



CIKLUM

SPEAKER'S
CORNER

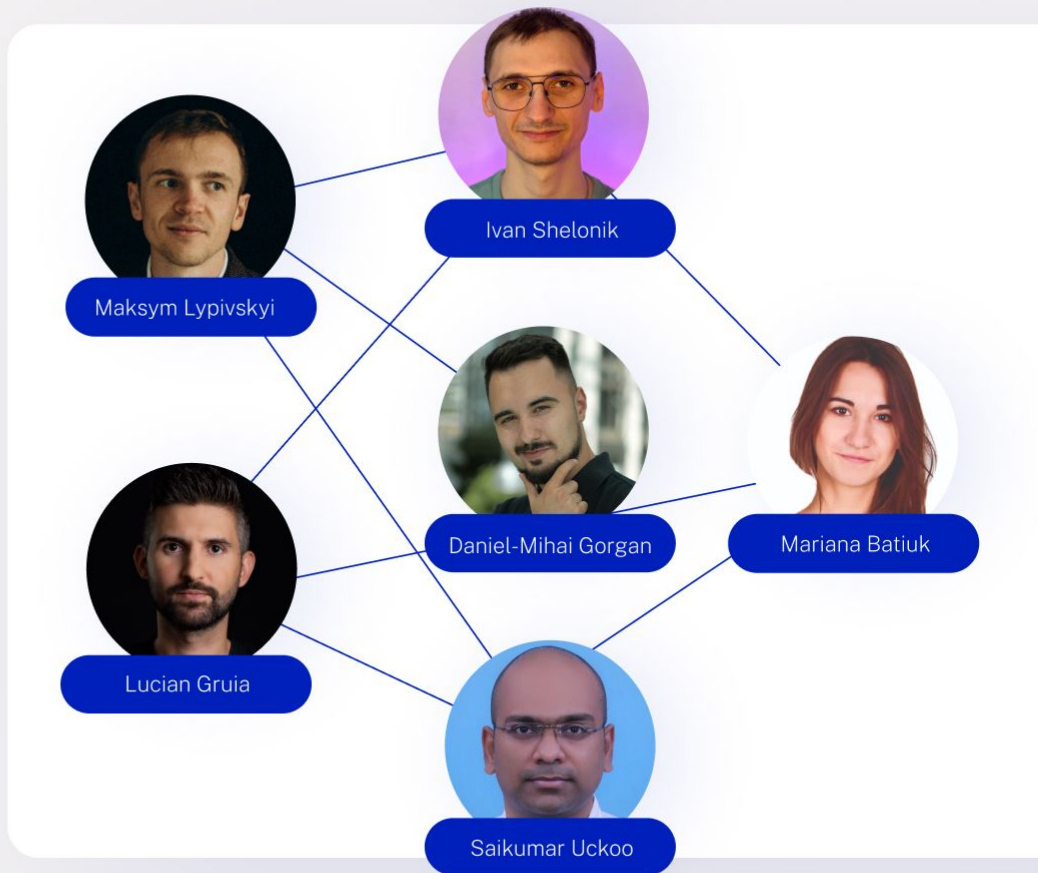
April, 16

16:30 (CET)

English

Architecting Scalable AI RAG Systems:

From Startup to Enterprise.
A Live Coding Session



Experiences of tomorrow. Engineered together.



We transform how people experience the business. All through next generation technology.

What we do:

Product
Engineering

Intelligent
Automation

Data &
Analytics

2002
founded

4000+
professionals

20+
offices

300+
clients

Leading companies choose us:









Our Global Delivery Centres





Global Reach, Local Insight -Ciklum bridges the best in tech from the three key IT regions



Central & Eastern Europe

-  Bulgaria
-  Czech Republic
-  Poland
-  Romania
-  Slovakia
-  Spain
-  Ukraine
-  United Kingdom

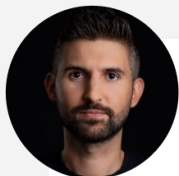
Asia

-  India
-  Pakistan

LATAM

-  Argentina
-  Uruguay

Our speakers



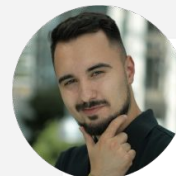
Lucian Gruia
Principal AI
Technology Lead

- AI Tech Lead with over 11 years of hands-on experience in Telecom, Fintech, and Aerospace. He specializes in AI, data integrity, fraud detection, system performance, architecting frameworks and solutions for real-time systems.
- Develops an AI upskill program for 300 engineers at Ciklum.



Ivan Shelonik
Expert Data Scientist

- Certified Professional Machine Learning Expert with 7 years of commercial experience in developing Machine Learning projects from the ground to delivery into the Cloud (AWS 5+YoE).
- Has worked and delivered primarily for customers from S&P 500



Daniel-Mihai Gorgan
Senior JS Developer

- Tech enthusiast specializing in Node.js, SQL/NoSQL and Cloud technologies with 5+ years of experience
- Hands-on experience in projects across outsourcing and product companies, contributing to the development of in-house products, smart chatbots, and voicebots by leveraging different AI technologies

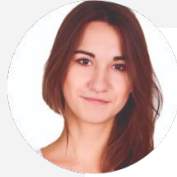
Our speakers



Saikumar Uckoo

Conversational AI expert

- Cloud Architect specialized in building, deploying, and maintaining AI solutions on Microsoft cloud platforms. Leads deliveries on platforms like Microsoft PVA, KoreAI, and custom GenAI solutions built on open-source tech.



Mariana Batiuk

Principal TCoE Lead

- Mariana leads the technical council on the QA maturity assessment, test strategy, pre-sales, new services development, initiatives, and quality engineering activities.
- Has proficient experience in QA Management, Agile Methodologies, Testing, Team Management, and Coaching.



