

GenAl/LLMs and Big Data Platforms

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Learning objectives

- Understand the role of GenAl/LLMs as services for big data platforms
- Able to support the development of GenAl/LLMs using techniques and methods studied from big data platforms

Up to now: what you have learned is very much about the past and the present

Big data platforms are complex

- we have studied basic, foundational techniques and models
- we have practiced with existing platforms, and developed our own use cases/solutions

Trends and new requirements

- real time data and analytics
- new concepts and platforms for data mesh, lakehouse, design patterns like medallion architectures
- o composibility and interoperability of modern data platforms



GenAl/LLMs as a service

GenAl/Large Language Models (LLMs)

- using generative models to analyze and generate text, code, images, data, etc.
- generative models learn patterns and build their capabilities based on data
- LLMs: foundational models trained with a lot of data, able to handle and generate natural languages and other contents

Al Agents

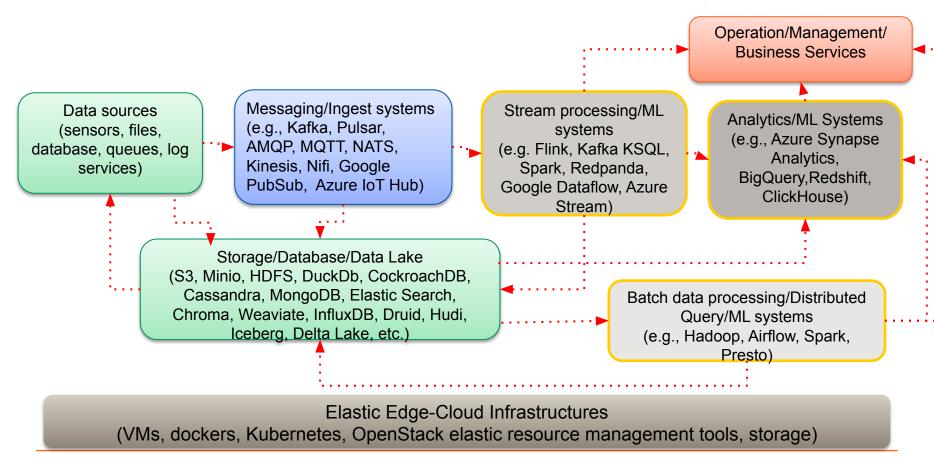
- software acting on behalf of the user/customer to plan and complete tasks for the user (goal-oriented)
- agent models built around/powered by GenAI/LLMs
 - autonomy, proactiveness, collaboration, environment sensing, memorization, uncertainty





GenAl/LLMs for Data Platforms vs Data Platforms for GenAl/LLMs

Where could GenAl/LLMs play a role?





GenAl/LLMs & data platforms (1)

- Exploring the benefits of GenAI/LLMs
 - o for the development and use cases in big data platforms
- Integrating GenAl/LLMs services
 - o for platform requirement analysis, design and development
- Providing GenAl/LLMs services as a service in the platform
 - for data analysis, visualization, and transformation



GenAl/LLMs & data platforms (2)

- Big data platforms as backbone for Al/ML/LLMs
 - building LLMs requires strong support from big data techniques, models and platforms
- Leveraging our expertise in big data platforms for building GenAl/LLMs
 - data pipeline, data services, data transformation, and data quality/governance





GenAl/LLMs for low code in big data programming

What have we had? look back your code and examples in the tutorials

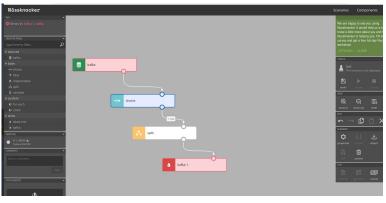
- Developer's daily tasks:
 - building lot of ETL, data analytics, etc.
- The Nifi way:
 - defining flows using drag and drop features
- The Airflow-alike way:
 - programing workflows with APIs and annotations
- The Flink/Spark way:
 - low-level data processing API
- Multiple runtime systems and microservices:
 - o utilizing containers (e.g., Airbyte), mapping to different underlying runtimes (e.g., Apache Beam)

