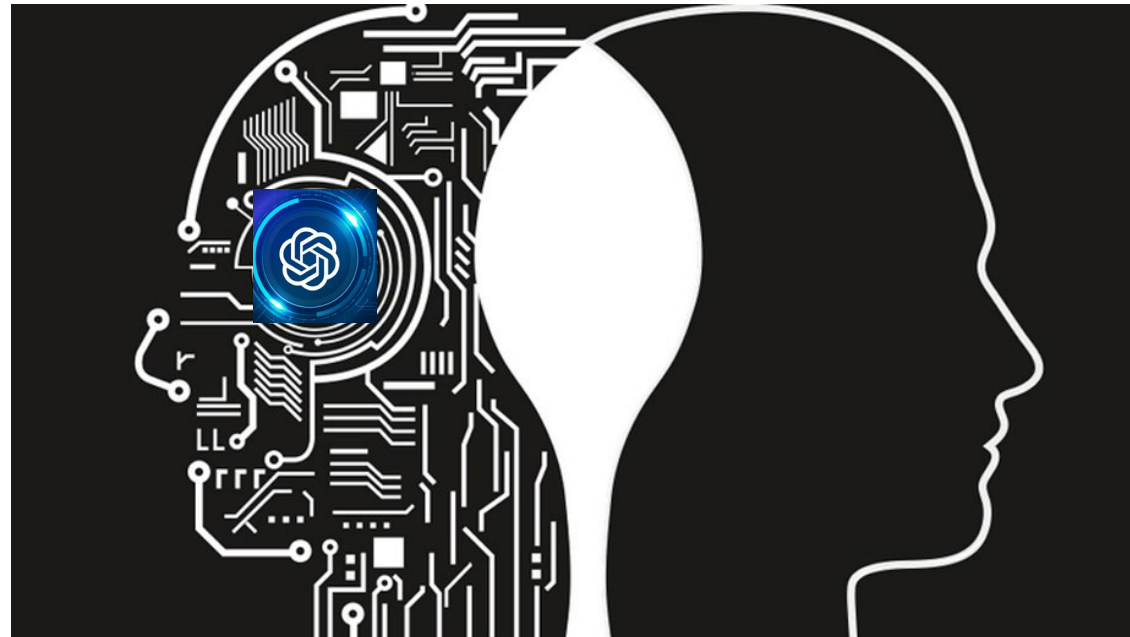


# Enhancing Data Precision with Large Language Models: Analyzing Failures and Innovating Database Curation

Georg Gottlob

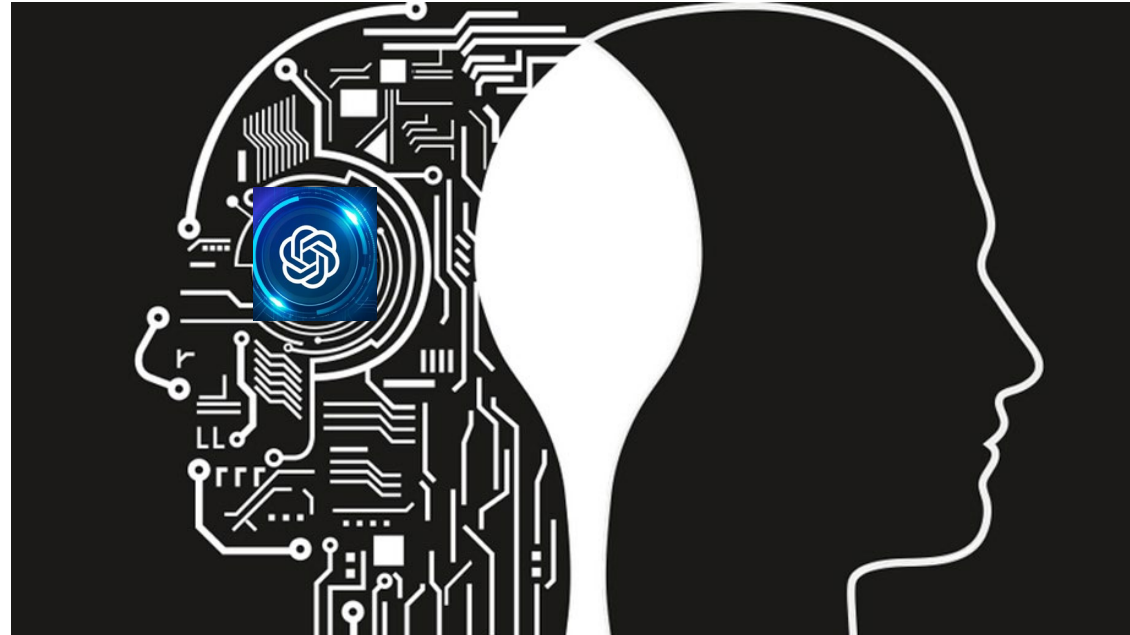
University of Calabria



# Psychoanalysis of Language Models & Therapy

Georg Gottlob

University of Calabria



<https://businessjournaldaily.com/artificial-intelligence-for-good-and-for-bad/>  
<https://businessjournaldaily.com/artificial-intelligence-for-good-and-for-bad/>