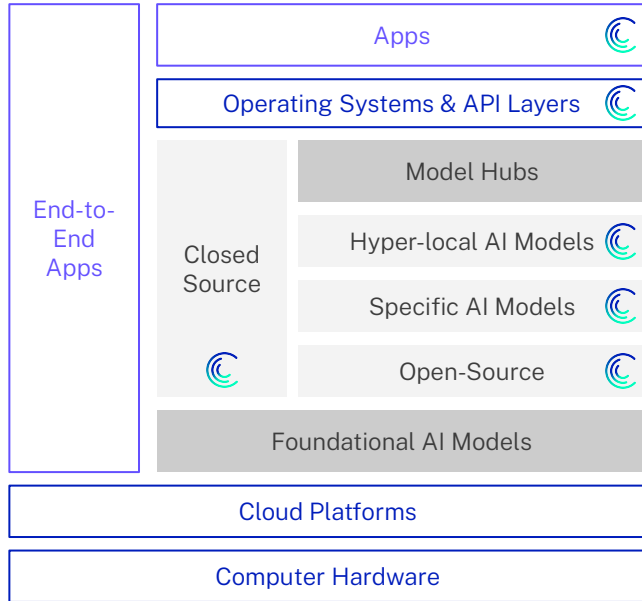
Maksym Lypivskyi

Global Head of Cloud Platforms

- Specializing in cloud computing architectures and generative AI applications, he focuses on creating, deploying, and optimizing cutting-edge solutions across global platforms.
- A mentor and community builder, he actively shares his insights on generative AI, cloud technologies, and leadership.

Playing in all parts of the AI stack

User Experiences & Engagement



□ Applications ■ Models □ Infrastructure Where we work

Emerging Stack Trends

Applications

The rise of cloud-based generative AI and LLMs, accessible via **APIs** and **embedded** in other applications, will allow companies to use them as-is or **customize** with their data

Fine-Tuning

The need for model fine-tuning will drive demand for a **diverse skill set**, such as software engineering, psychology, linguistics, etc.

Foundation Models

The market will evolve and diversify with the emergence of **more pre-trained models**, offering **options** for size, transparency, versatility & performance balance

Data

Mastery of **new and diverse data types** and volumes will be crucial for success, with **GenAI features in modern data platforms** facilitating **adoption at scale**

Infrastructure

Essential for GenAI deployment, **cloud infrastructure** will help manage costs and **carbon emissions**, necessitating data center retrofitting and advancements in chipset architectures, **hardware** & algorithms

Partners

OpenAI
 Weights & Biases
 Humanloop

HUGGING FACE
 Pinecone

OpenAI

appen redis
 snowflake databricks

Azure **aws**
Google Cloud
NVIDIA.

Agenda

01 What is RAG

02 LLM Wrappers and Docker

03 Build with Java

04 Build with Python

05 Build with Javascript

06 Deploy RAG app in AWS

07 Deploy RAG app in Azure

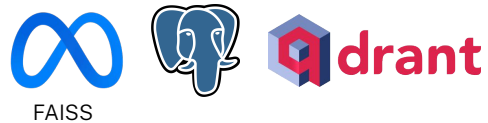
08 Challenges in QA and more

Session's Tech map

Programming languages



Databases



Infrastructure

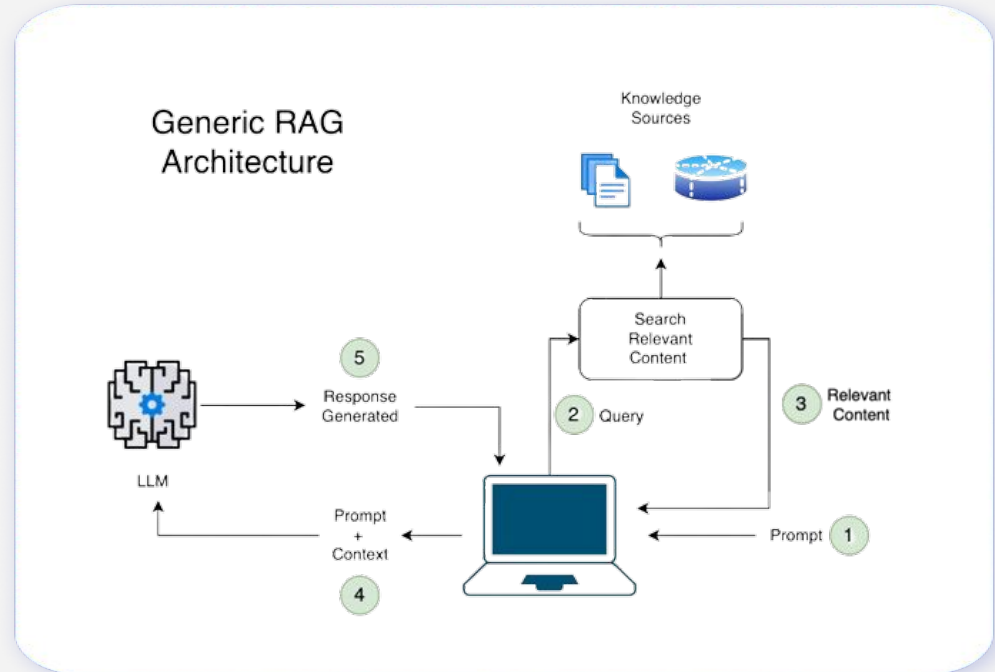


What is RAG

A RAG system essentially correlates a **user's prompt** with a relevant **data chunk**. It does this by identifying **the most semantically similar** chunk from the database.

