



## EngineTalk:

Supporting maintenance of diesel engines aboard navy ships through a RAG enabled LLM system

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# Contemporary challenges in naval operations:

- Maintaining operational capability despite:
  - Reduced crew sizes
  - Increasing complexity and number of on-board systems
  - Challenges in staffing expertise
  - Anticipated expertise turnover rates



# Deciding with Words

How LLMs are becoming Defence's new strategic partner

DEFENSE ONE

**U.S. Army commissions tech CEOs as reserve officers**

[25 jun 2025](#)

- Goal: Innovate faster with top-tier civil expertise.
- Strategic: AI as a core capability, not a gadget.
- Ethics: Explicitly address conflicts of interest and transparency.

DIGITAL WATCH OBSERVATORY

**Pentagon deploys LLMs for command and planning**

[2 jul 2025](#)

- Operational: LLMs in production for command and planning.
- Cases: Document-based planning, analysis, and decision support.
- Governance: Human-in-the-loop, logging, access control.

MCKINSEY & DATABRICKS

**78% of enterprises use GenAI; RAG as grounding layer**

[13 jun 2025](#)

- Adoption (78%): Broad use ≠ guaranteed impact.
- Colleague: From tool to data-driven teammate in processes.
- Value: Still limited — integration and ownership are crucial.

# Research Question

Our research poses the following:

**“To what extent can an LLM&RAG solution support naval engine service engineers in their maintenance tasks?”**

From which we study the following:

- To what extent can information from manuals best be processed to improve information delivery?
- How can historical maintenance data from the SAP system be integrated?
- How can our solution be evaluated?

# Expected outcome

Prevent unnecessary calls for land support, and having to fly in senior maintenance crews



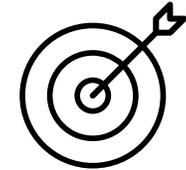
Thereby reducing costs

Doing more, with a less skilled crew, in fewer time.



Thereby increasing uptime

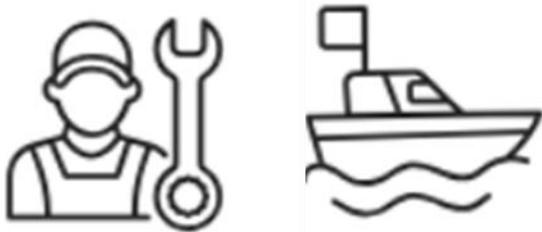
Create a better data fundament by aiding maintenance crews in documenting their work.



Thereby increasing quality

# User groups

## Maintenance crew (onboard)



- Small maintenance (regular, planned, reactive)
- Relatively unexperienced

## Operational support (Den Helder)



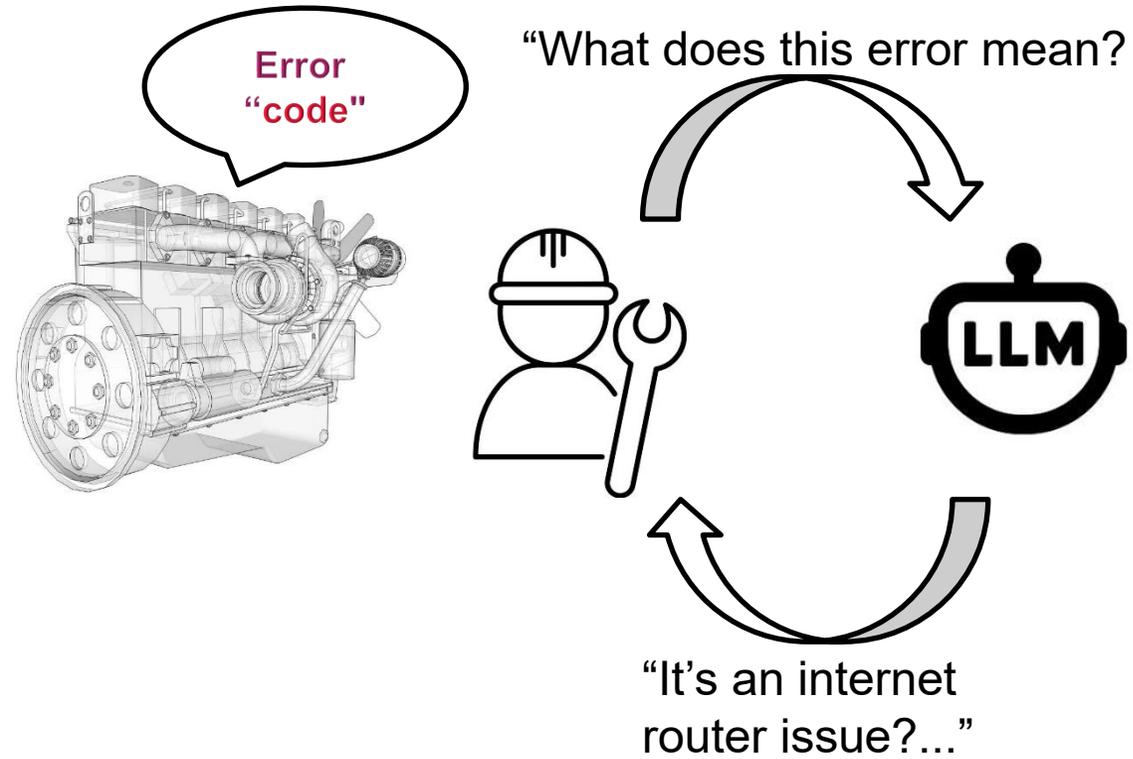
- Shore support for multiple ships
- Very experienced

## Installation manager (Den Helder)

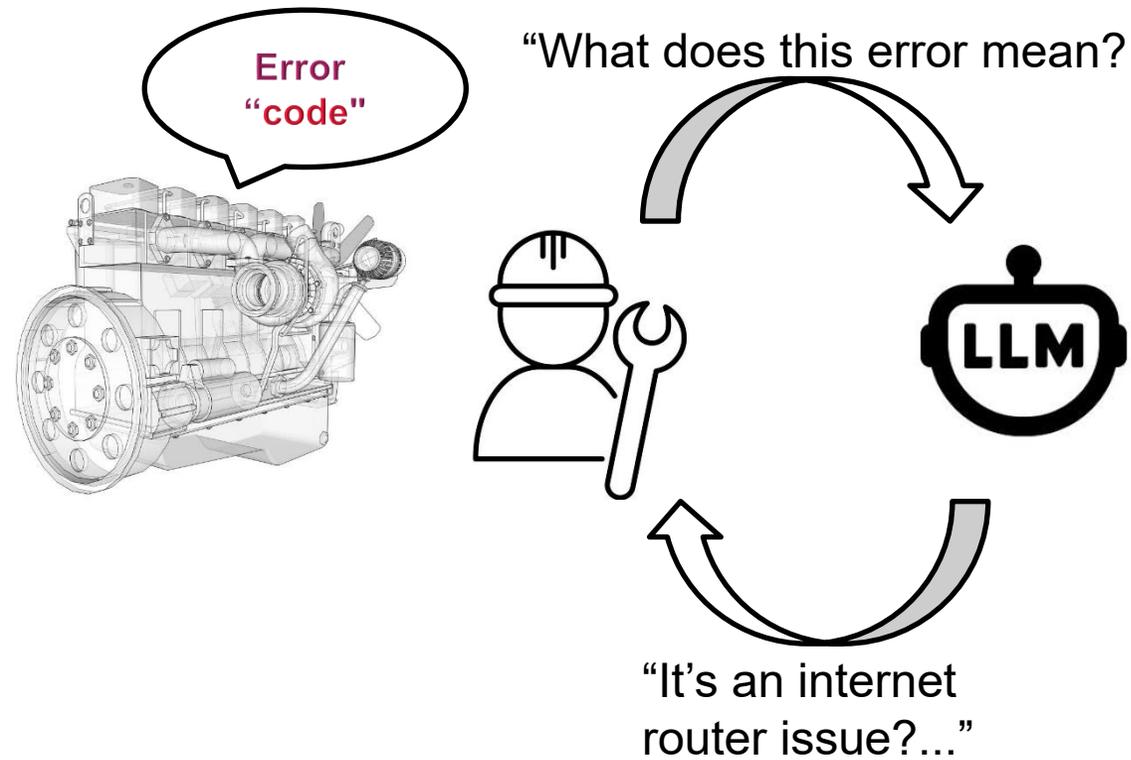


- Plans and coordinates large maintenance with specialised external crews and suppliers
- extremely experienced