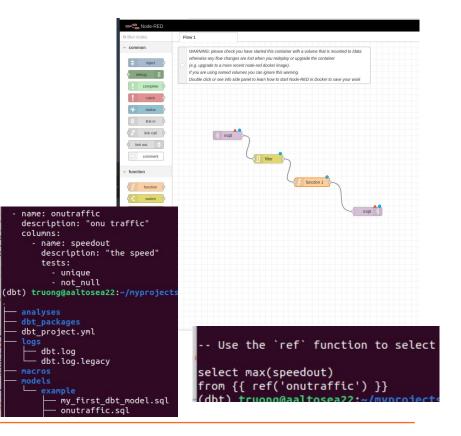


Some snapshots

(a snapshot from Beam)









Difficulties

- Nice UI, simple drag and drop, and easy composition
 - difficult to solve complex processing and quality control requirements
- Programming solutions
 - powerful, but low-level programming, mostly difficult for users who do not know programming languages/technologies well
- Handling streaming data is still hard
- How could low-code and GenAl/LLMs techniques help to generate powerful transformation code?
 - lowering cognitive load for users and empowering generalists (who can work on code, data and ML models)



GenAl/LLMs as a solution?

- Can GenAl/LLMs reduce programming tasks?
- Can GenAl/LLMs help for speeding up designs of big data platforms?
- Can GenAl/LLMs do the analytics of data by invoking suitable algorithms?
- etc.



pls. tell me how can I determine which type of data and which algorithms that can be used to detect anomalies of electricity grid usages?



Aalto Al Assistant

Detecting anomalies in electricity grid usage involves monitoring the electricity consumption data to identify unusual patterns that might indicate problems such as equipment failures, unauthorized usage, or other irregularities. Here's how you can approach this task:

Types of Data

The data you need typically includes:

- Timestamp: The time at which the measurement was taken.
- Usage Data: The amount of electricity consumed during the timestamp (e.g., kilowatt-hours).
- Voltage and Current: Measurements of voltage and current, which can help identify issues related to power quality.
- Frequency Data: The frequency of the grid, deviations from normal frequency could be an indicator of anomalies.
- Device/Infrastructure Data: Information about the devices or infrastructure being monitored, such as sensor IDs, geographical location, and device health metrics.
- Weather Data: Optional external data such as weather conditions, which can be correlated with usage patterns.

Algorithms for Anomaly Detection

Several algorithms can be used for anomaly detection in electricity usage. The choice of algorithm depends on the nature of the data and the specific types of anomalies you want to detect

Source: GPT4o integrated with Aalto Al Assistant, 19.03.2025



Write the

question

seeking for a

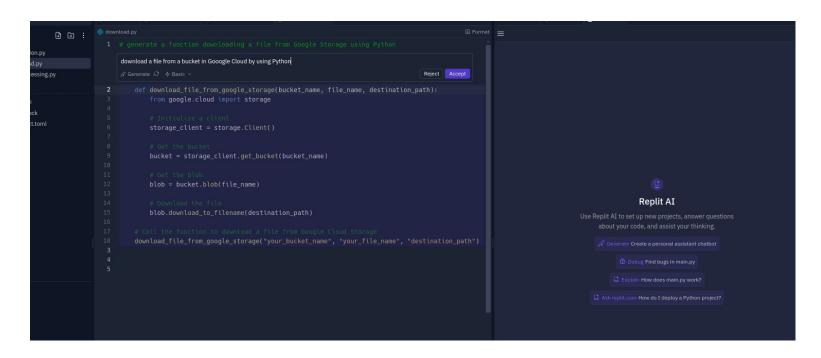
solution, but

answer help?

how much

does the

GenAl/LLMs for generating code

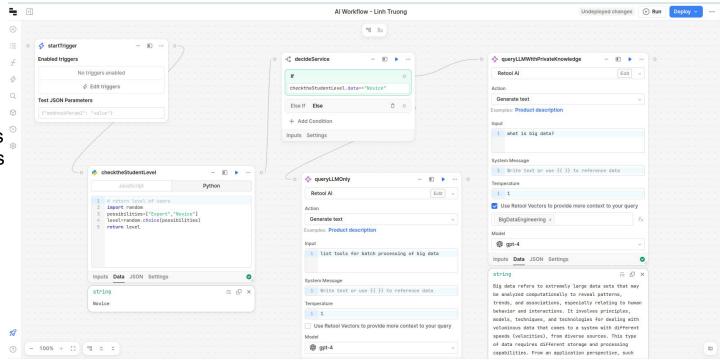


Note: Not necessary for big data platforms only!