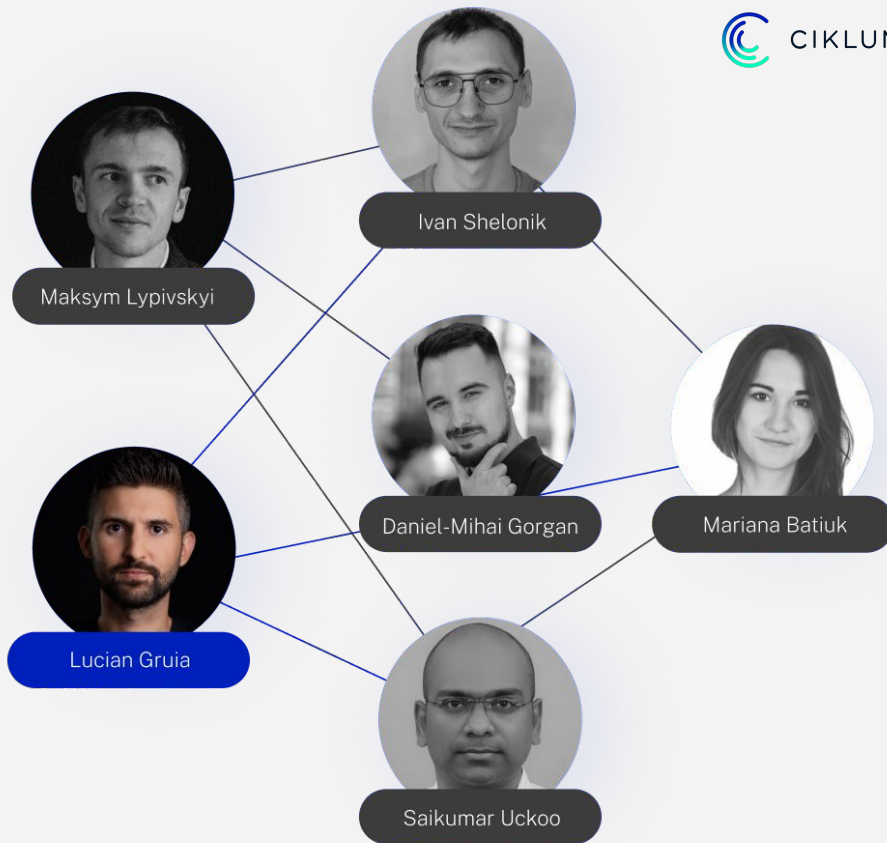
This chunk then becomes **the context** for the prompt.

When **passed to the Large Language Model (LLM)**, it enables the system to provide a relevant answer within the **given context**.



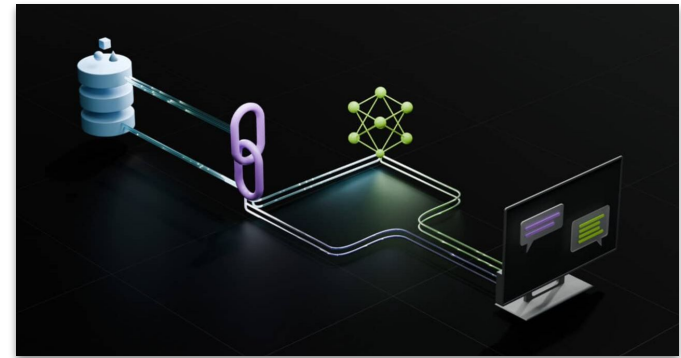
LLM Wrapper

- Build with **Java**
- Deploy locally
- Integrate a 3rd party client



Why do we need RAG?

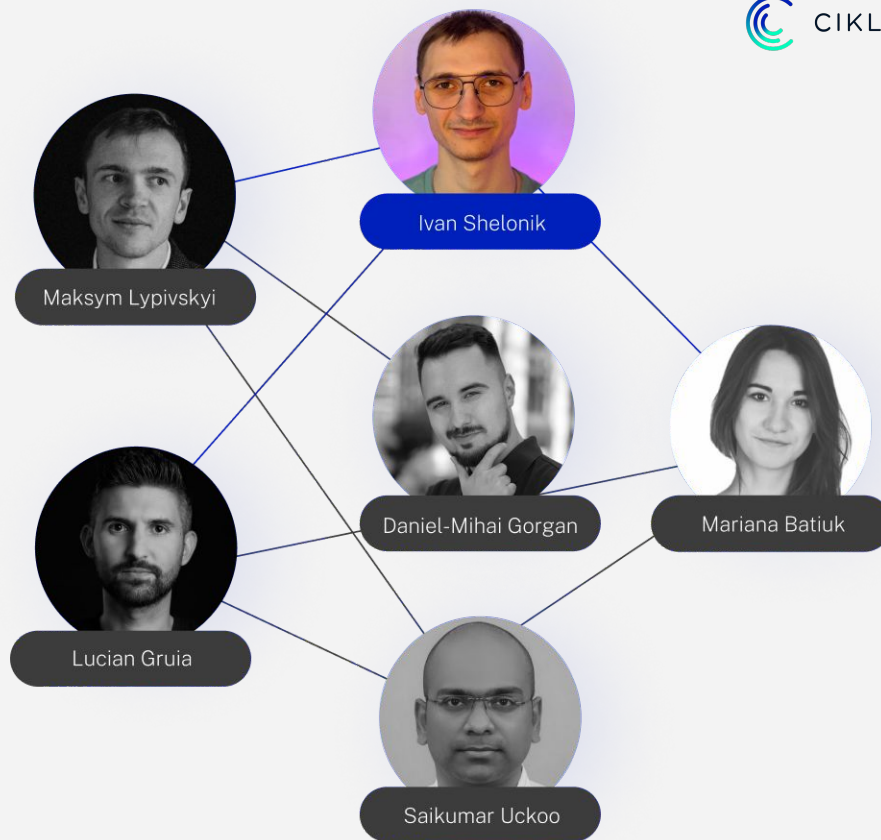
- **Expands Knowledge Base**
RAG accesses a vast external database, enriching its knowledge beyond initial training data
- **Improves Accuracy**
Enhances response precision by integrating relevant, real-time information
- **Adaptable**
Effectively handles novel and niche queries
- **Increases Efficiency**
Streamlines information retrieval and generation process
- **Versatile Applications**
Useful across various fields, from customer support to research



Source: [What Is Retrieval-Augmented Generation, aka RAG?](#)

AWS

- Build with **Python**
- Build Docker images
- Semantic search with FAISS
- Deploy on AWS



Data Chunking and LLMs

LLMs also have a limited capacity for context.

Just as humans **cannot digest unlimited context**, these models have a specific size limit for the content they can process.

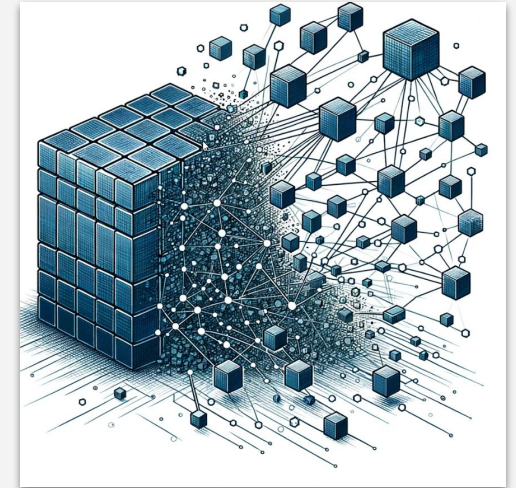
So, what about situations involving very large amounts of data?

