produkt	
Bezeichnung	Sat_Produkt_Details	
Preis	Sat_Produkt_Details	



We are interested in **optimizing an existing data vault model** and wish to get recommendations and explanations

TASK → PROMPT → RESULT

We give the model an existing but flawed data model:



The Firstname doesn't belong into the hub, the satellite is missing meta data fields

We prompted ...

"What can be improved in this data vault model?"

"Create me the SQL statements to apply these changes"

"Why did you split the customer data into personal and contact information?"

"2. Remove Firstname from Hub_Customer"
"3. Add Record Source to Satellite Tables"

```
CREATE TABLE Sat_Customer_Personal_Info (
  Customer_ID INT NOT NULL,
  Name VARCHAR(255),
  Gender VARCHAR(10),
  Date_of_Birth DATE,
  Load_Date DATE,
  Record_Source VARCHAR(255),
  FOREIGN KEY (Customer_ID) REFERENCES Hub_Customer(Customer_ID)
);

CREATE TABLE Sat_Customer_Contact_Info (
  Customer_ID INT NOT NULL,
  Phone_Number VARCHAR(20),
  Email VARCHAR(255),
  Load_Date DATE,
  Record_Source VARCHAR(255),
  FOREIGN KEY (Customer_ID) REFERENCES Hub_Customer(Customer_ID)
);
```

"Improved Organization, Enhanced Flexibility, Better Performance, Increased Security, Easier Maintenance"

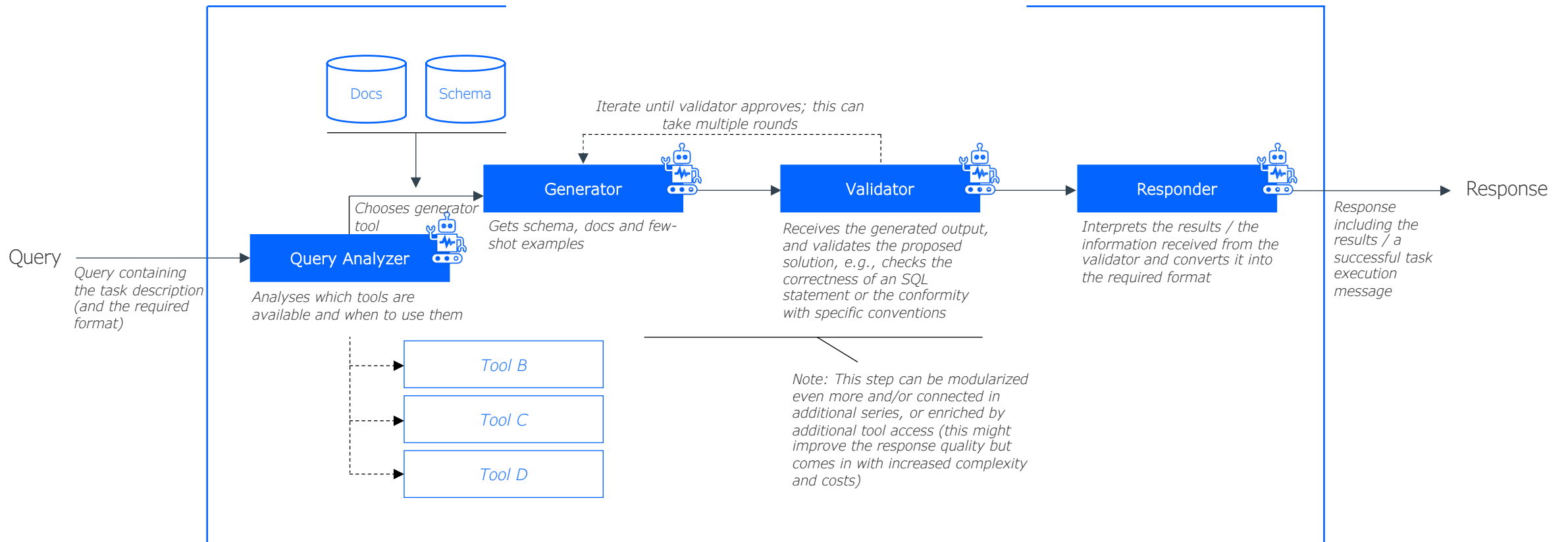
The GenAI automation toolbox offers a **variety of methods** to further **improve the quality and reliability** of the results