[https://en.m.wikipedia.org/wiki/File:ChatGPT\\_logo.svg](https://en.m.wikipedia.org/wiki/File:ChatGPT_logo.svg)

# **Large Language Models (LLMs) An AI Revolution**

# LLMs: Based on 3 main innovations

- 1 **Distributional “Word Embedding”** (statistical semantics of natural language)
- 2 **Transformer architecture**
- 3 **Attention mechanism** (word disambiguation based on context)



training  
compression

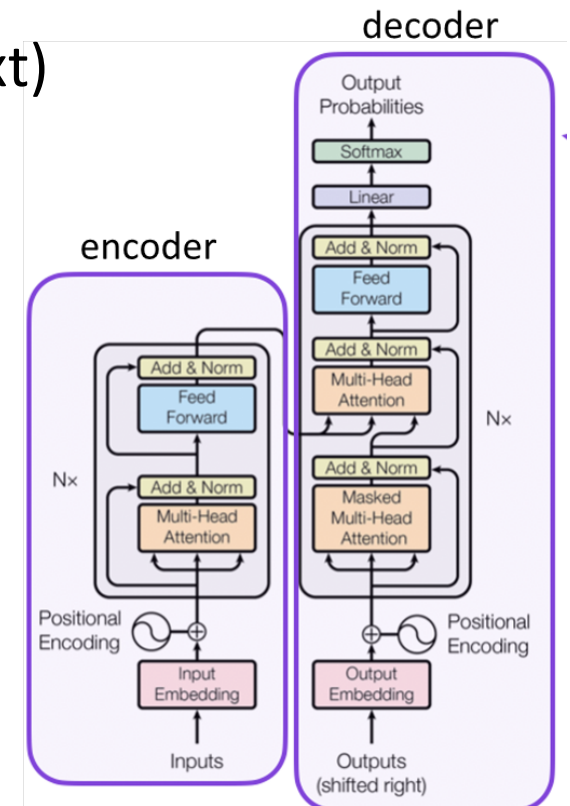
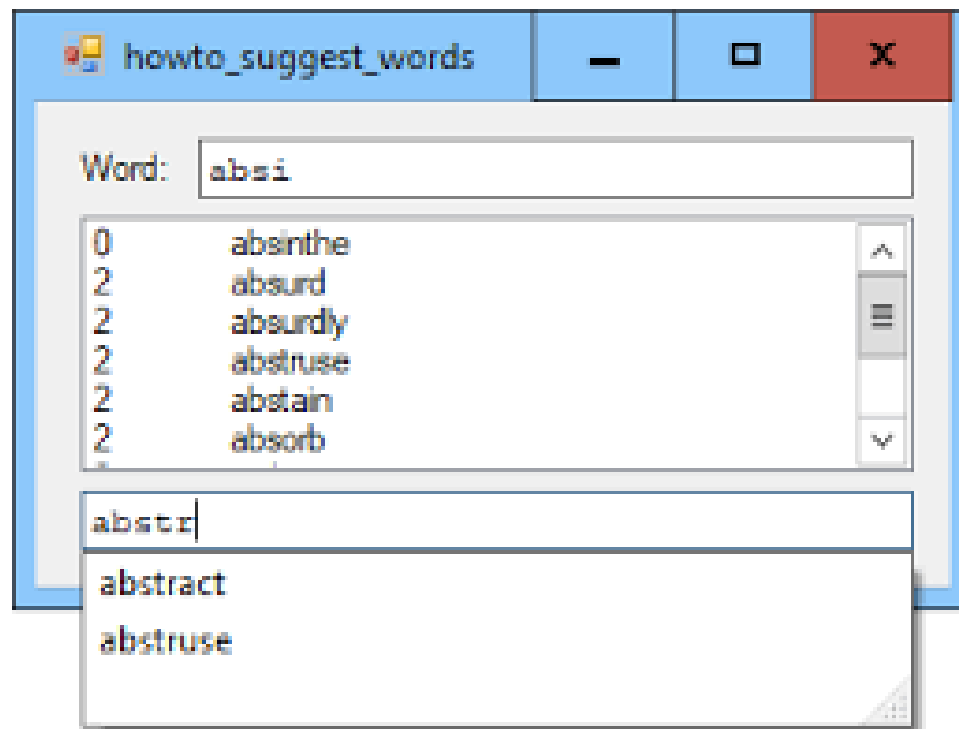