Consider a specific use case, such as a book. It's too large to pass the entire book as **the context** for the current prompt, so it **needs to be divided** before being stored in the database.

This process is known as **data chunking**.

Types of Data chunking (by size):

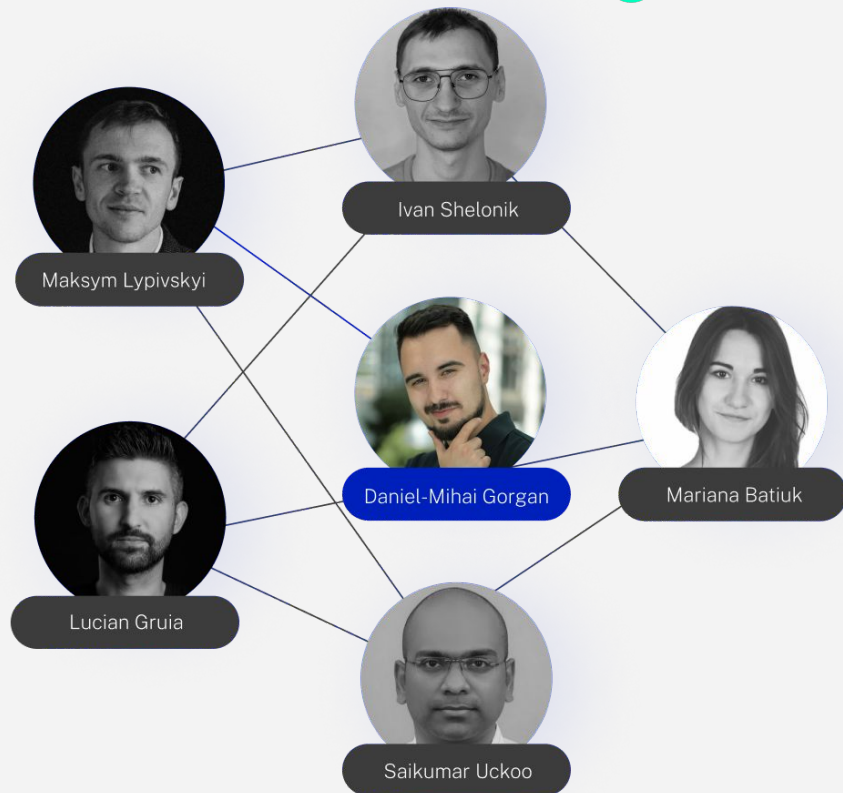
- Fixed-size
- Variable Chunking
- Semantic Chunking



Generated with DALL-E 3

JavaScript

- Build with **TypeScript**
- Semantic Search with Pg vector



Embeddings. Similarity

- **Embeddings**

Numerical representations of concepts, in a high-dimensional space, capturing semantic meaning.

- **Similarity:**

- **Lexical:** entities are alike in appearance
- **Semantic:** entities are alike in meaning

- **In RAG we represent entities by describing them.**

This is a form of knowledge representation.

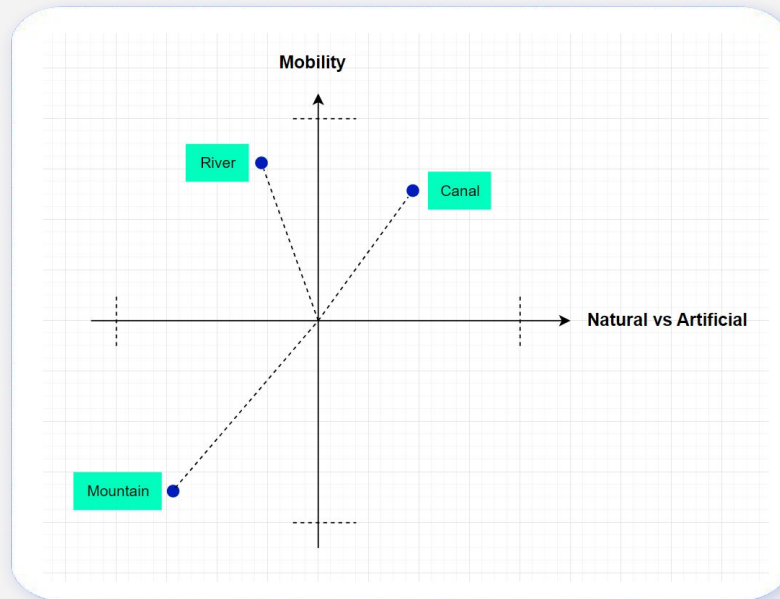
Example: Mountain, River, Canal

One hot encoding

Mountain: 1
River: 2
Canal: 3

2-Dimensional Space

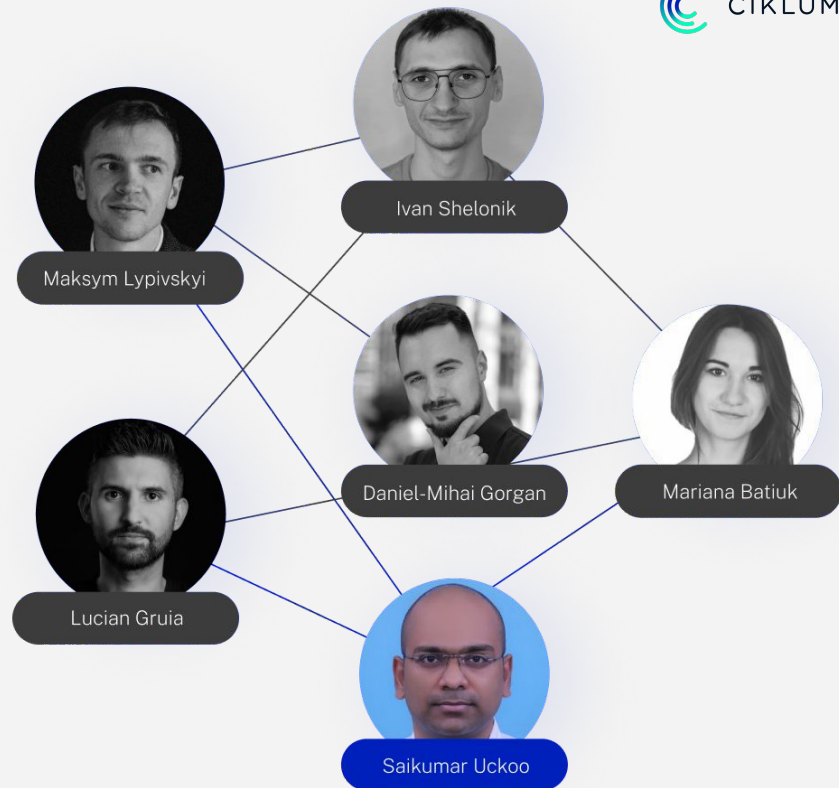
[Natural vs Artificial, Mobility]
Mountain: [-0.7, -0.8]
River: [-0.3, 0.7]
Canal: [0.4, 0.5]



