

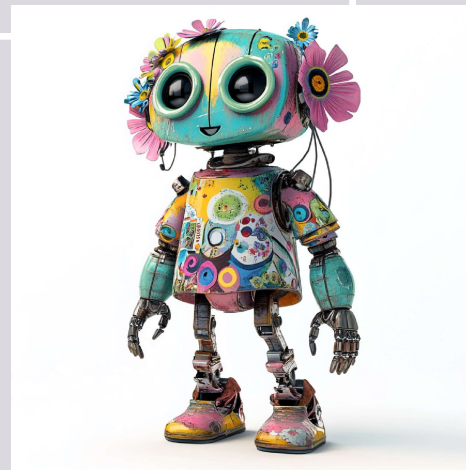
# GPTx und RAG in der Praxis

**Schluss mit Prototyp**

Olliver Zeigermann  
Christian Hidber

data2day, Heidelberg, September 2024

Chef:  
mein Enkel kann das auch...

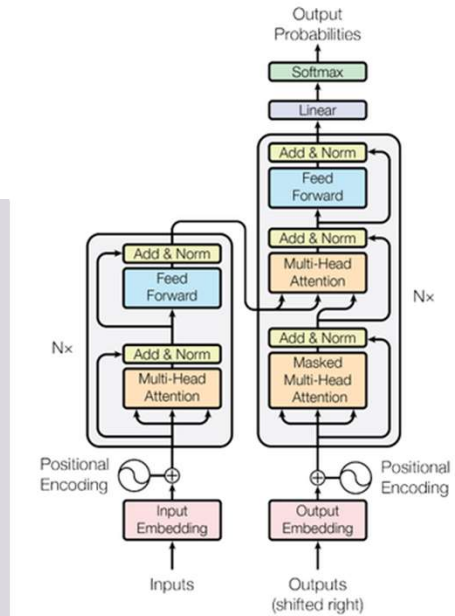


# LLM Intro

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## Transformers, LLMs, Encoder, Decoder: WTF?

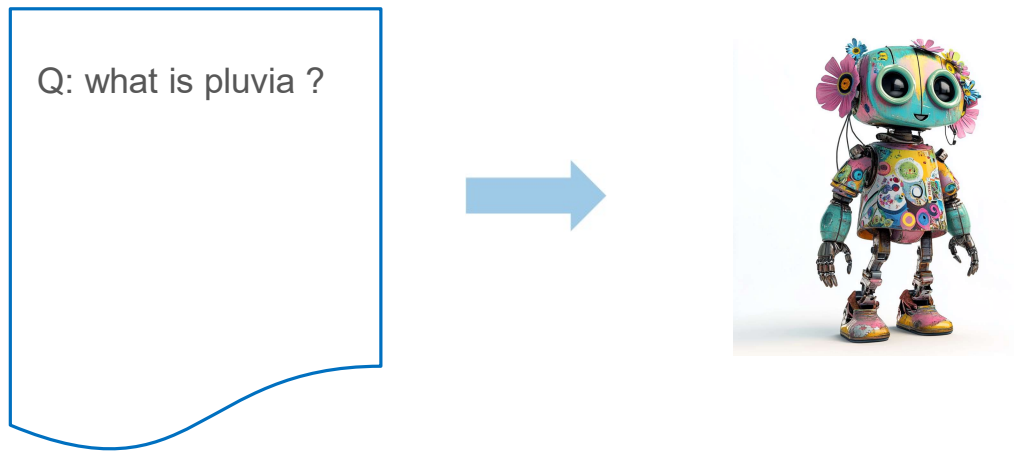
- **Transformers:** A flexible architecture that uses self-attention to process sequential data efficiently.
- **LLMs:** Large-scale Transformer models trained on extensive text datasets to perform various language tasks.
  - **Encoder Models:**
    - Part of the Transformer architecture focused on understanding and interpreting input data (e.g. *BERT*)
    - Instrumental for Embedding Models
  - **Decoder Models:**
    - Part of the Transformer architecture focused on generating sequential output based on the interpreted inputs or prior outputs
    - Instrumental for GPT-style Models like **Llama, Mistral or OpenAI GPT**



# Decoder Models

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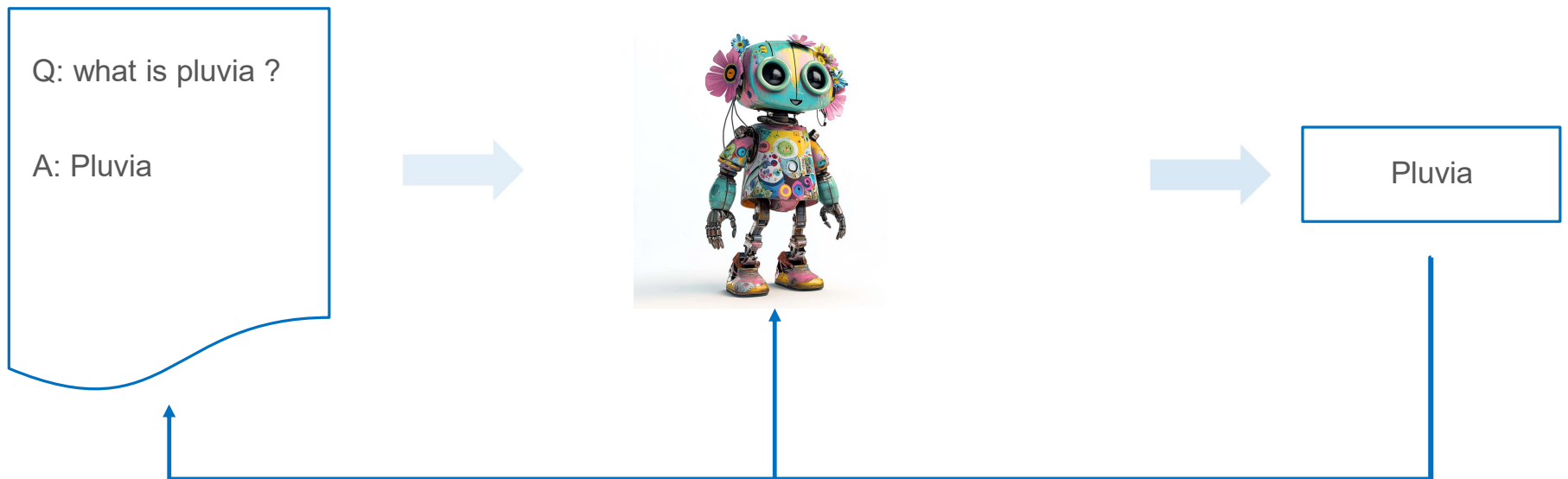
## How does a Decoder Model work ?