Workflow of conventional tasks and LLMs-based tasks

Examples with retool, some knowledge is trained based on our basic big data materials (https://github.com/linhs olar/basicbigdata)

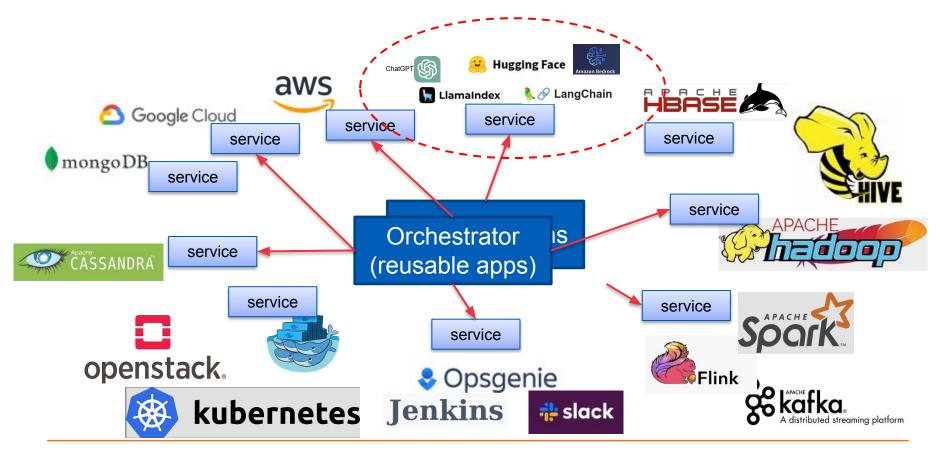






If we want to include GenAl/LLMs as service in a big data platform

Recall: service orchestration in data platforms





Understand the expected quality of results from GenAl/LLMs

Aspects/Views

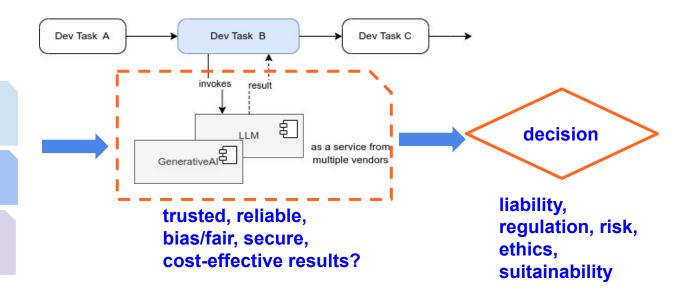
as a process

(e.g., inference process for an input)

as an artefact (e.g., output)

as a service

(e.g., an ML service for a type of tasks)





Understand the need to coordinate LLMs and services for development tasks

Targets

- focused tasks and customized environments for the developer in big data
- Encapsulating knowledge about the big data platform and application domains
 - knowledge not easily found in the public space/open sources
 - a kind of "internal" data services, not available in LLMs



Understand the need to coordinate LLMs and services for development tasks

- Composition of LLMs with other development tools/knowledge sources
 - integrated with conventional highly accurate and relevant services
 - cloud pay-per-use and on-prem LLMs services
- Human-in-loop as workflow tasks
 - for uncertainty handling and quality feedback
- Adaptive coordination workflows
 - based on quality associated with individual LLM capabilities



Employing LLMs: service selection and integration problems

Big LLMs

- mostly from well-known providers
- which tasks can we use as we may not know how the GenAI/LLMs services deal with our own data

Small LLMs

o can be hosted within a platform, dedicated for individual tenants

Diversity of LLMs

functionality: generating analytics reports, code, sample of data

Engineering challenges

scalability, data privacy/governance, and multitenant models



Tools

Code generation

- Many cloud services (with close and open source LLM models)
- ChatGPT, Azure Mistral, together.ai

Text-to-SQL for analytics

- Vanna https://vanna.ai/docs/
- https://github.com/HKUSTDial /NL2SQL Handbook

LLMs for data management

 https://github.com/weAIDB/aw some-data-llm

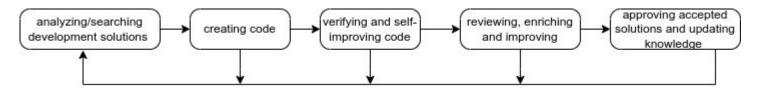
Table 4: Pass@1 performance of pretrained code models (top), instruction finetuned code models (middle), in comparison with some of the best general language models (bottom), with models in each category ordered chronologically. The sources of these figures can be found in Section 5.3, Section 5.4, and Table 1.