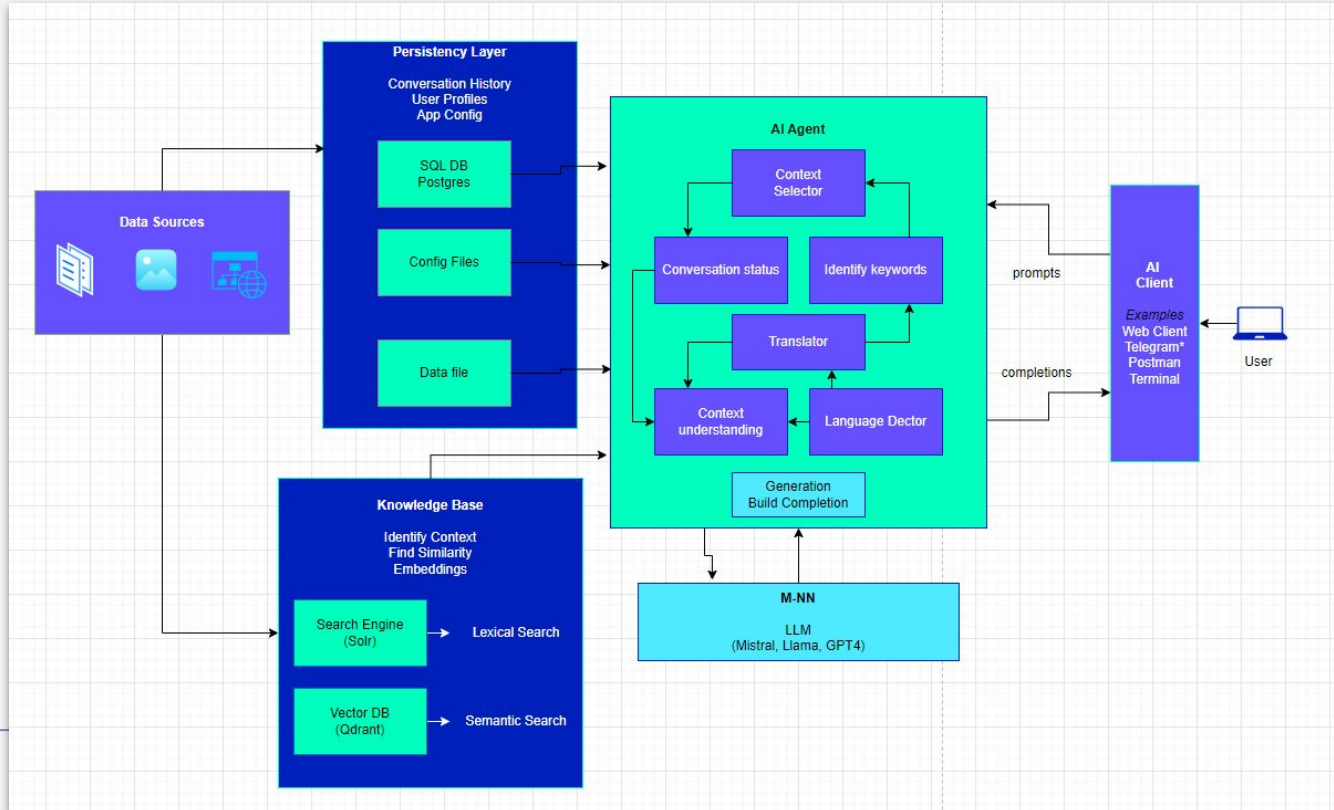
Read more: [Wikipedia - Cosine Similarity](#)

Azure

- Deploy on **Azure**
- Semantic Search with Qdrant
- Conversation history



RAG Architecture



Benefits of RAG

1. Providing up-to-date and accurate responses

RAG ensures that the response of an LLM is not based solely on static, stale training data. Rather, the model uses up-to-date external data sources to provide responses.

2. Reducing inaccurate responses, or hallucinations

By grounding the LLM model's output on relevant, external knowledge, RAG attempts to mitigate the risk of responding with incorrect or fabricated information (also known as hallucinations). Outputs can include citations of original sources, allowing human verification.

3. Providing domain-specific, relevant responses

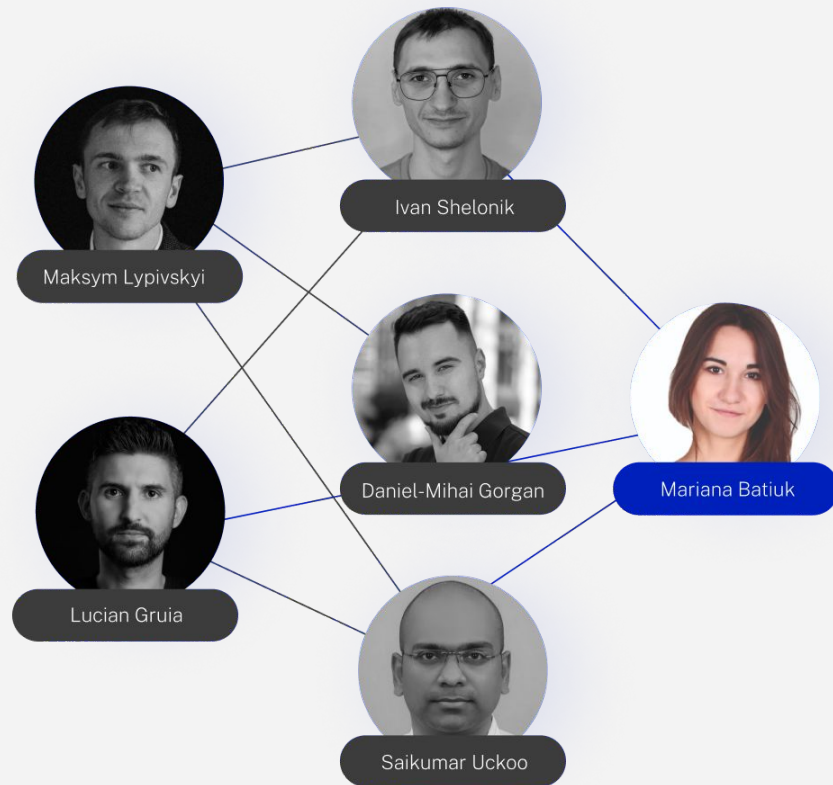
Using RAG, the LLM will be able to provide contextually relevant responses tailored to an organization's proprietary or domain-specific data.