Figure 1: The Transformer - model architecture.

LLMs work like word autocompletion but are much more complex.



[http://www.csharpHelper.com/howtos/howto\\_suggest\\_words.html#google\\_vignette](http://www.csharpHelper.com/howtos/howto_suggest_words.html#google_vignette)

Word-by-word text autocompletion - conditioned by a given context.

Instead of precise statistics, approximation of statistics via a neural network.

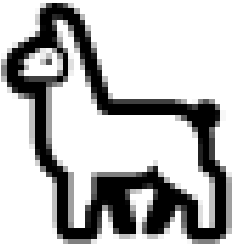
# The most powerful LLMs



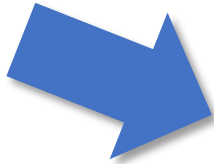
GPT 3.5 (OpenAI)



GPT 4 (OpenAI)



LLAMA-2/3



*online access to Web*



GPT 4o (OpenAI, limited Web access via Bing Chat)



BING-Chat (OpenAI+Microsoft)

BARD (Google)





*Pippo Rossi è un alunno che disturba in continuazione in classe. Anche i suoi colleghi di banco non lo supportano più. E' già stato rimproverato tante volte senza risultato. L'insegnante, la dottoressa Rosa Invernizzi, vuole scrivere una lettera al padre di Pippo, dicendogli con delicatezza ma anche con determinazione che Pippo deve cambiare il suo atteggiamento, altrimenti rischia l'espulsione. Proponi una lettera di 10 righe circa.*



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Gentile Sig. Rossi,

Mi rivolgo a Lei con rispetto e preoccupazione riguardo al comportamento di suo figlio, Pippo, nelle ore di lezione. Nonostante i numerosi tentativi di correggere il suo atteggiamento in classe, la situazione non ha mostrato miglioramenti.

Anche i suoi compagni di banco hanno manifestato crescente disagio a causa delle continue interruzioni. È essenziale che Pippo comprenda la gravità della situazione e la necessità di un immediato cambiamento.