| Model | Size | HumanEval | MBPP |
|-------------------------|-------|-----------|------|
| PolyCoder | 2.7B | 5.6 | - |
| CodeGen-Mono | 16.1B | 29.3 | 35.3 |
| InCoder | 6.7B | 15.2 | 19.4 |
| PyCodeGPT | 110M | 8.3 | - |
| Pangu-Coder | 2.6B | 23.8 | 23.0 |
| SantaCoder | 1.1B | 14.0 | 35.0 |
| CodeGeeX | 13B | 22.9 | 24.4 |
| StarCoder | 15.5B | 33.6 | 52.7 |
| CodeT5+ | 16B | 30.9 | |
| Phi-1 | 1.3B | 50.6 | 55.5 |
| CodeFuse | 13B | 24.8 | - |
| DeepSeek Coder | 33B | 56.1 | 66.0 |
| InstructCodeT5+ | 16B | 35.0 | - |
| WizardCoder | 15.5B | 57.3 | 51.8 |
| Pangu-Coder 2 | 15.5B | 61.6 | - |
| OctoCoder | 15.5B | 46.2 | 2 |
| CodeFuse | 34B | 74.4 | - |
| DeepSeek Coder-Instruct | 33B | 79.3 | 70.0 |
| GPT-4 | | 67.0/82 | - |
| PaLM 2* | S | 37.6 | 50.0 |
| Code LLaMA | 34B | 53.7 | 56.2 |
| Phi-1.5 | 1.3B | 41.4 | 43.5 |

Source: Zhang et al., "Unifying the Perspectives of NLP and Software Engineering: A Survey on Language Models for Code", https://arxiv.org/abs/2311.07989

Collms example: for edge-cloud software modernization & new development

AI/ML/LLMs as services in development workflows

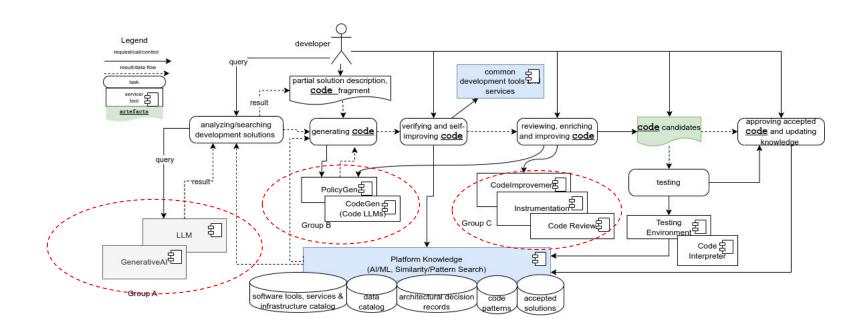


- Cloud, on-prem and personal LLMs services
 - o composition of LLMs with other development tools/knowledge sources
- Adaptive coordination workflows based on quality associated with concrete aspects/views of individual LLM capabilities
 - explainability; robustness, reliability, resilience & elasticity

H. -L. Truong, M. Vukovic and R. Pavuluri, "On Coordinating LLMs and Platform Knowledge for Software Modernization and New Developments," 2024 IEEE International Conference on Software Services Engineering (SSE) doi: 10.1109/SSE62657.2024.00036.



Collms: a high level view

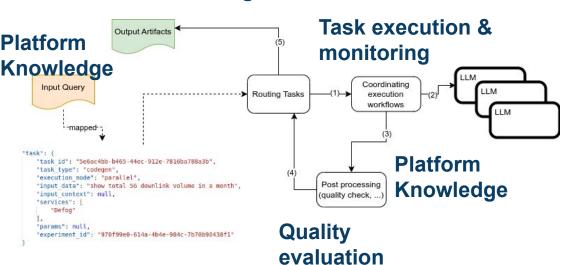


Service group: for specific type of tasks, at runtime an ensemble from the group will be used