- Depends on users goal
- Unique for each chat & user
- Contains the chat history
- «**the context**»

- Trained on huge datasets
- Does not change
- Same for all users
- «**the model**»

## How does a Decoder Model work ?

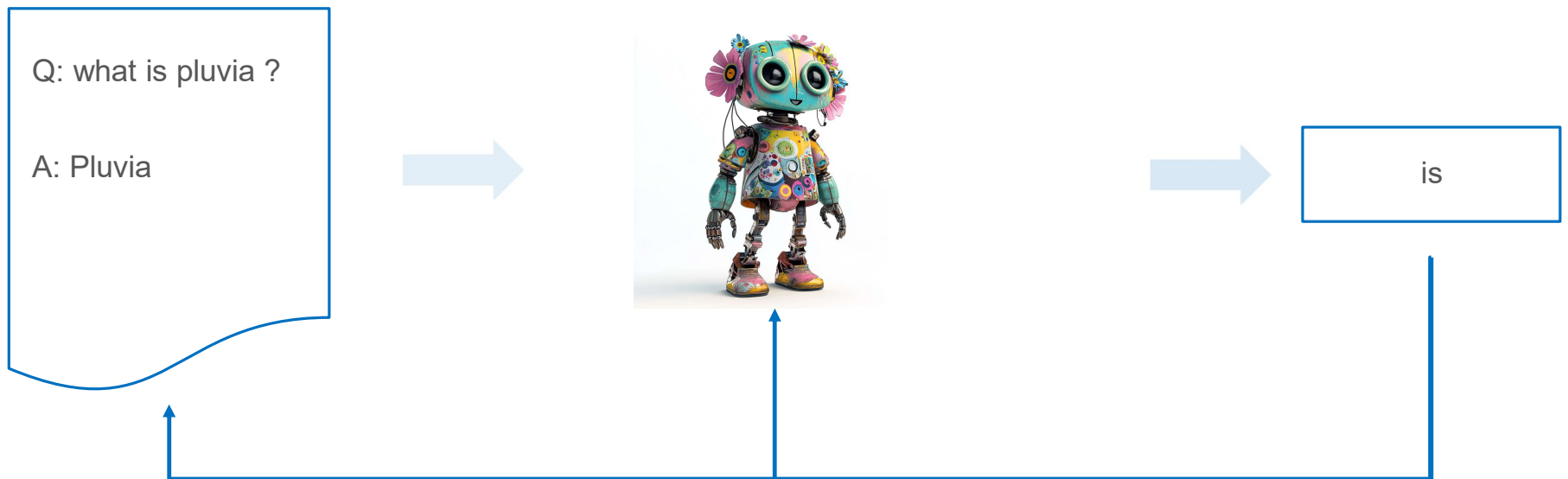


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- Single «word»
- Depends on context and model
- **«the token»**