# Workflow of an LLM...



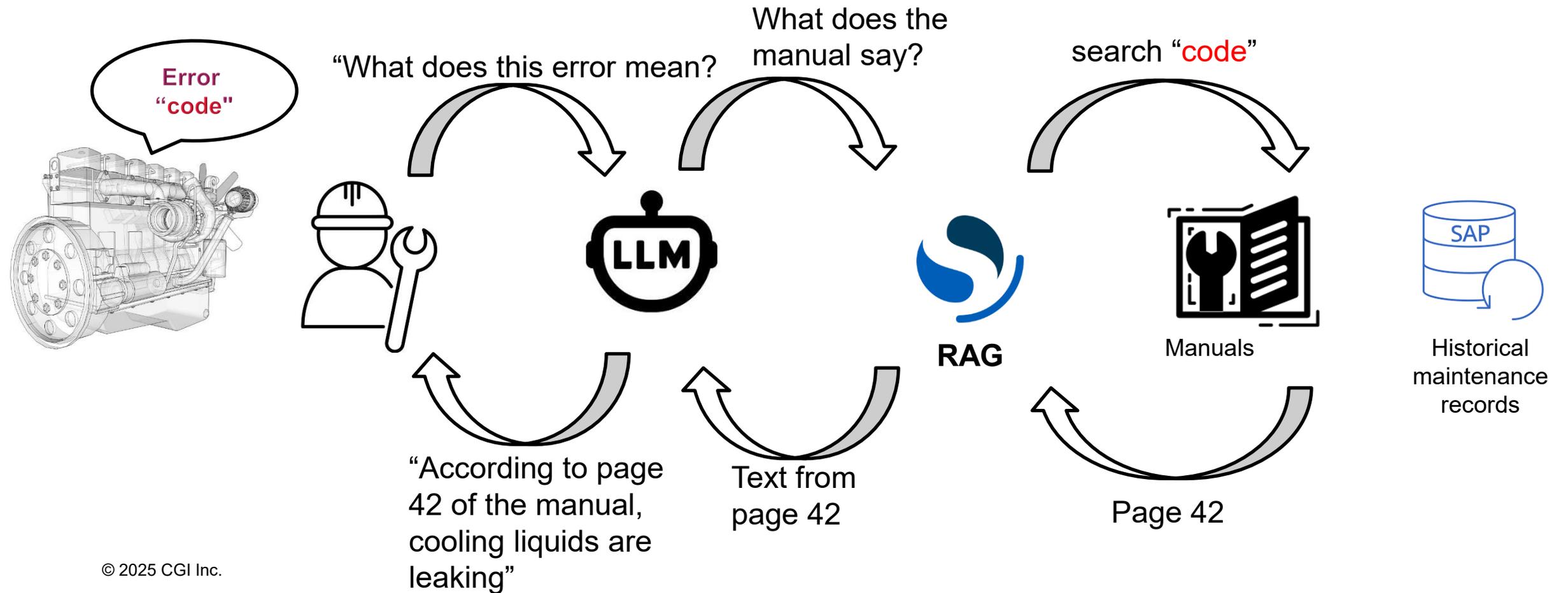
# Workflow of an LLM...



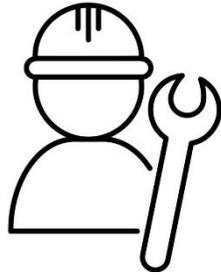
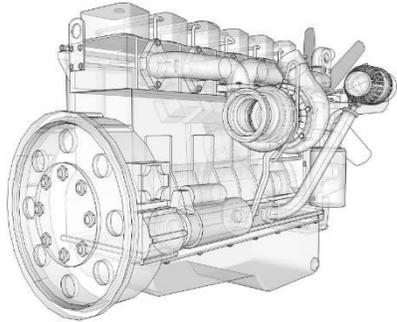
**Hallucination:** *an LLM doesn't possess enough knowledge about the domain, yet it is compelled to answer any question*