Method	Description	UseCases
Prompt Engineering ∨	Add specific goals , commands or output formats to the prompt	<ul style="list-style-type: none">▪ Narrow down the options, e.g. what exact model technique▪ Prevent / guardrail certain unwanted outputs
Retrieval Augmented Generation ∨	Additional data is retrieved from a (vector) database and handed in along with the query	<ul style="list-style-type: none">▪ Internal data (e.g. from your knowledge base) shall be used▪ Bigger amounts of text shall be considered
Large Action Models ∨	Implements a feedback cycle provided by another model	<ul style="list-style-type: none">▪ From simple compilation checks▪ To complex validation via second LLM
Fine-Tuning the Foundation model	Use additional data to train the foundation model new knowledge	<ul style="list-style-type: none">▪ Learn on domain knowledge▪ Train on specific best-practice patterns



Large Action Models (LAMs) focus on **understanding actions and orchestrating sequences of actions** to accomplish specific goals without requiring assistance

Engineering Flow of a multi-stage, graph-based AI approach



Looking Ahead

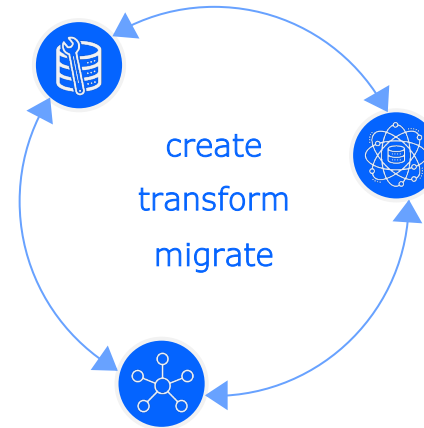
What we expect from the development in the field of GenAI in 2024 and beyond



Our sample evaluation of general-purpose LLMs shows **impressive out-of-the-box functionality** on data modeling and sheds light on how **next level data modeling automation** might look like

3rd Normal Form (3NF)
according to Inmon

Write optimized



Star schema
according to Kimball

Read optimized

Data Vault
according to Linstedt

Agile approach

We believe that **modeling, optimizing and migration** between data models is soon going to be **largely supported** by specialized tools

We have found **strengths and weaknesses with LLM's** in the context of data management

Recommendations

Be **specific about your target** model to get meaningful results

Use tools that **close the gap** between your working environment and the LLM API

Anticipate the **cost aspect** before setting up a scalable solution

Leverage **LLMs to get you started** but do not rely on end-to-end solutions yet

Limitations

Don't expect LLMs running in **business critical** production environments soon

Large-scale automation is not yet supported by tools – you need to built it yourself

We have **6 general hypotheses on GenAI** for the year 2024 and believe we are going to see **productionized AI features in DWA tools by end of this year**

Larger Generalist Models

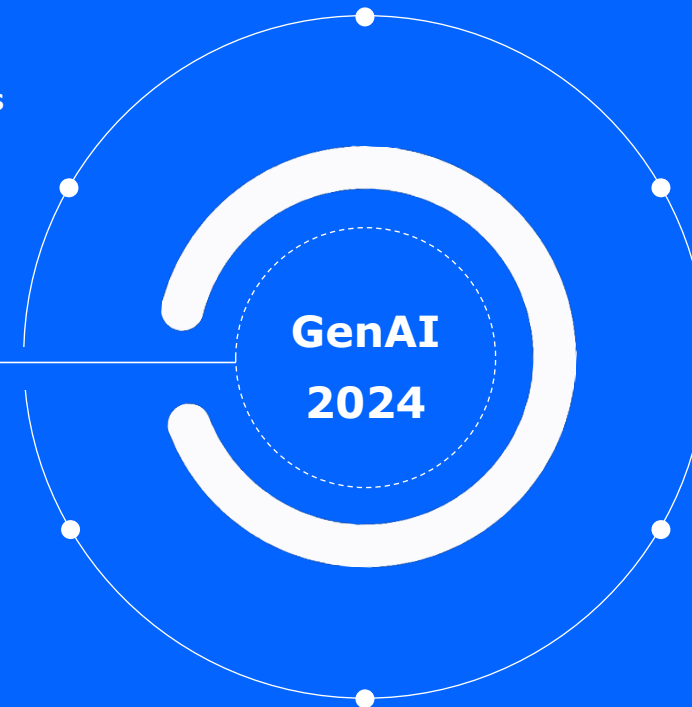
- Large foundation models
- Trend to larger context lengths

Smaller, built-in Expert Models

- Model sizes decrease, while maintaining same performance
- Efficient, specialized models e.g. for data vault modeling in specific domains

Maintained Market Dominance of Big Tech

- OpenAI, Google, Meta, Anthropic, Mistral, etc.



Multimodality will unify

- Text, image, audio, video, structured data
- Unified and simplified solutions from just reading to seeing, hearing, speaking

New Skill Requirements

- Interaction with AI for all
- Not prompt engineer, but standard skill for everyone

Guardrailing & Security

- Protection against malicious attacks (e.g., prompt injection)
- Prevention from extraction of raw training data or other confidential information

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