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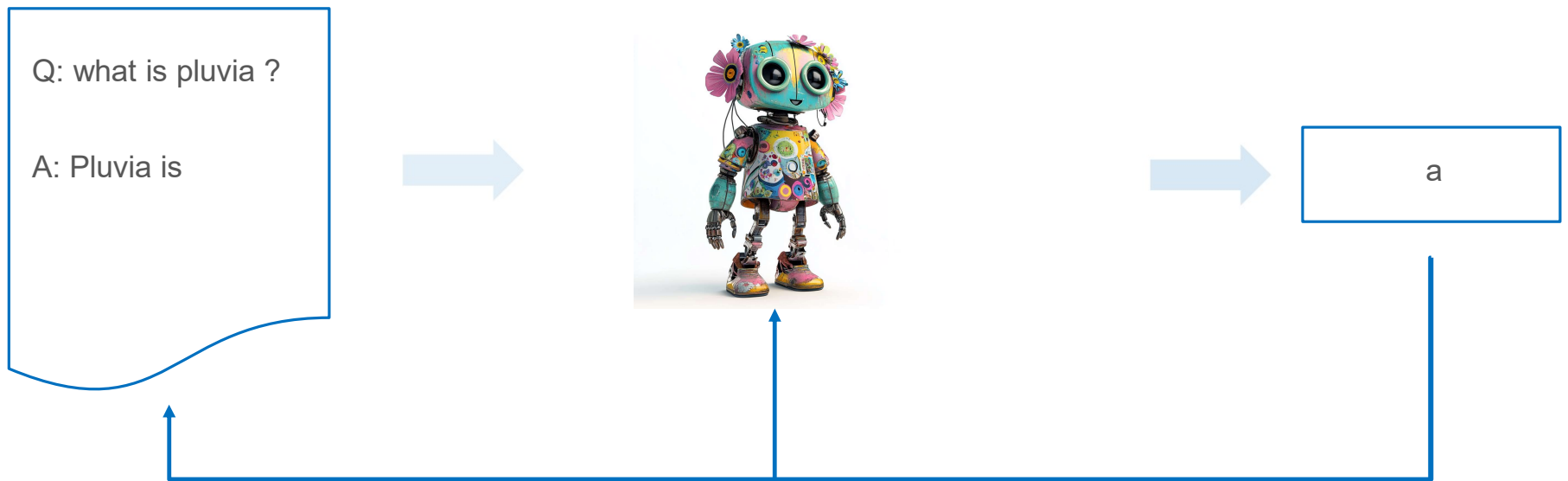
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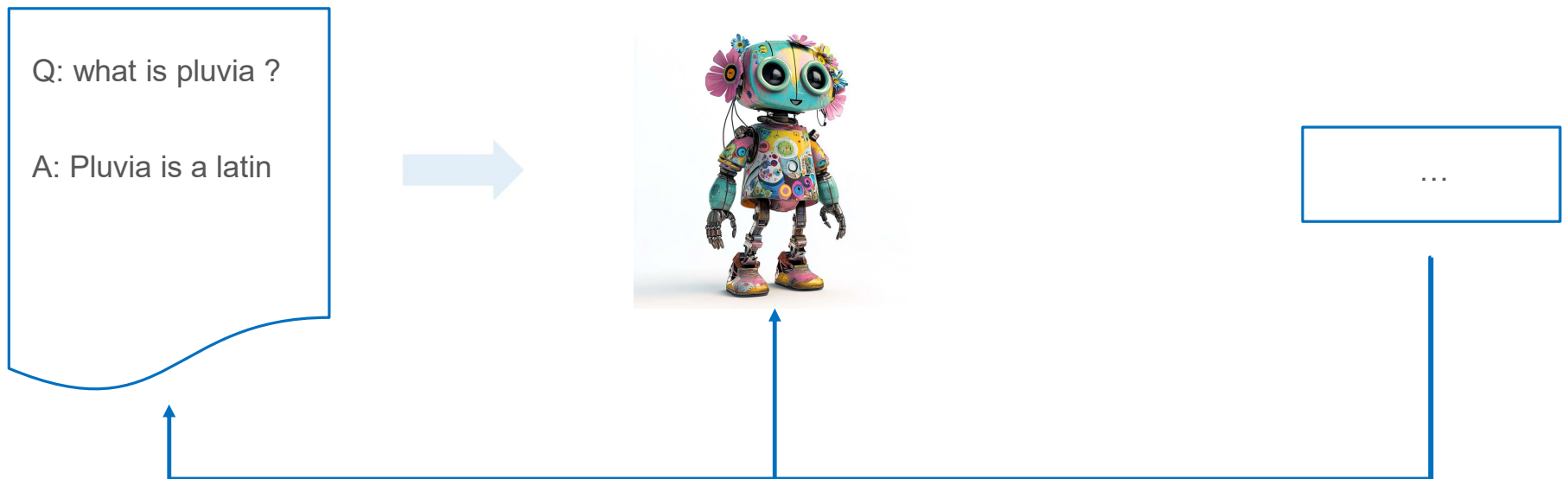
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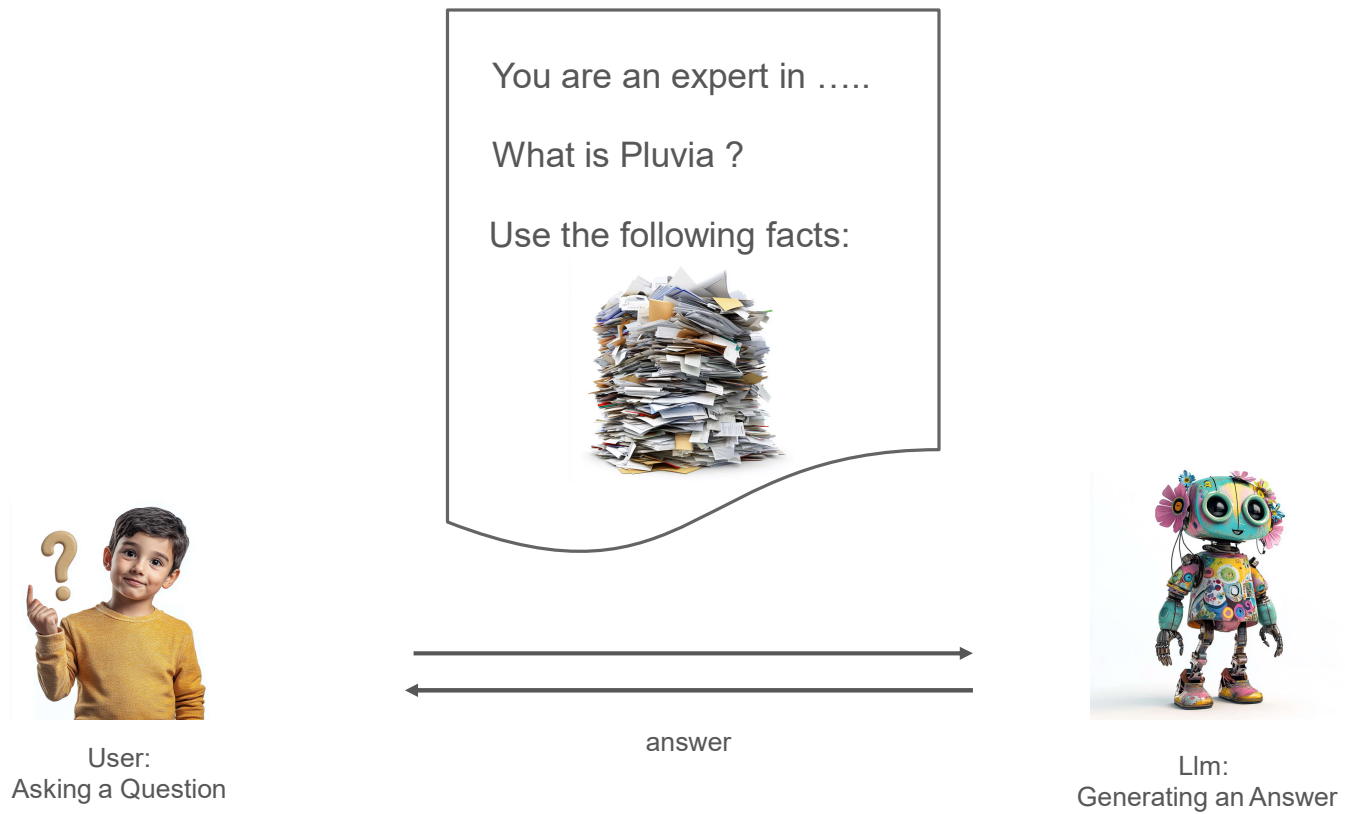


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## Naïve Approach



Idea: just a few pages

You are an expert in .....

What is Pluvia ?