Collms: a high level view

Cross tasks lineage



Task models & (de)composition

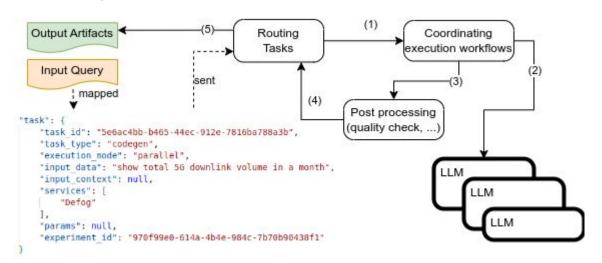
Trails of task execution & quality

```
"task instance id": "2f25cd24-e5dc-4437-8949-95788371c353",
"start ts": 1698430168.4745324,
"end ts": 1698430184.2641177,
"service name": "Defog",
"service qoa": {
    "total token": null,
    "responsetime": 15.789584357000422,
    "cost": null
"task": {
    "task id": "5e6ac4bb-b465-44ec-912e-7816ba788a3b",
    "task type": "codegen",
    "execution mode": "parallel",
    "input data": "show total 5G downlink volume in a month",
    "input context": null,
    "services": [
        "Defoa"
    "params": null,
    "experiment id": "970f99e0-614a-4b4e-984c-7b70b90438f1"
```



Collms: configuring and run-time quality-aware scheduling of tasks execution

Patterns in coordination: at the ensemble level (composition/group coordination) and at the individual LLM level (RAG and LLM parameters)



LLM service management complexity

- controllable parameter spaces for coordination
- customized invocation pipelines of individual LLMs with in a group
- scalable service communication handling (REST and AMQP)



Collms: Observability

- End-to-end tracing and logging of cross LLMs and platforms
 - allowing for detail explainability

- Linkages/trails between accepted solutions/results and the goal of the developments
 - types of tasks, types of target solutions, and development contexts



Collms: few snapshots of a prototype

Coordinating LLMs and Platform Knowledge for Application Modernization Showing some thoughts and concepts Platform Knowledge Search Solution Search/Refinement Code Generation Testing and Verification Enrichment/Improvement Platform Knowledge Update Code Generation with Code LMs Platform Knowledge Search Solution Search/Refinement Code Generation Testing and Verification Enrichment/Improvement Platform Knowledge Update Code, Policy and Configuration Testing and Verification with Virtual Testing Environments Select executor ensembles Parallel service invocations A majority of services violation[[input_client_info_*ResponseTime violation on small resource machine*]] input.service info.machinetypes == "small" def read_data_as_df(self,table_name,size,fields): input.service_info.metric[_] == "ResponseTime" if (self.conn==None): return None join_fields=", ".join(fields) Result from CodePolicyValidation Generate "errors": [Result from StarCoder Result from CodeLlama Result from InCoder "message": "unexpected eof token: expected \\n or ; or }", def read_data_as_df(self,table_name,size,fields): def read_data_as_df(self,table_name,size,fields): Model facebook/incoder-6B is currently loading if (self.conn==None): if (self.conn==None): "file": "/tmp/tmphkclpgog/policy file", return None join_fields=", ".join(fields) join_fields=", ".join(fields) if (size >0): if (size >0): sql=f'SELECT {join_fields} from {table_name} LIMIT {si sql=f'SELECT {join_fields} from {table_name} LIMIT {si

sql=f'SELECT {join_fields} from {table_name}'

print(f'Running {sql}')

with self.conn.cursor() as cur:

cur.execute(sql)

rows=cur.fetchall()



print(f'Running {sql}')

with self.conn.cursor() as cur:

cur.execute(sql)

df=pd.DataFrame

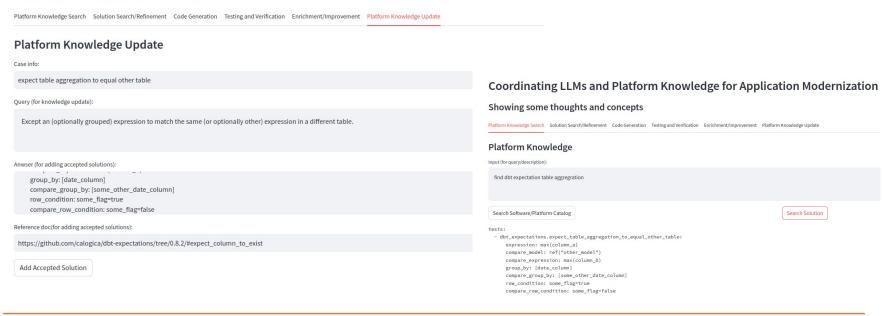
rows=cur.fetchall()

sql=f'SELECT {join_fields} from {table_name}'