4. Being efficient and cost-effective

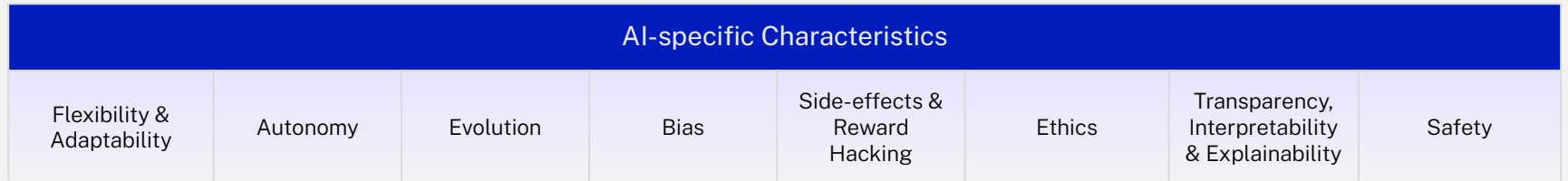
Compared to other approaches to customizing LLMs with domain-specific data, RAG is simple and cost-effective. Organizations can deploy RAG without needing to customize the model. This is especially beneficial when models need to be updated frequently with new data.

QA & Testing

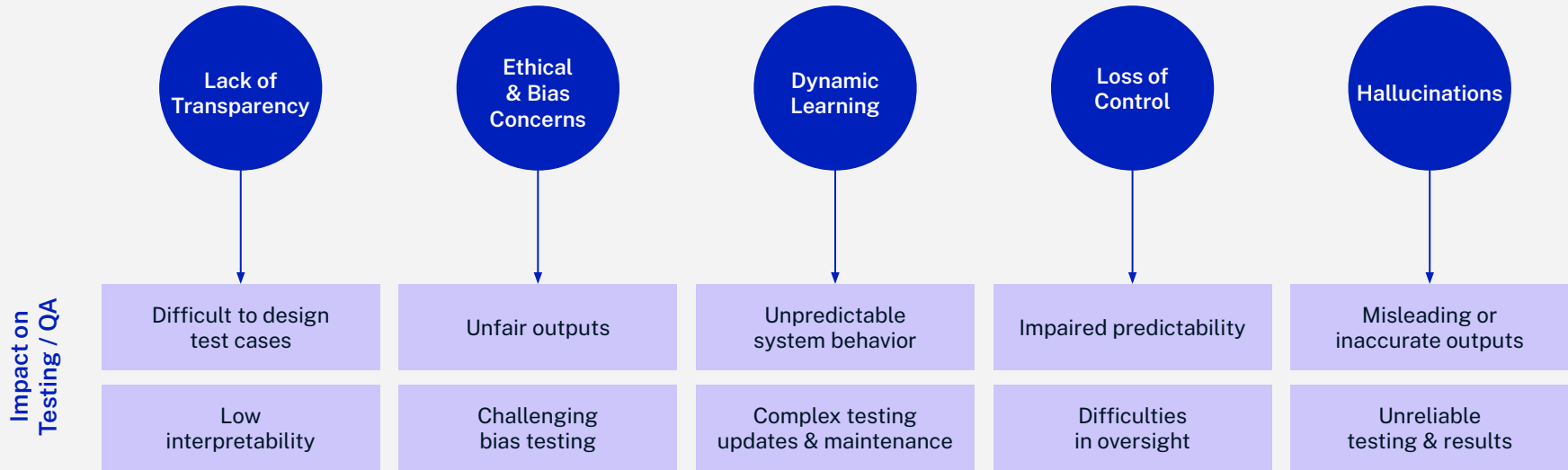
- SW characteristics
- Top 5 **risks**
- Methods and tools
- Balanced **success** factors