Use the following facts:

**18.1.2 Vorteile von Gebert Pluvia gegenüber**  
Durch die Vollführung des Pluvia Dachentwässerung mehrer Dachentwässerung mehrer

**Planungsregeln für Regen**  
Die Dimensionierung des Regen-Pluvia Dachentwässerung mehrer Dachentwässerung mehrer

**18.1.4 Funktionsprinzip Gebert Pluvia**  
Die Gebert Pluvia Dachentwässerung mehrer Dachentwässerung mehrer

**Gebert Pluvia Nachbaurufe**  
**Grundlagen**  
Der Gebert Pluvia Nachbaurufe ist ein System zur Regen-Pluvia Dachentwässerung mehrer Dachentwässerung mehrer

**Praxisregeln**  
Die Gebert Pluvia Dachentwässerung mehrer Dachentwässerung mehrer



User:  
Asking a Question



answer



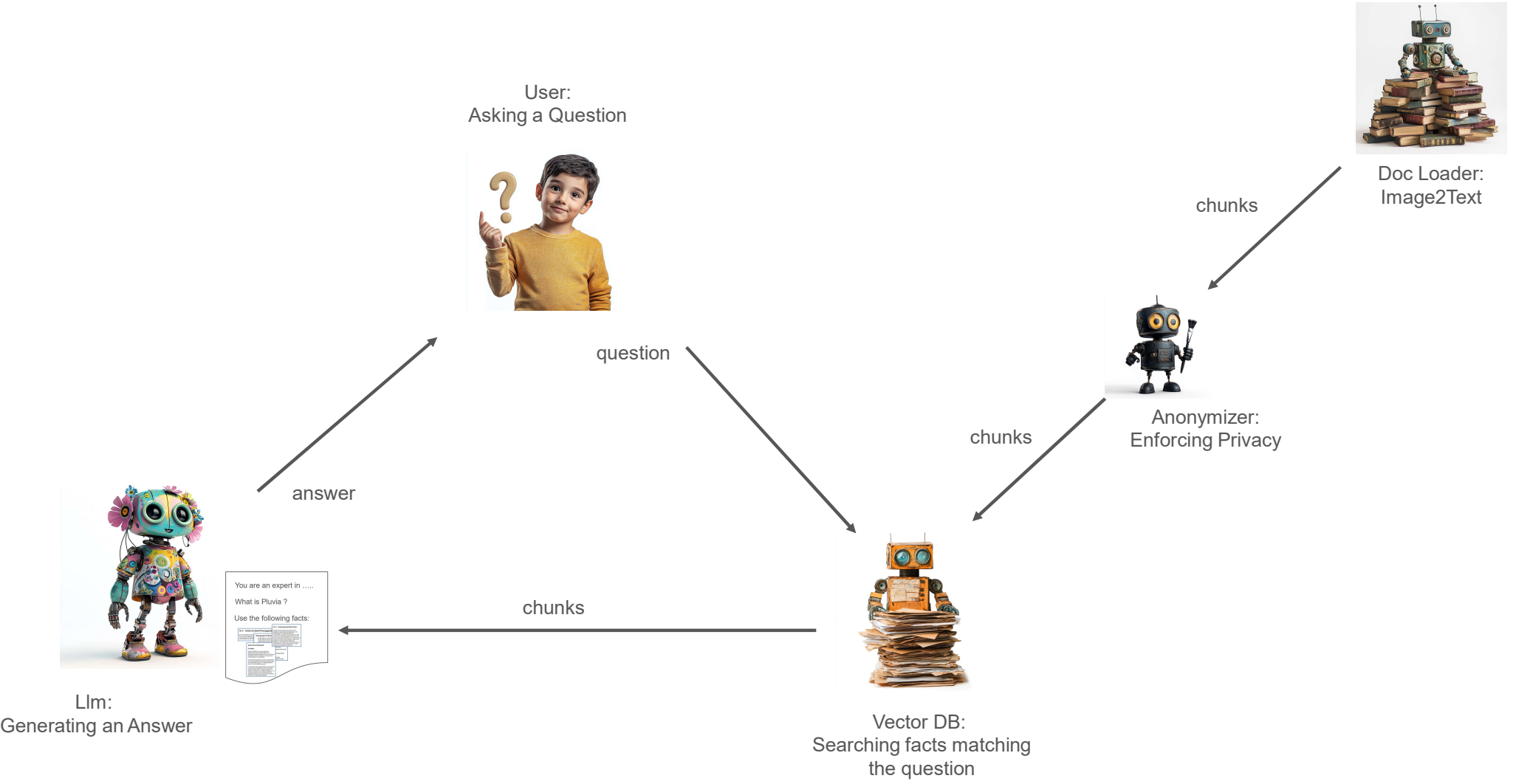
Llm:  
Generating an Answer

# **RAG**

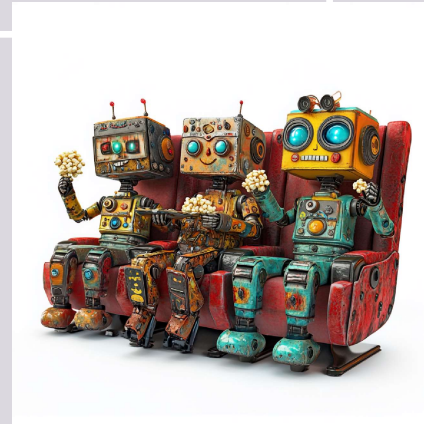
## **Retrieval Augmented Generation**

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# RAG System Architecture



Demo:  
Low Risk RAG Applications





# Choosing an application

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## Low Risk, but nice benefit

- What is the biggest risk we are facing?
- What is the worst thing that could happen and how to mitigate that?
- Choose something that is low risk, but nice benefit
- Low profile
- Failures should be ok
- Let the whole organization learn
- Management likes it, but is afraid

# **From Prompt Hacking to Production**

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## Der kleine Heimwerker vs Ingenieur Tätigkeit

- hohes Maß an Automatisierung
- Generalisierung: Modell auf zukünftige Daten verallgemeinert anwendbar?
  - Der Nutzen ergibt sich durch Vorhersage auf bisher unbekannten Daten in der Zukunft.
  - Auf diesen muss das Modell eine gute Leistung bringen. Nur das ist relevant.
- über einen längeren Zeitraum stabil bleiben
- **Beispiel LLM und Prompting - können wir das nicht alle?**
- Von welcher Art Prompting sprechen wir ? Muss man unterscheiden von ad hoc Prompting
- Bei Ad hoc sieht man direkt, ob es geht. Man hat ein hohes Maß an menschlicher Überwachung.
- Unterschied internes Werkzeug und stabiler Service. Plattform Team