Collms: few snapshots of a prototype

Coordinating LLMs and Platform Knowledge for Application Modernization

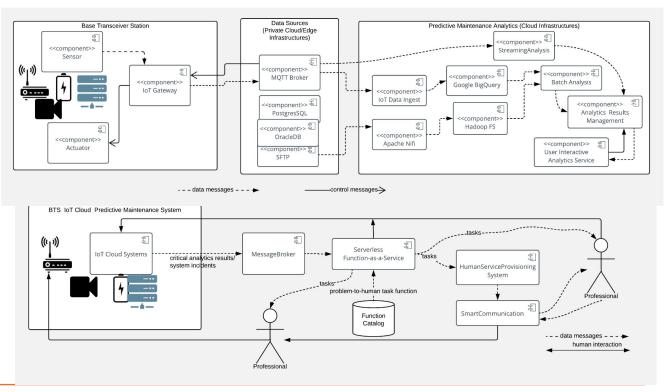
Showing some thoughts and concepts





Where could workflows of LLMs calls and Al Agents help? (1)

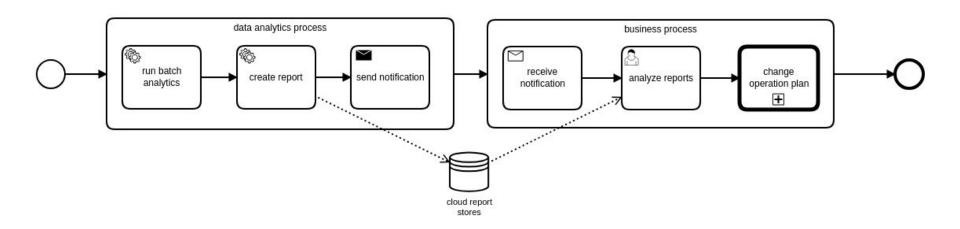
Complex platform tasks for predictive maintenance or security orchestration





Where could workflows of LLMs calls and Al Agents help? (2)

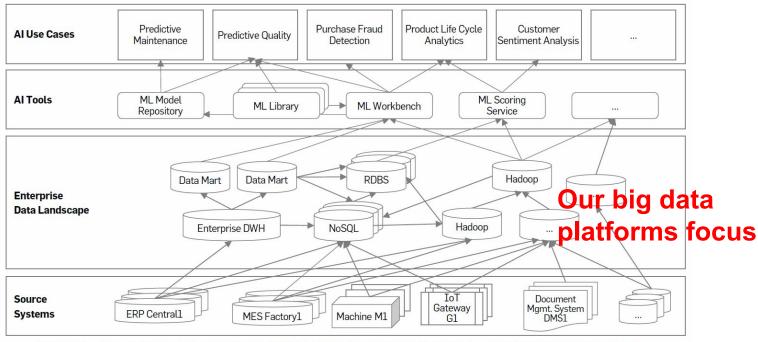
- data analytics processes and business processes
 - include human-in-the-loop





Using techniques/methods studied in Big Data Platforms for GenAl/LLMs

"No Al Without Data": before LLMs

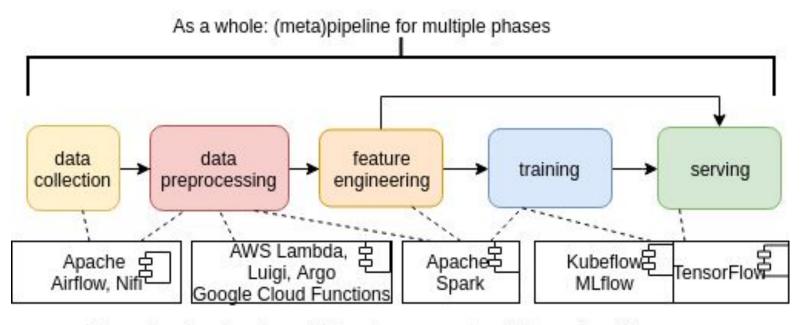


DWH: Data Warehouse, ERP: Enterprise Ressource Planning, MES: Manufacturing Execution System, ML: Machine Learning, RDBS: Relational Database System

Figure source: There Is No Al Without Data, by Christoph Gröger, Communications of the ACM, November 2021, Vol. 64 No. 11, Pages 98-108, 0.1145/3448247