→ **It starts making things up**

# Workflow of an LLM with Retrieval-Augmented Generation



# LLM with Retrieval-Augmented Generation



Engine  
Manuals

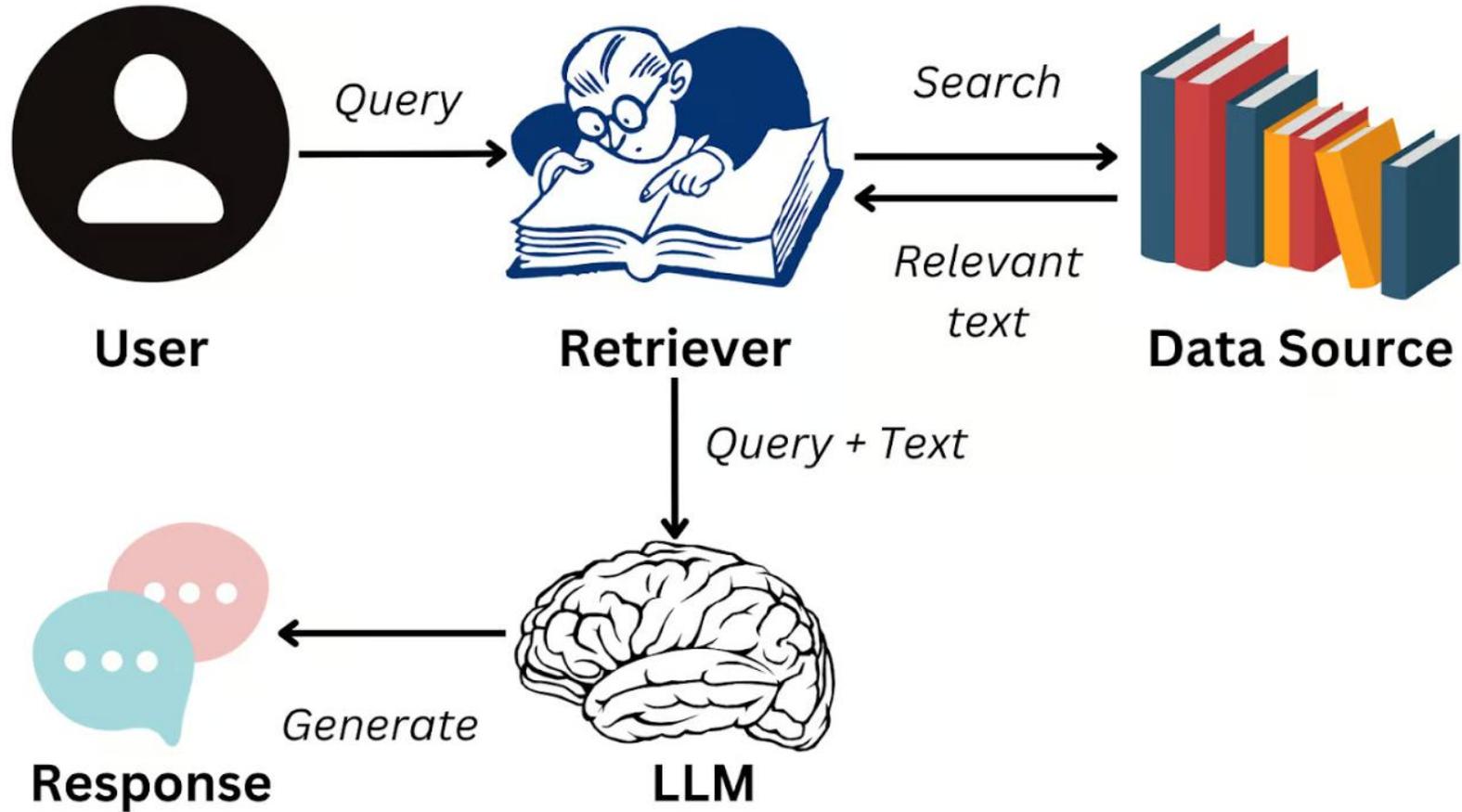


Maintenance  
Records

Through RAG, generated answers of an LLM become more:

- Reliable
- Explainable
- Traceable
- Grounded
- Multi-faceted

# LLM & Retrieval-Augmented Generation (RAG)



# LLMs, RAG, & Vector Embeddings

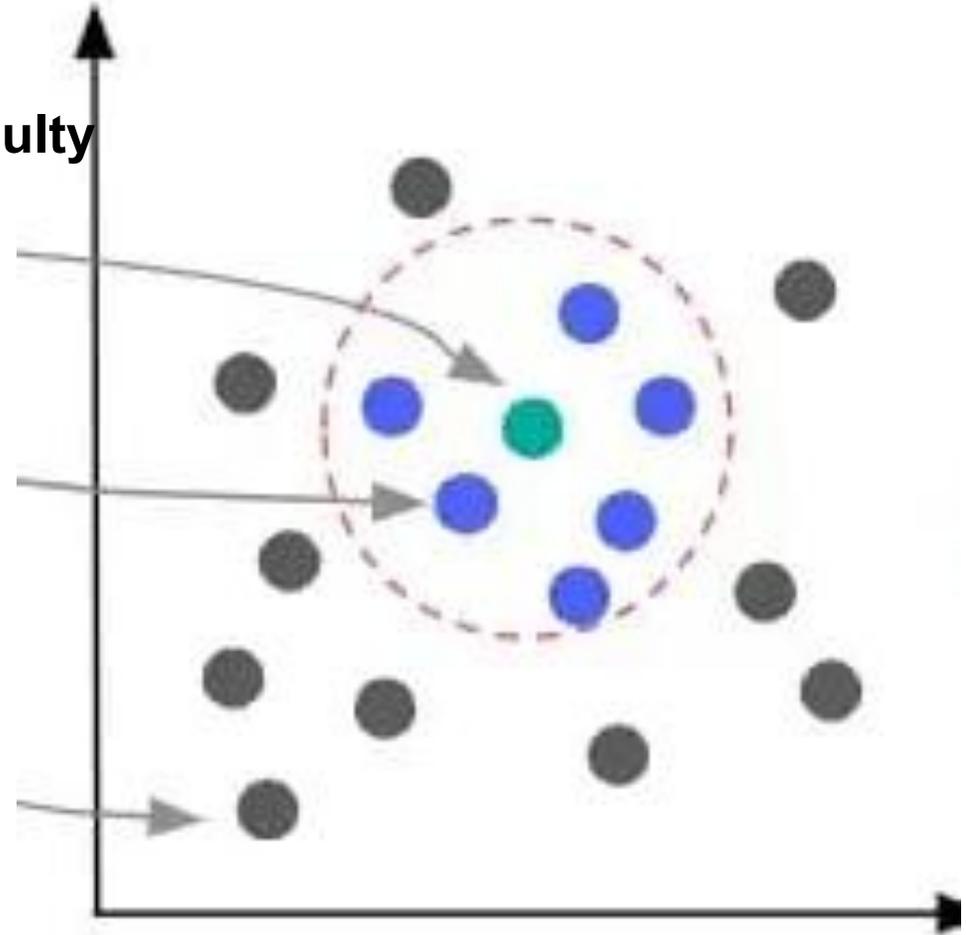
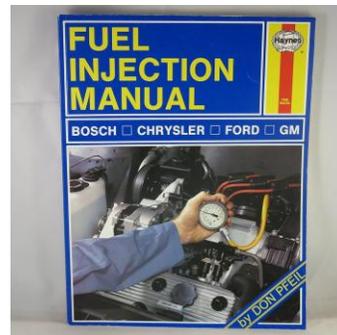
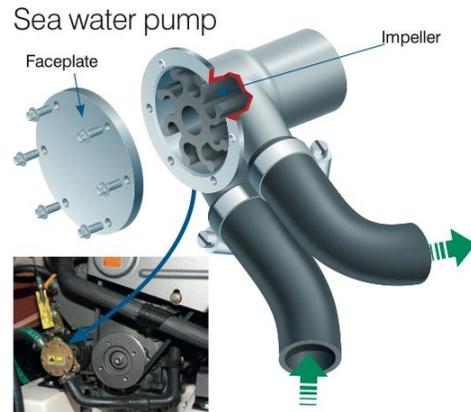
Embedding space  
(Typically a vector space of dimension ~500-1000)



User

Query →

“What procedure do I need to diagnose a **faulty water pump?**”



# RAG-improvements

RAG seldom works out-of-the-box...

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*How can we ensure that retrieved contexts are more likely to be relevant to the user's questions?*

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RAG seldom works out-of-the-box...

*How can we ensure that retrieved contexts are more likely to be relevant to the user's questions?*

*How do we test our solution? How do we know when it “works”?*

# RAG-improvements



RAG

- Hybrid search

I'm working on the impeller of a sea-water cooling pump. What are the disassembly instructions?



- ✓ Disassembly instructions for sea-water pump:[...]
- ✗ Disassembly instructions for backup generator for water pump:[...]
- ✗ 'I'm working on the power supply, and after following disassembly instructions [...]

# RAG-improvements

- Hybrid search: word-matching

## Meaningful words:

- Impeller
- Sea-water
- Cooling pump
- Disassembly instructions

## Non-meaningful words:

- On
- Of
- Are
- The
- Working
- after



RAG

I'm working on the **impeller** of a **sea-water cooling pump**. What are the **disassembly instructions**?



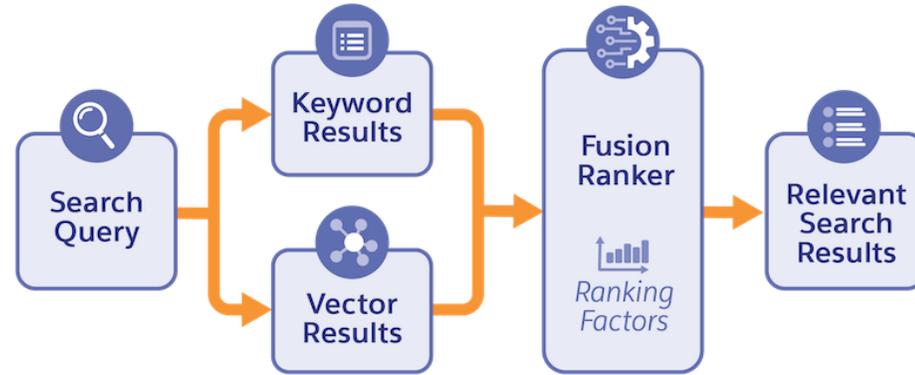
✓ **Disassembly instructions for sea-water pump:[...]**

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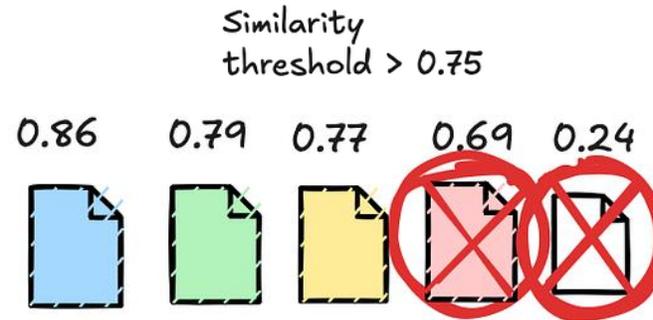
✗ 'I'm working on the power supply, and after following **disassembly instructions** [...]