# Evaluation

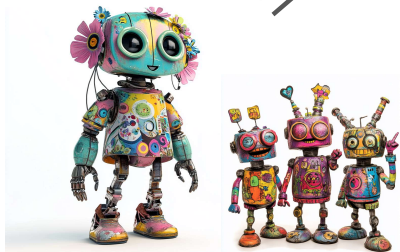
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## Evaluation on text results

User:  
Asking a Question



answer



Llm:  
Generating an Answer

Human Eval

Question

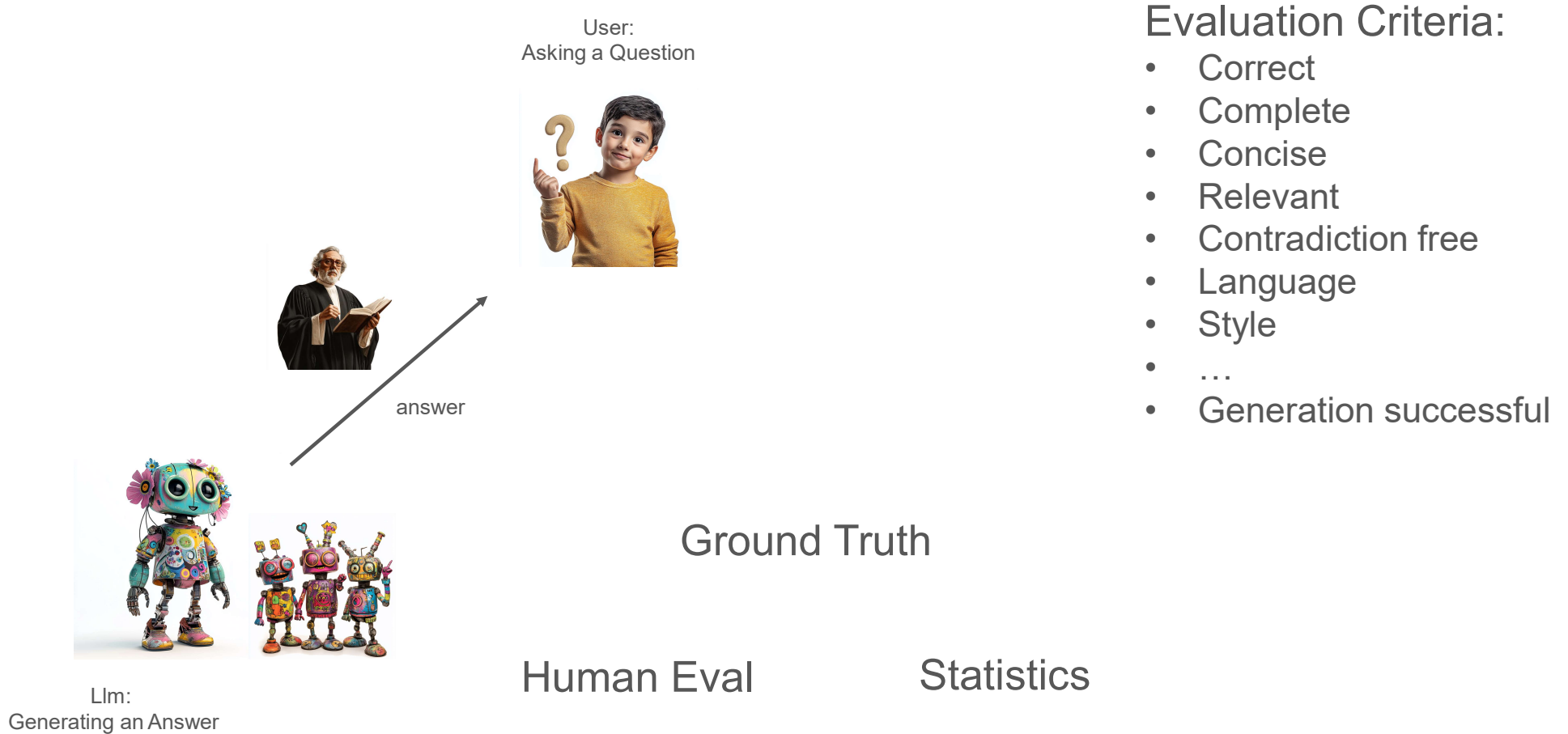
- What is Pluvia ?