Big data and ML pipelines



Examples of subsystems: different components and internal workflows

Big data platforms and ML

Example: Michelangelo ML from Uber

It is easy to see the role of big data components we study in this figure

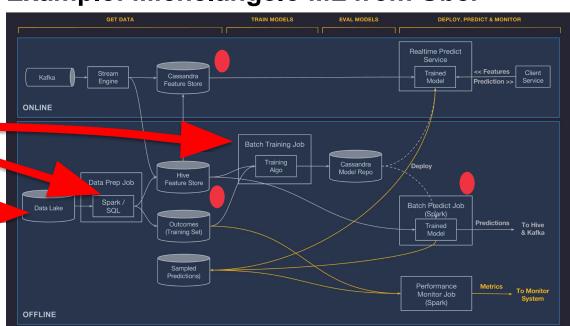


Figure source: https://eng.uber.com/michelangelo-machine-learning-platform/



Techniques and methods in big data platforms help to build GenAl/LLMs

- GenAl/LLM as a key part that big data platforms must support
 - analytics workflows and service integration
- Data management for GenAI/LLMs
 - enable sharing, retrieving and managing big data
- Techniques and methods for GenAl/LLMs development
 - connectors, transformation, data pipelines, data governance



Support LLMs: the big data pipeline for RAG in GenAl/LLMs

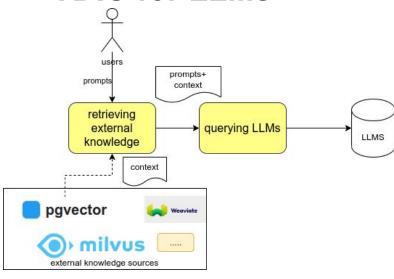
RAG: Retrieval-Augmented Generation

- getting facts/relevant accurate knowledge from an external source for LLMs
- providing context for improving LLM inferences

Key components

o pipelines and databases

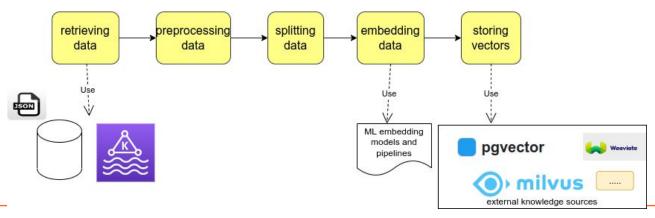
RAG for LLMs





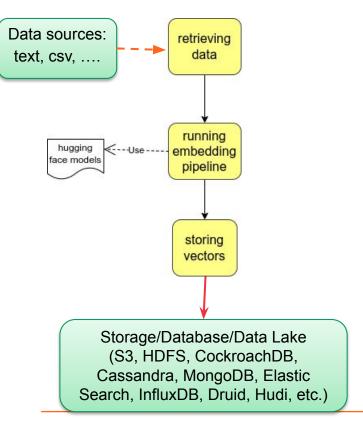
Support LLMs: the big data pipeline for RAG in GenAl/LLMs

- The process to build RAG is a "big data" pipeline
 - o getting data and determining vectors as indexes for data
 - storing data and indexes into databases
 - using common vector databases → data services
 - Postgres with pgvector, ChromaDB, Milvus, Weaviate, ...





An example with LlamaIndex



```
from llama index.core import VectorStoreIndex, SimpleDirectoryReader, Settings
from llama index.core.embeddings import resolve embed model
#assume the data is under "data" (e.g., csv and text file)
documents = SimpleDirectoryReader("data").load data()
#specify embedding model for extracting vectors
Settings.embed model = resolve embed model("local:BAAI/bge-small-en-v1.5")
#configure LLM, set None as it illustrates the RAG
Settings.llm = None
# specify the embedding pipeline/task
index = VectorStoreIndex.from documents(
   documents,
#Now we can query Vector to get a context
retriever = index.as retriever()
query=input("Enter your query:")
contexts = retriever.retrieve(query.strip())
# show context, assume that it context=NodeWithScore with node=TextNode
for context in contexts:
   print(context.node.text)
# also query LLM (but none in this code)
query engine = index.as query engine()
result = query engine.query(query.strip())
print(result)
```



Summary

- Complex design and engineering issues in big data platforms
 - o many big systems, very complex designs and requirements
 - require us to continuously upskill
- New GenAl/LLMs can help simplifying certain tasks
 - GenAI/LLMs and AI Agents are services and paradigms that can be considered as fundamental elements for a programming model
- Your expertises from Big Data Platforms can help
 - integrate GenAI/LLM services
 - o build GenAI/LLMs capabilities for big data problems



Thanks!

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rdsea.github.io