# RAG-improvements

- Hybrid search

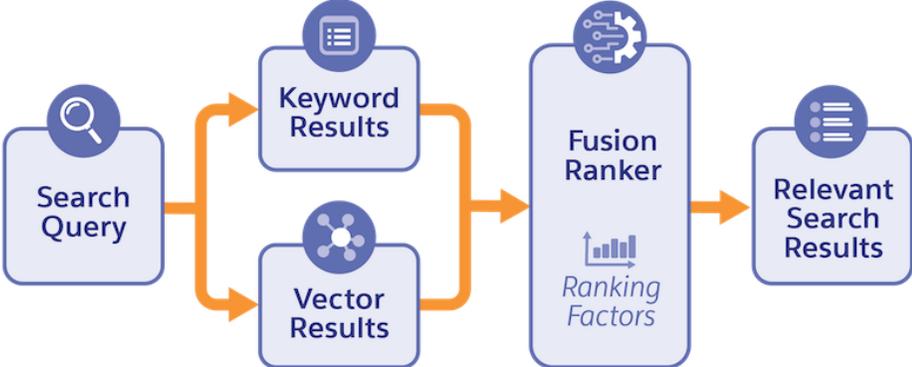


- Minimum-threshold matching

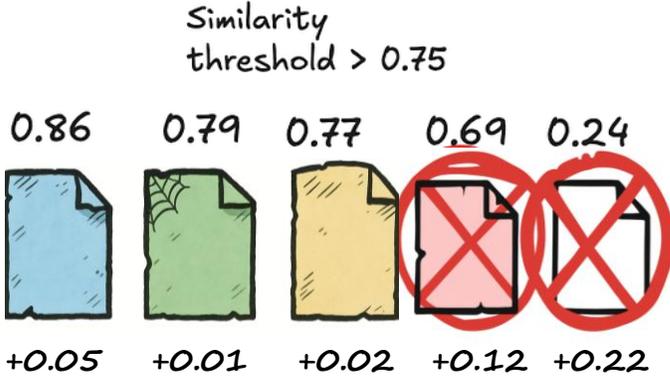


# RAG-improvements

- Hybrid search



- Minimum-threshold matching
- Recency-boosting



# RAG

RAG seldom works out-of-the-box...

*How can we ensure that retrieved contexts are more likely to be relevant to the user's questions?*

*How do we test our solution? How do we know when it “works”?*

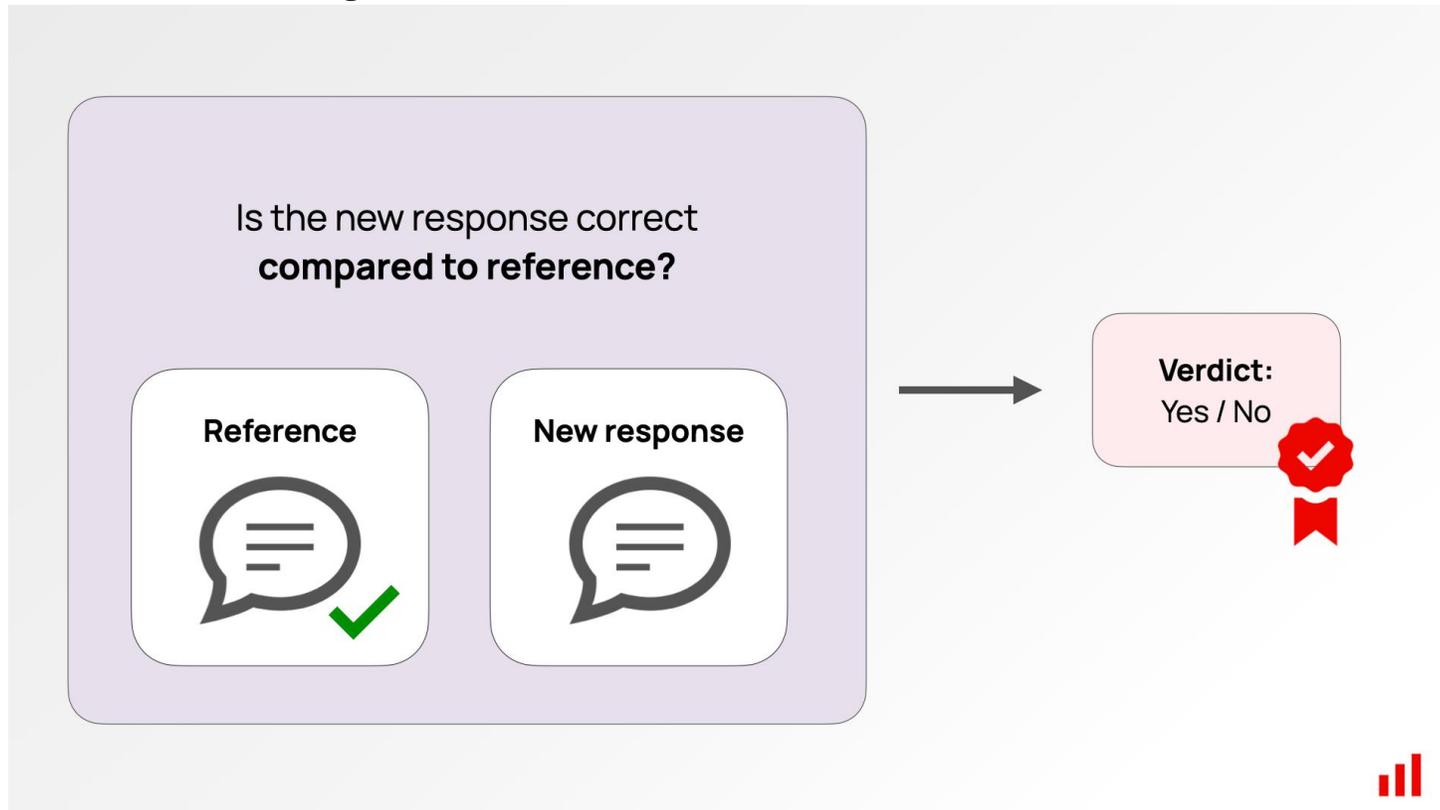
# Evaluating an LLM application

- Establishing an **evaluation set**

<b>User query</b> 	<b>RAG context</b>  <small>RAG</small>	<b>Generated answer</b> 	<b>Reference answer</b> 
“How big was the Titanic?”	“[...] Titanic was listed to be a staggering 270 [...]” - Wikipedia	“According to Wikipedia, the Titanic was 270 meters in length”	“The Titanic was 270 meters long”
...	...	...	...
...	...	...	...