Answer

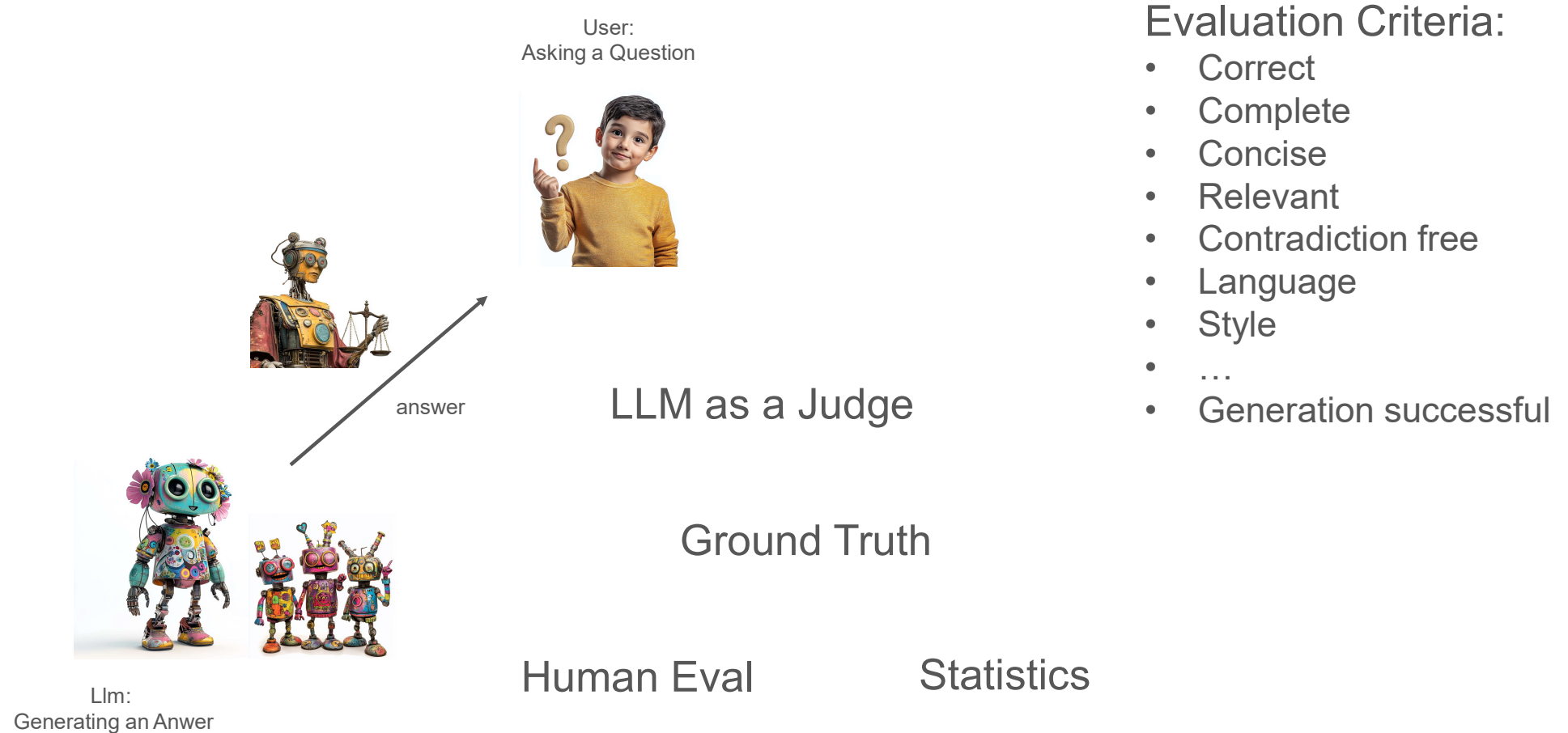
- Pluvia is a latin word meaning rainfall.
- The latin word for rainfall.
- ....