Software Characteristics






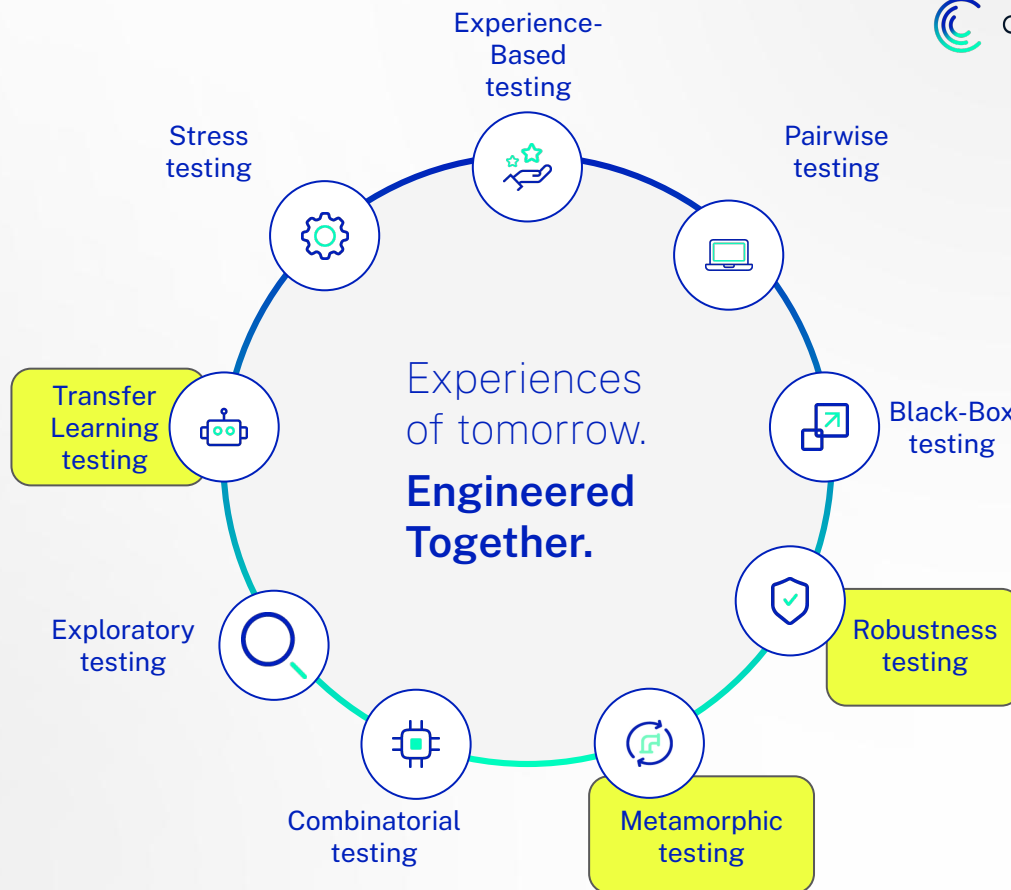
Top 5 current shortcomings and risks



Methods & tools

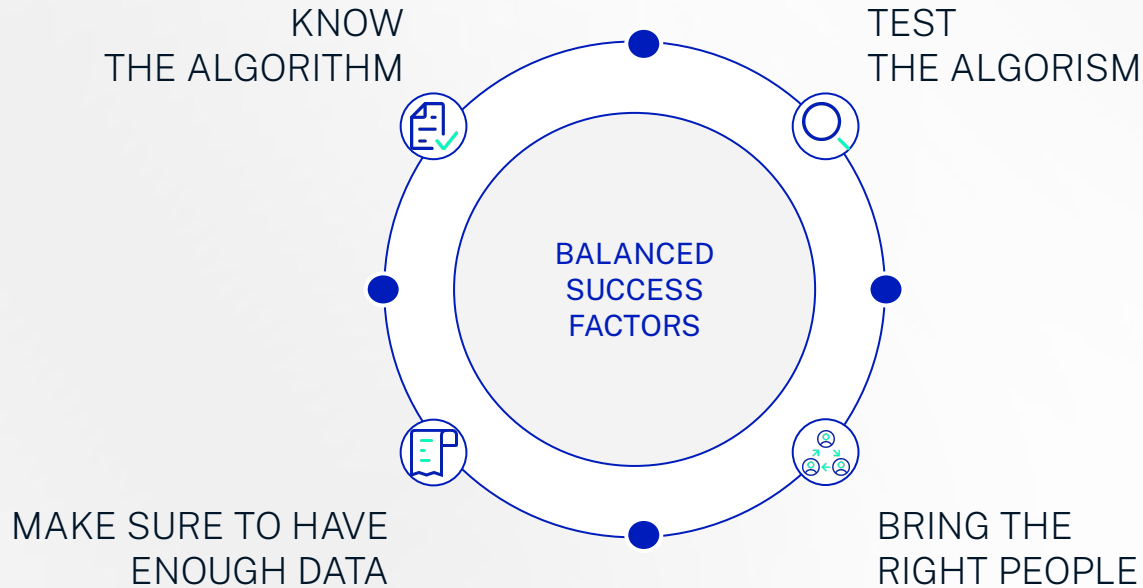
that help us mitigate risks and ensure proper testing of AI