# Evaluating an LLM application

- Establishing an **evaluation set**



# Evaluating an LLM application

- Establishing an **evaluation set**

- Computing evaluation metrics:

- Factual correctness
- Context Recall
- Faithfulness

User query	RAG-context	Generated answer	Reference answer
“How big was the Titanic?”	“[...] Titanic was listed to be a staggering [...]” - Wikipedia	According to Wikipedia, the Titanic was [...]	The Titanic was 270 meters long [...]
...	...	...	...
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# Evaluating an LLM application

- Establishing an **evaluation set**

- Computing evaluation metrics:

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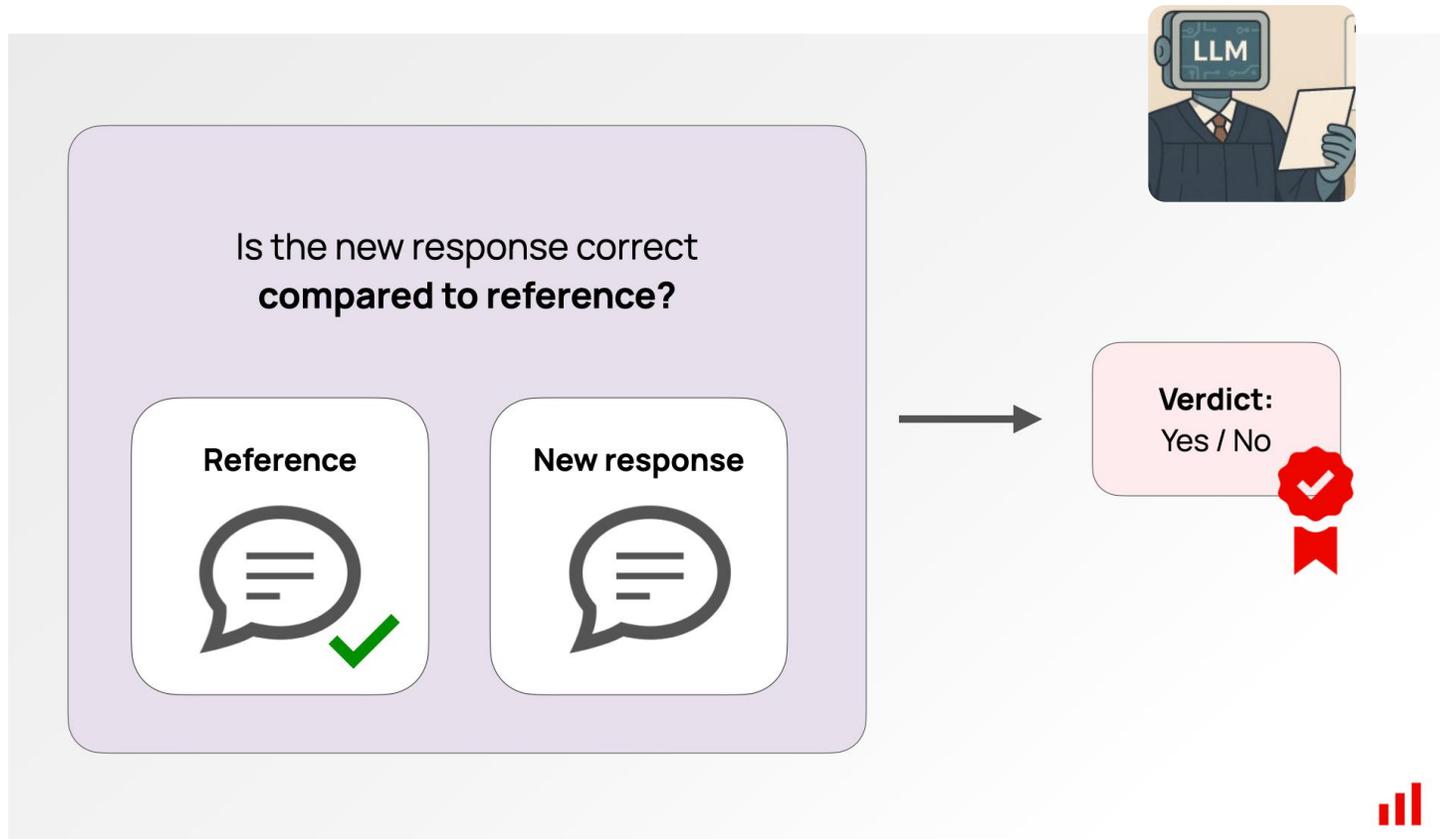
Using **LLM-as-a-judge**

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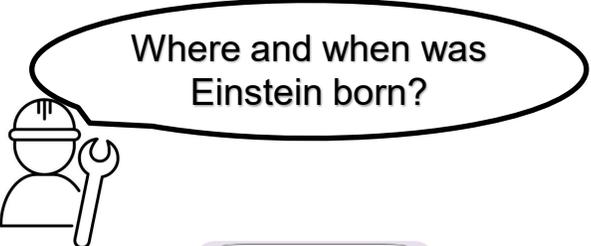
# Evaluating an LLM application



# Evaluating an LLM application



# Evaluating an LLM application: Factual Correctness



*“Albert Einstein was a renowned physicist, born in Germany in 1879. He was best known for developing the theory of relativity.”*

Einstein was a renowned physicist

Einstein was born in Germany

Einstein was born in 1879

Einstein developed the theory of relativity



Einstein was born in Germany

Einstein was born in 1879

Einstein was born on 14<sup>th</sup> of March



**Albert Einstein was born in Germany on March 14<sup>th</sup>, 1879**

# Evaluating an LLM application: Factual Correctness

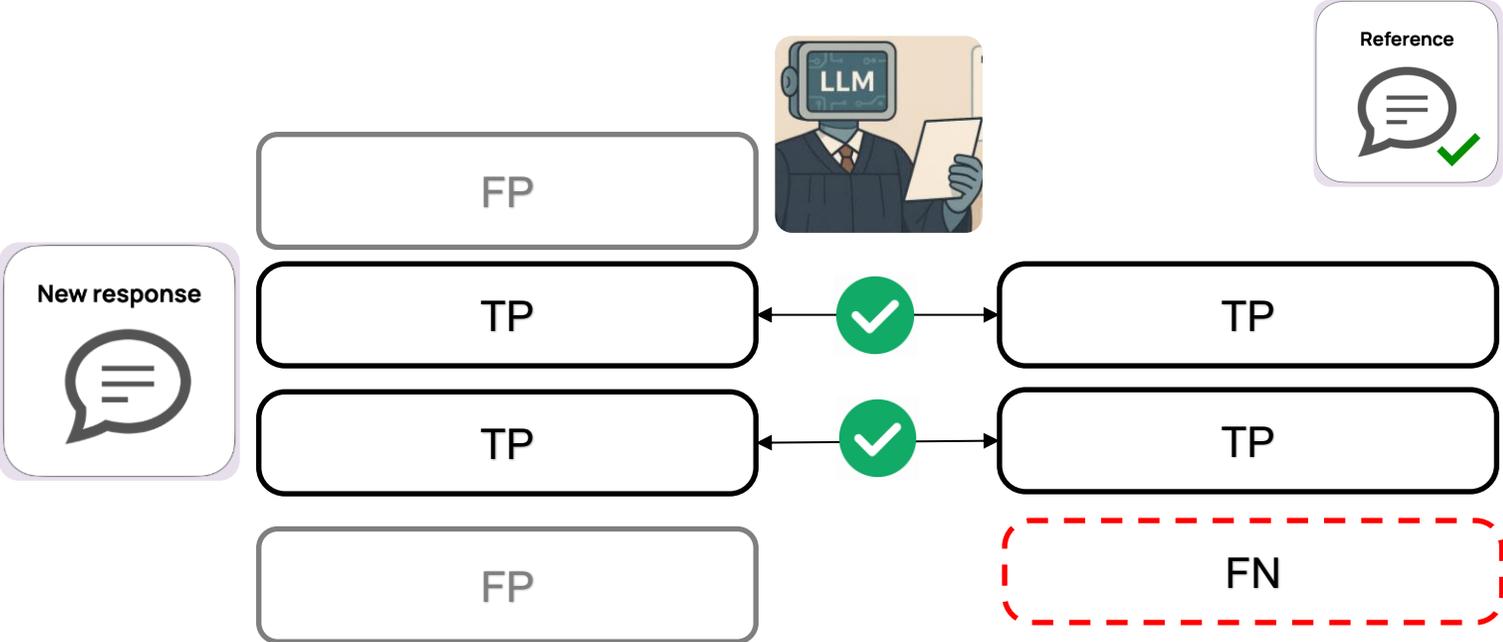
True Positive (TP) = Number of claims in response that are present in reference