=> equality not an option

## Evaluation on text results

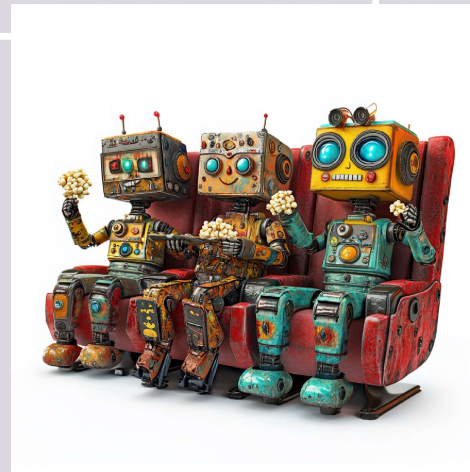


## Evaluation on text results



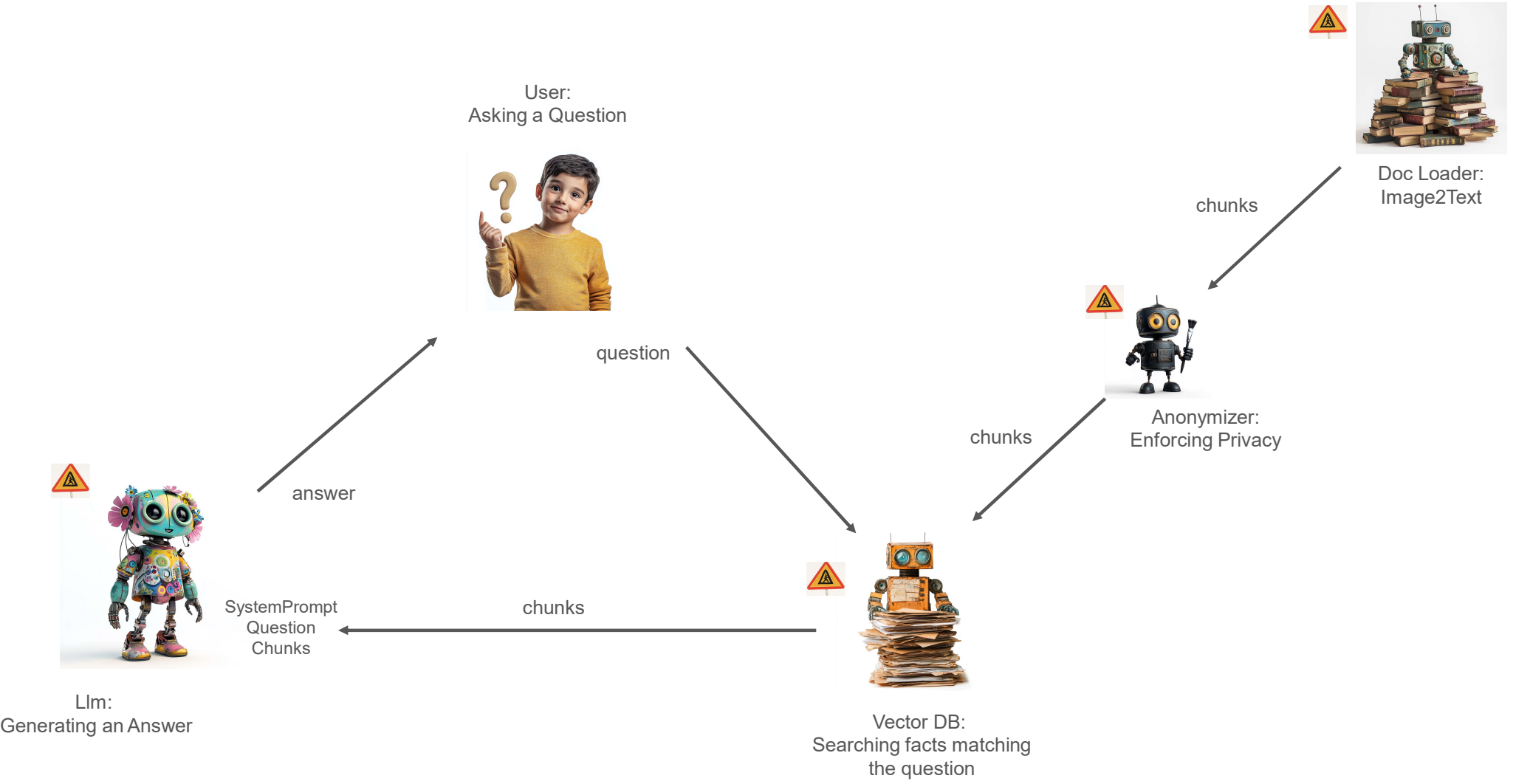


## Demo: Evaluation Notebook

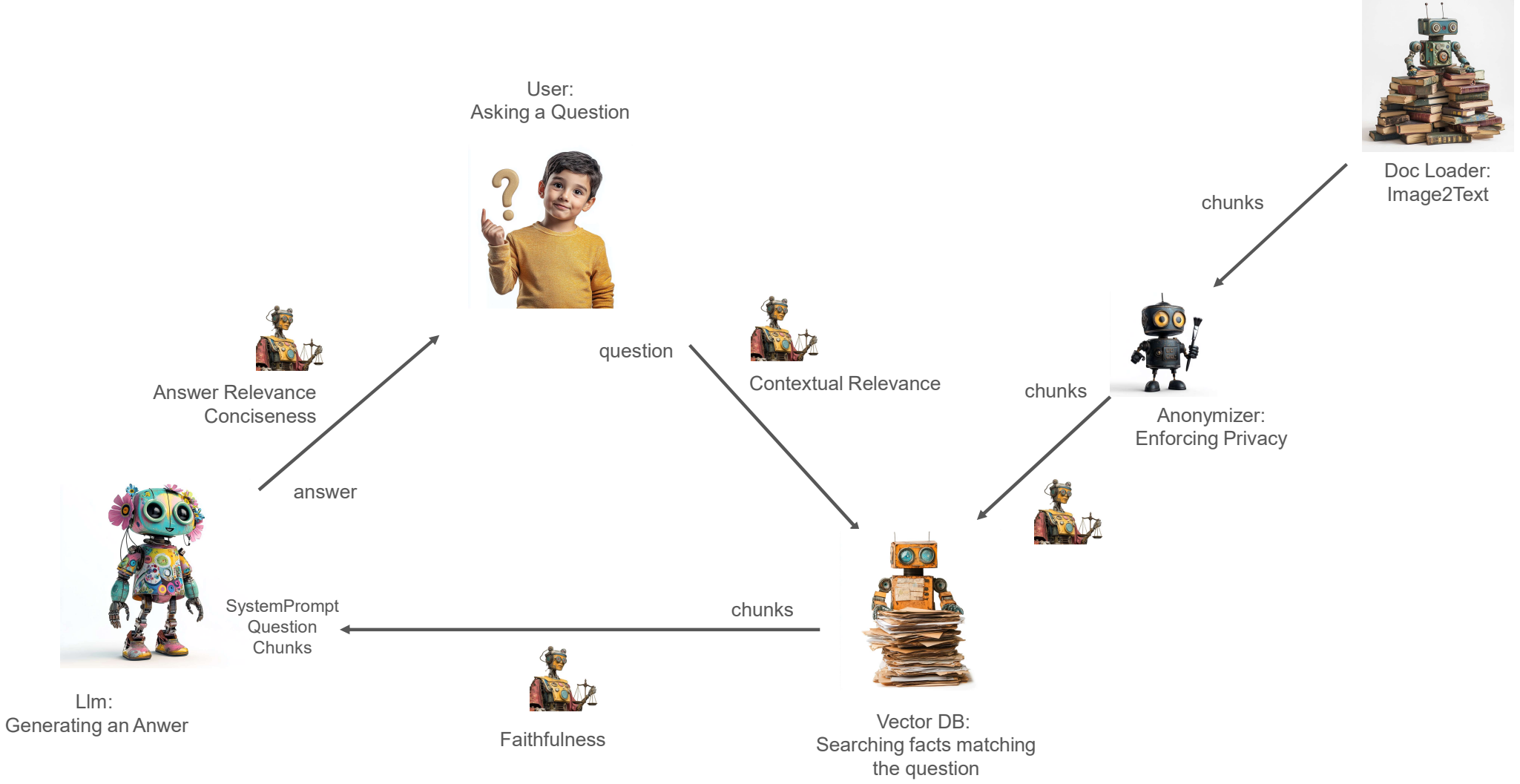


<https://colab.research.google.com/github/DJCordhose/llm-from-prototype-to-production/blob/main/Eval4pptx.ipynb>

# RAG System Architecture



# RAG System Architecture: Online Evaluation



## Online Eval: Example

```
[07:56:37 INF] POST "https://[REDACTED].azurewebsites.net/"eval succeeded in 4.91s with response={
  "Metadata": {
    "Answer": "Der Artikel Sigma20 Bet  tigungsplatte dient zur Steuerung der 2-Mengen-Sp   lung bei Geberit UP-Sp   lk  sten. Sie erm  glicht die Auswahl zwischen einer gro   en und einer kleinen Sp   lmenge, um W",
    "CreateDate": "2024-09-10T07:56:37.744166Z",
    "DeepEval": {
      "Answer_Relevancy": {
        "reason": "The score is 1.00 because the response directly addresses the purpose of the Sigma20 BetPl. article without any irrelevant statements.",
        "score": 1.0
      },
      "Conciseness_(GEval)": {
        "reason": "The output is somewhat concise but includes unnecessary details about materials and suitability that could be omitted for brevity.",
        "score": 0.6
      },
      "Contextual_Relevancy": {
        "reason": "The score is 0.33 because the context discusses various models and specifications of flushing systems but does not provide any information about the article 'Sigma20 BetPl.' or its purpose.",
        "score": 0.3333333333333333
      },
      "Faithfulness": {
        "reason": "The score is 0.80 because the actual output inaccurately generalizes the material of the Bet  tigungsplatte, stating it could be made of Edelstahl, while the retrieval context clarifies that",
        "score": 0.8
      }
    },
    "ElapsedSeconds": 4.85,
    "EvalType": "deep_eval",
    "EvalVersion": "240903",
    "Input": "Wozu dient der Artikel Sigma20 BetPl., f   r 2-Mengen-Sp   lung wei    / wei    matt ?"
  },
  "Metrics": {
    "Answer_Relevancy": 1.0,
    "Conciseness_(GEval)": 0.6,
    "Contextual_Relevancy": 0.3333333333333333,
    "Faithfulness": 0.8
  },
  "Score": 0.6833333333333333
}
```