  ragas  Giskard



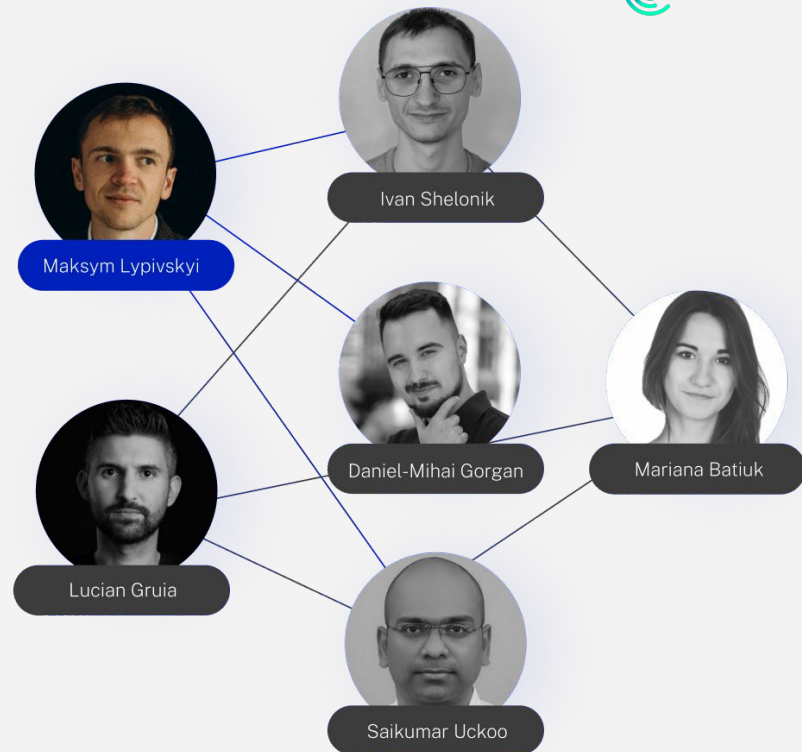
Some essential elements

that should be considered when verifying AI systems

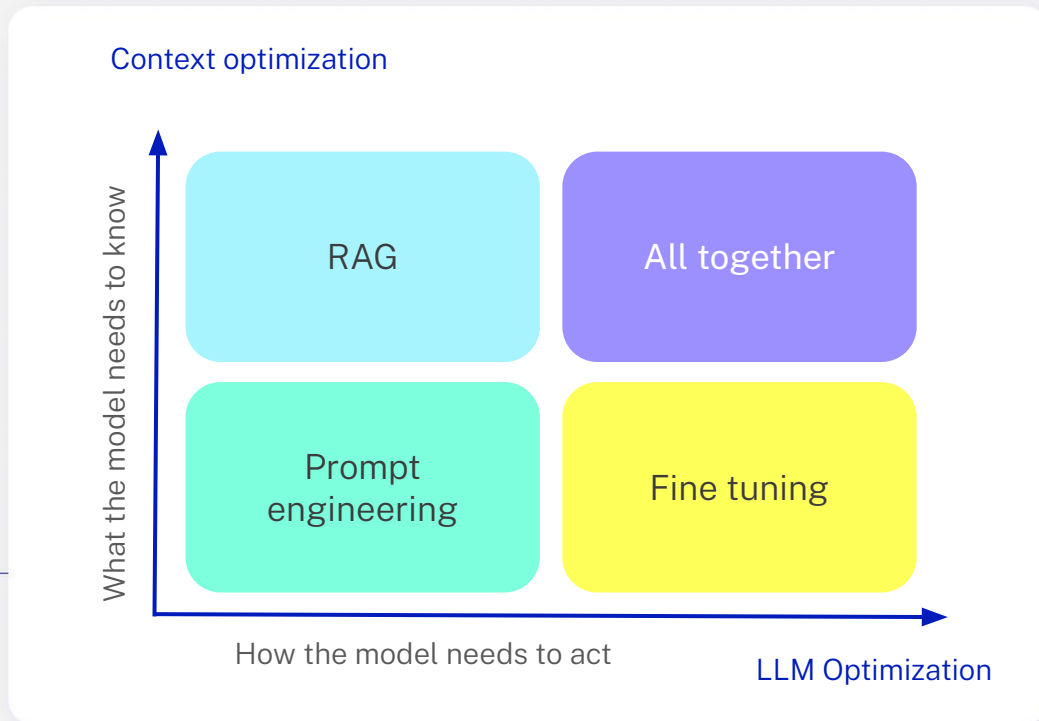


Interact

- **Prompt** Engineering
- Fine-tuning



The optimization flow



What is a good prompt

Act as an experienced Learning specialist. I need to improve my upselling skills. Prepare an educational program for me to improve that skills. Program should be for 2 month with 4 hours effort per week.

Please provide answer with the next output:

Topic: Name

- blocks
- ...

Books:

Example:

Topic: Negotiation basics

- Win-win strategy
- Active listening strategy

Books: "Getting to Yes" by Roger Fisher and William Ury

Instruction

Context

Role

Formatting

Tone

Examples

Prompt tactics

* Shot Prompting

Zero
Add 2+2:

One
Add 3+3: 6
Add 2+2:

Few
Add 3+3: 6
Add 5+5: 10
Add 2+2:

Model-guided prompting

Before answering, I want you to first ask for any extra information that helps you produce a better answer.

If you got no questions, please provide an answer instead.

Self-evaluating prompting

Can this program be improved?

Chain of thoughts

Virma has three bags, each of which fits five shirts. How many shirts can Virma fit in her bags?

Let's think step-by-step.

Prompt

Question + "Let's think step by step"

Response

Thought 1

Thought 2

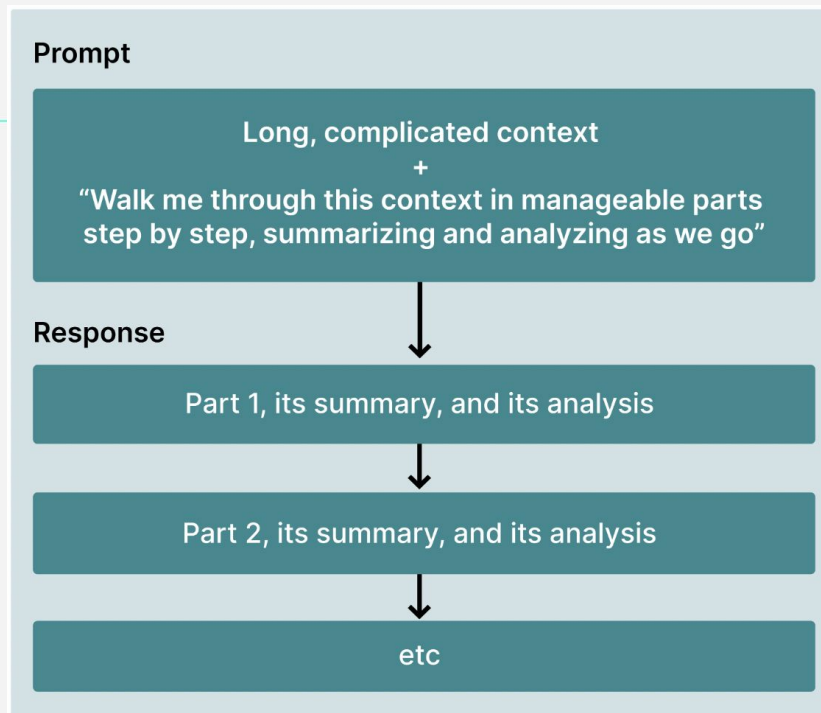
Thought 3

Answer

Thread-of-Thought

Virma has three bags, each of which fits five shirts. How many shirts can Virma fit in her bags?

Walk me through this context in manageable parts step by step, summarizing and analyzing as we go.

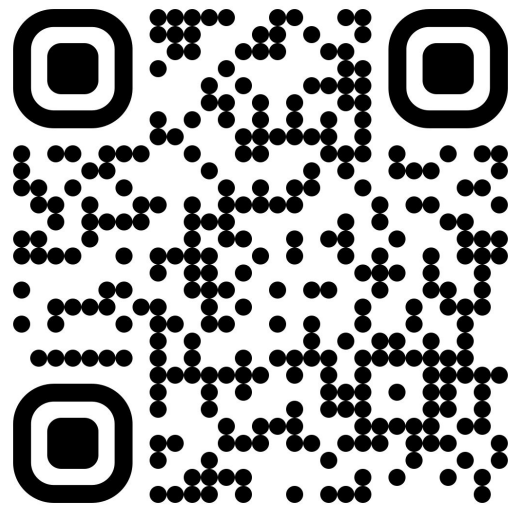




Thank you!



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feedback!



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