False Positive (FP) = Number of claims in response that are not present in reference

False Negative (FN) = Number of claims in reference that are not present in response

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

$$\text{Recall} = \frac{TP}{(TP + FN)}$$



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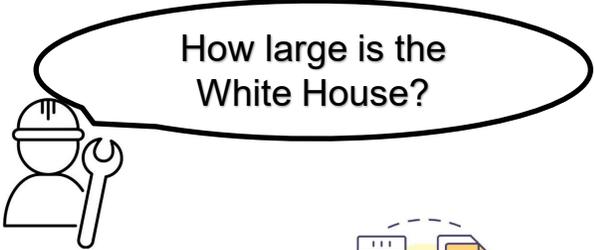
Factual correctness:

*How close is the answer generated by the LLM to the “correct” answer?*

- *How much irrelevant extra information did the LLM give?*
- *How much information did the LLM fail to provide, that should have been part of its answer?*

# Evaluating an LLM application: Context Recall

Computing evaluation metrics:



RAG

- Height: 22 m
- Width: 52 m
- 16 main rooms
- 6 restrooms



- Height: 22 m
- Width: 52 m
- Depth: 26 m

$$\text{Context Recall} = \frac{\text{Number of claims in the reference supported by the retrieved context}}{\text{Total number of claims in the reference}}$$

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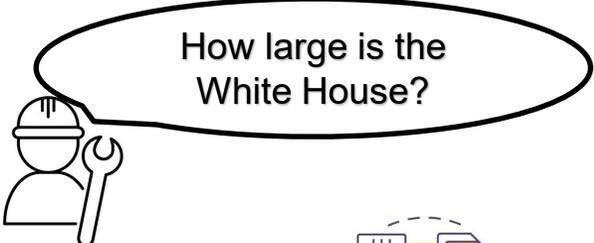
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*“How many of the claims in the reference answer were present in the retrieved contexts?”*

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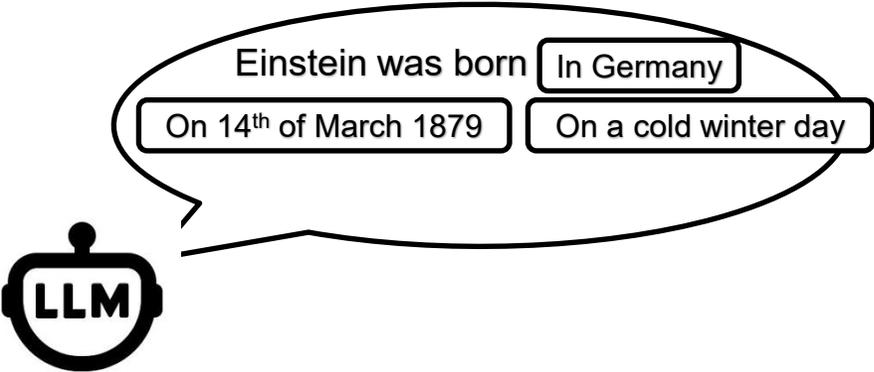
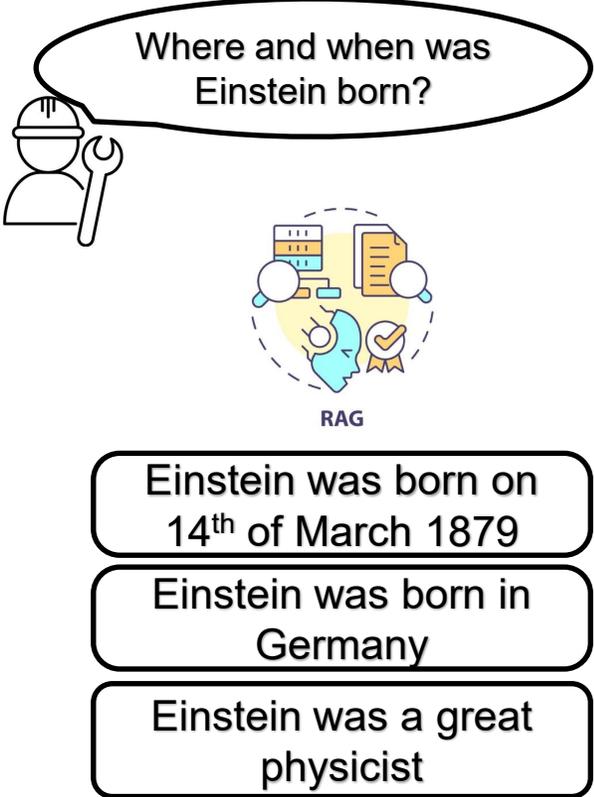
*“How many of the claims in the reference answer were present in the retrieved contexts?”*

i.e: “Did RAG manage to retrieve the information that would suffice a perfect LLM agent to generate a correct answer?”

# Evaluating an LLM application: Faithfulness

Computing evaluation metrics:

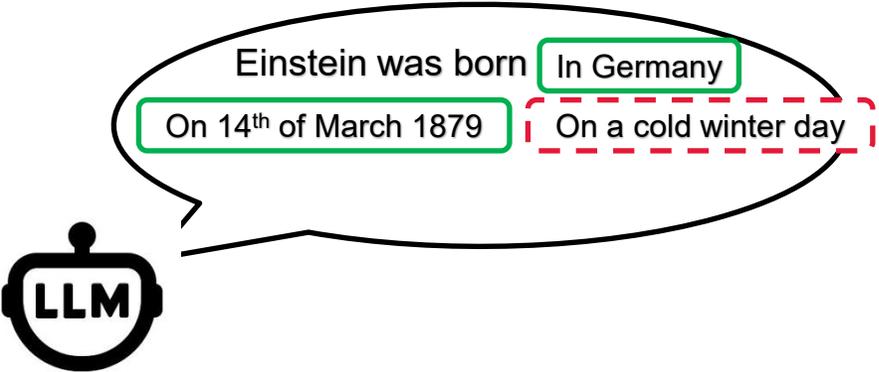
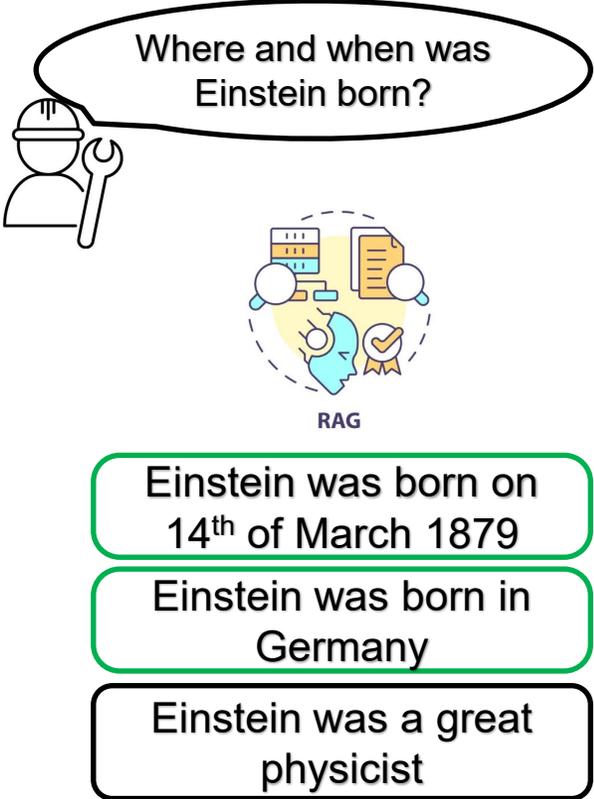
$$\text{Faithfulness score} = \frac{|\text{Number of claims in the generated answer that can be inferred from given context}|}{|\text{Total number of claims in the generated answer}|}$$