## Online Eval: Example

```
LlmDesc germany W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 242,242]
LlmDesc germany W.240820_C.240625_E.240903: Answer_Relevancy=0.962 Conciseness_(GEval)=0.628 Contextual_Relevancy=0.341 Faithfulness=0.890 Score=0.705 TextGenerated=1.000
LlmDesc switzerland W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 140,140]
LlmDesc switzerland W.240820_C.240625_E.240903: Answer_Relevancy=0.943 Conciseness_(GEval)=0.613 Contextual_Relevancy=0.534 Faithfulness=0.851 Score=0.735 TextGenerated=1.000
LlmFp germany W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 4,4]
LlmFp germany W.240820_C.240625_E.240903: Answer_Relevancy=0.964 Conciseness_(GEval)=0.595 Contextual_Relevancy=0.739 Faithfulness=0.842 Score=0.785 TextGenerated=1.000
LlmFp switzerland W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 8,8]
LlmFp switzerland W.240820_C.240625_E.240903: Answer_Relevancy=0.984 Conciseness_(GEval)=0.624 Contextual_Relevancy=0.621 Faithfulness=0.757 Score=0.747 TextGenerated=1.000
LlmHelp german W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 66,66]
LlmHelp german W.240820_C.240625_E.240903: Answer_Relevancy=0.992 Conciseness_(GEval)=0.692 Contextual_Relevancy=0.731 Faithfulness=0.897 Score=0.828 TextGenerated=1.000
LlmSi germany W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 6,6]
LlmSi germany W.240820_C.240625_E.240903: Answer_Relevancy=0.987 Conciseness_(GEval)=0.615 Contextual_Relevancy=0.827 Faithfulness=0.864 Score=0.823 TextGenerated=1.000
LlmSi switzerland W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 8,8]
LlmSi switzerland W.240820_C.240625_E.240903: Answer_Relevancy=0.985 Conciseness_(GEval)=0.623 Contextual_Relevancy=0.904 Faithfulness=0.822 Score=0.833 TextGenerated=1.000
LlmTtp english W.240820_C.240625_E.240903: Answer_Relevancy=1.000 Conciseness_(GEval)=0.500 Contextual_Relevancy=0.000 Faithfulness=1.000 Score=0.625 TextGenerated=1.000
LlmTtp french W.240820_C.240625_E.240903: Answer_Relevancy=1.000 Conciseness_(GEval)=0.600 Contextual_Relevancy=0.000 Faithfulness=1.000 Score=0.650 TextGenerated=1.000
LlmTtp german W.240820_C.240625 : Score=0.000 TextGenerated=0.000 [counts 74,74]
LlmTtp german W.240820_C.240625_E.240903: Answer_Relevancy=0.925 Conciseness_(GEval)=0.611 Contextual_Relevancy=0.442 Faithfulness=0.899 Score=0.719 TextGenerated=1.000
[09:21:55 INF proplanner] HTTP POST /api/descriptions responded 200 in 25.1855 ms
```

## Evaluation Issues

- Online Performance impact on LLM
  - Eval may call 10x more often, but have less output tokens
- Which LLM do you use ? Same ? Faster ? Most Powerful ?
- What Dimensions do you eval ?
  - Toxicity, Conciseness, Answer Relevance ?
  - Ground Truth available ?
- Human Feedback from your users ?
- Interpretation of the Scores ?

## Eval Frameworks

- **DeepEval** <https://docs.confident-ai.com/>
- Ragas <https://ragas.io/>
- TruLens <https://www.trulens.org/>
- Evidently <https://www.evidentlyai.com/>
- Ares <https://ares-ai.vercel.app/>
- ...

## Your Experience ?

- Anyone doing RAG ? In Production ?
- Do you do evaluation ? By humans ?
- What else do you use for evaluation ?



**Wrap Up**

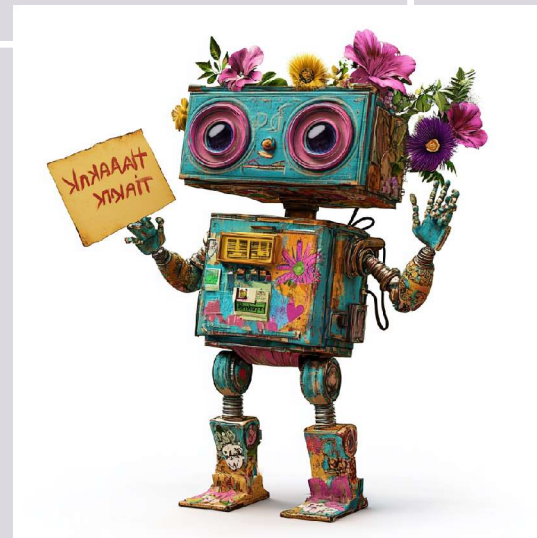
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## Key takeaways

- Human Eval is a great starting point
- LLM-as-a-Judge works, but take the scores with a grain of salt
- Use a strong LLM for evaluation
- Evaluation is even more crucial when using potentially less powerful models
- Getting the Documents & keeping them up-to-date can be painful

**Vorsicht vor dem Enkel des Chefs...**

Thank you



## Llm-as-a-judge: Idea

Actual Output:

```
Witing texts is painful,  
caus im making mitakes.
```

Prompt:

```
You are an expert on  
english language. Grade  
a students text...
```

```
Answer with a Json  
containing scores &  
reason..
```

```
Students Text:  
Witing texts is...
```

```
{  
  "score": 2,  
  "reason": "Multiple grammatical errors  
            such as 'witing' and ..."  
}
```

# Llm-as-a-judge: G-Eval