# Evaluating an LLM application: Faithfulness

Computing evaluation metrics:

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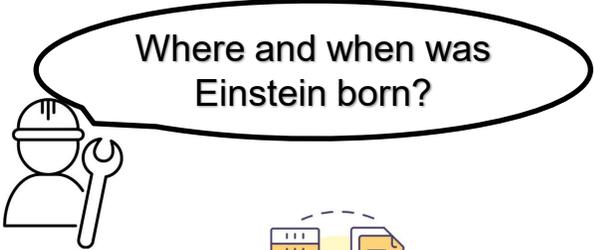


*“How faithful was the LLM in only using claims that were backed by its RAG context?”*

# Evaluating an LLM application: Faithfulness

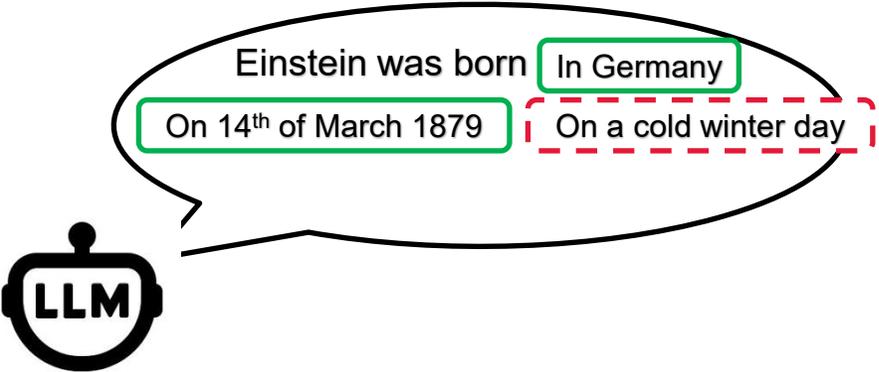
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RAG

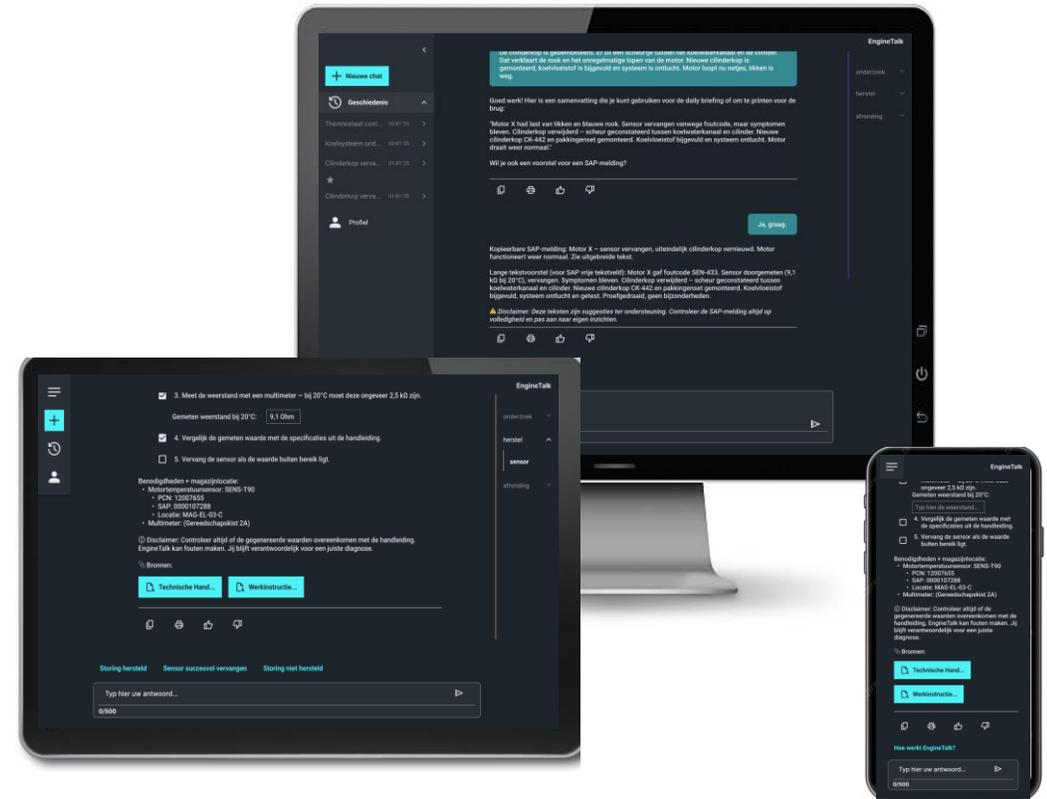
- Einstein was born on 14<sup>th</sup> of March 1879
- Einstein was born in Germany
- Einstein was a great physicist



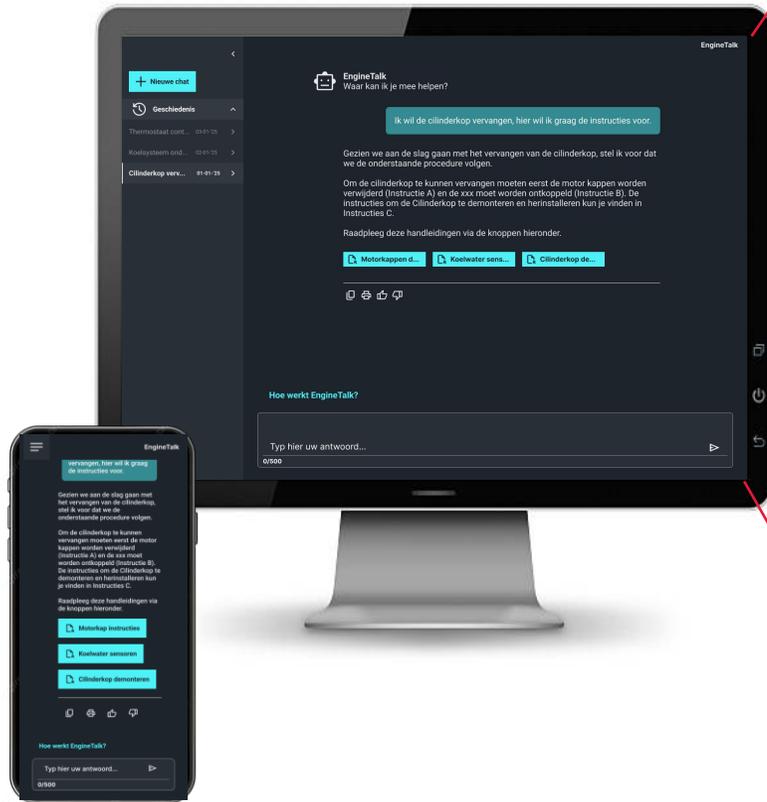
*“How faithful was the LLM in only using claims that were backed by its RAG context?”*

→ Gives a measure of **Hallucinations**

# Results



# Results



EngineTalk

+ Nieuwe chat

Geschiedenis

- Thermostaat cont... 03-01-25
- Koelsysteem ond... 02-01-25
- Cilinderkop verv... 01-01-25

EngineTalk  
Waar kan ik je mee helpen?

Ik wil de cilinderkop vervangen, hier wil ik graag de instructies voor.

Gezien we aan de slag gaan met het vervangen van de cilinderkop, stel ik voor dat we de onderstaande procedure volgen.

Om de cilinderkop te kunnen vervangen moeten eerst de motor kappen worden verwijderd (Instructie A) en de xxx moet worden ontkoppeld (Instructie B). De instructies om de Cilinderkop te demonteren en herinstalleren kun je vinden in Instructies C.

Raadpleeg deze handleidingen via de knoppen hieronder.

Motorkappen d... Koelwater sens... Cilinderkop de...

Hoe werkt EngineTalk?

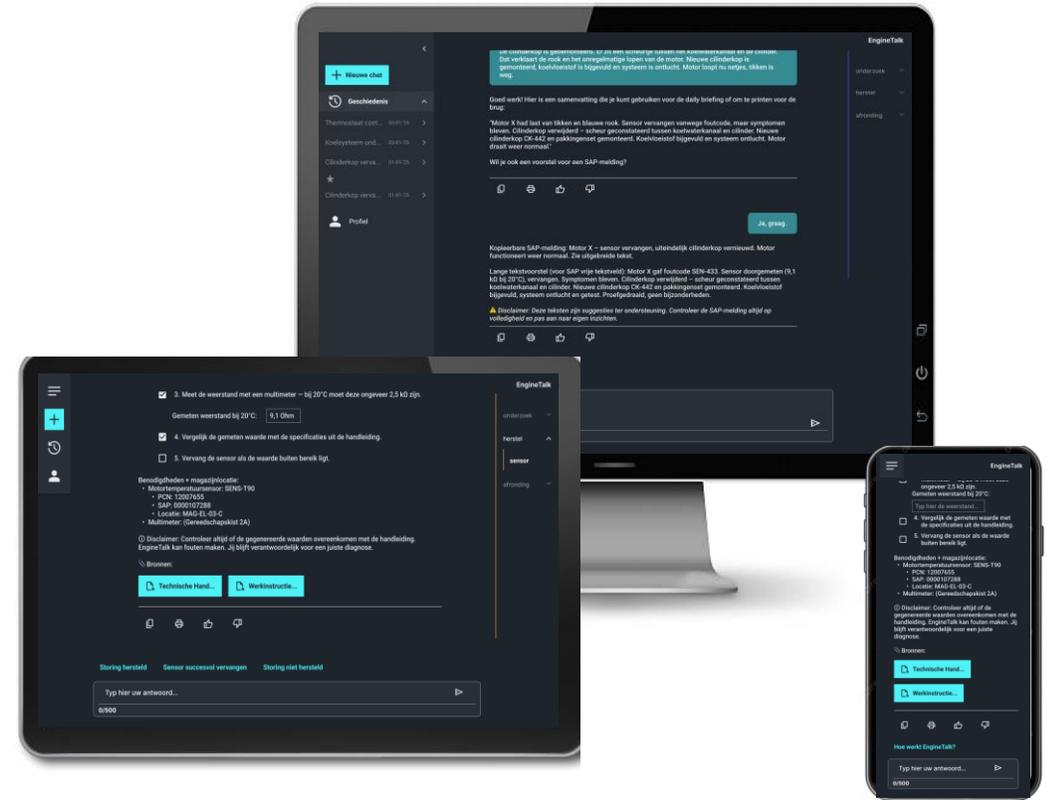
Typ hier uw antwoord...  
0/500

# Results

Early results are promising:

Functionally:

- Positive feedback from end-users
- Especially inexperienced personnel
- RAG shown to reduce hallucinations



# Results

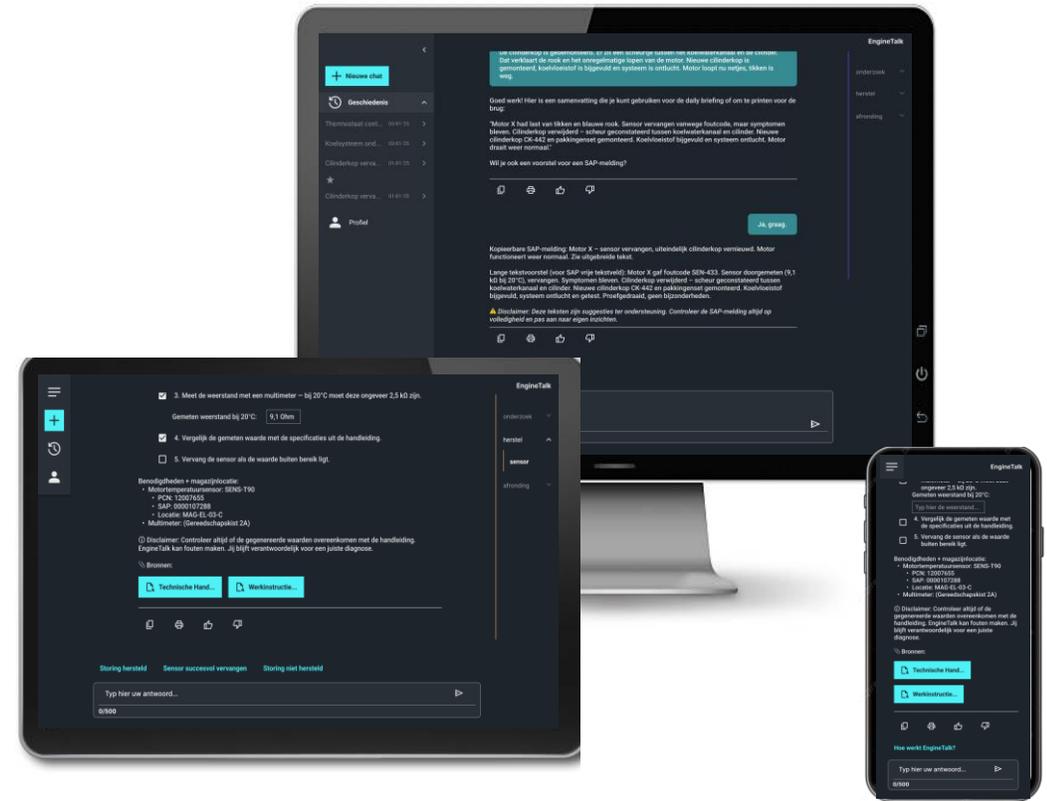
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Functionally:

- Positive feedback from end-users
- Especially inexperienced personnel
- RAG shown to reduce hallucinations

LLM-evaluation:

- Promising early results,
- but still pending due to complexity



# Conclusions

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- An LLM&RAG solution can substantially reduce time spent on diagnosis and repair
  - Especially for inexperienced crews.
- The integration of historical maintenance records is highly dependent on quality of such records.
- Thorough LLM-evaluations exist
  - but remain experimental, and prone to complexity

# Future prospects

- On-vessel deployment of EngineTalk
- Expanding scope to different user-groups, and other IT systems
- Utilizing LLMs with real-time system components

# Any questions?



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