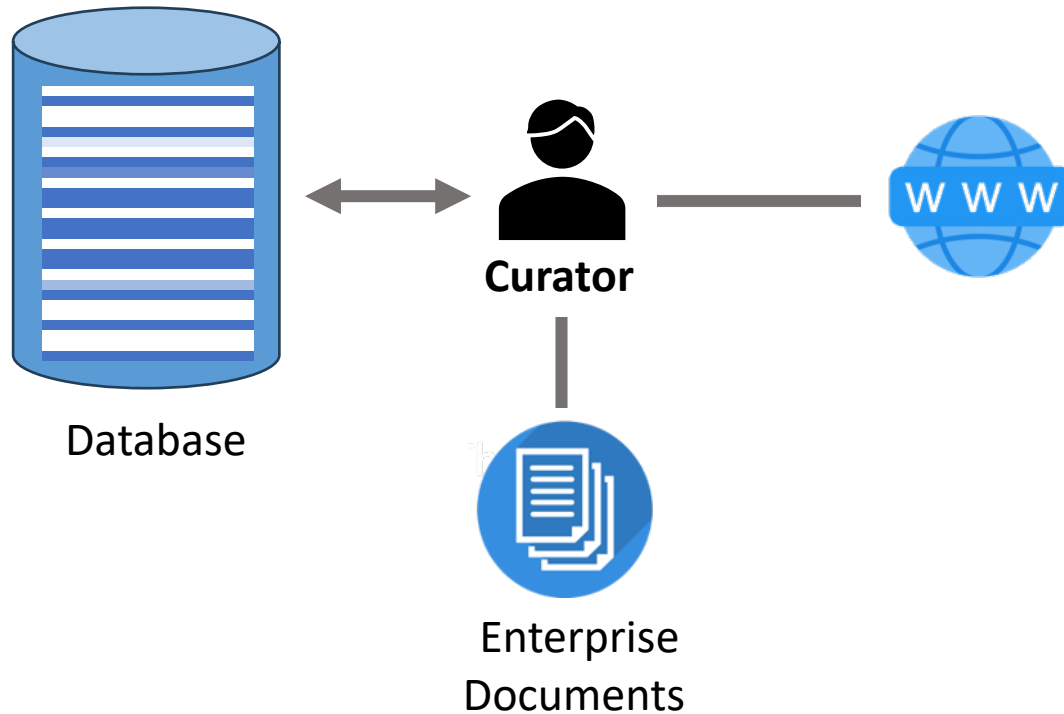
Le chiedo, per il bene di suo figlio e della classe, di intervenire affinché Pippo modifichi il suo comportamento. Se le azioni distruttive continuassero, saremmo, con rammarico, costretti a considerare l'espulsione come ultima soluzione.

Distinti saluti, Dott.ssa Rosa Invernizzi



# Original Research Goal: Fully Automated Database Curation via LLMs

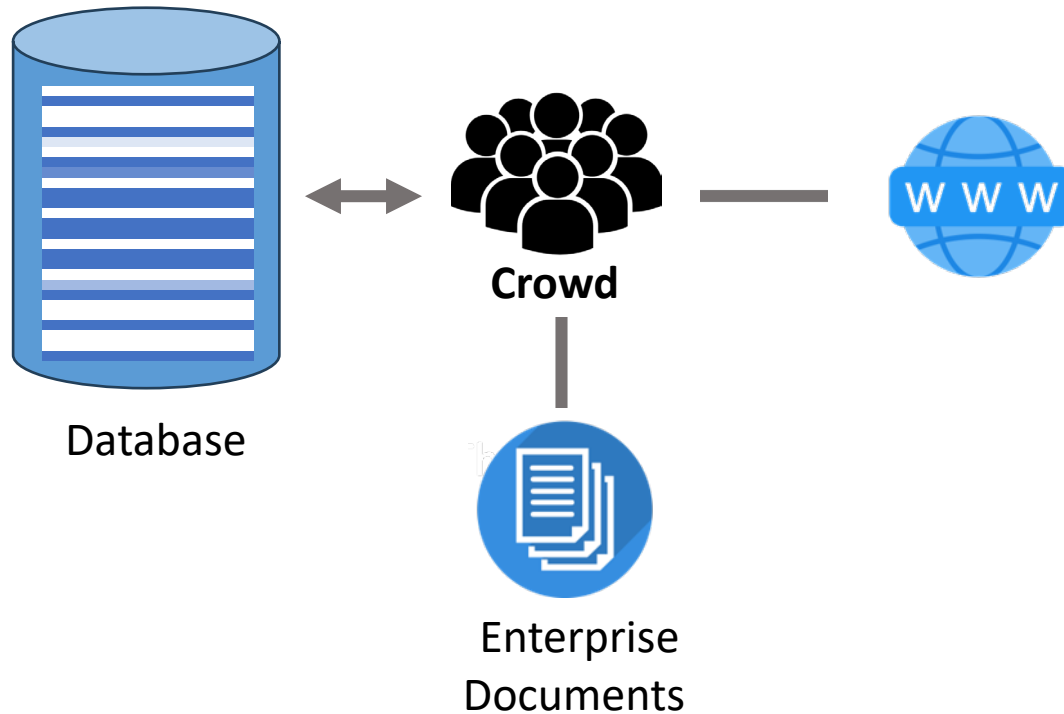
**Classical DB curation by DB admin(s)/curator(s):**



- For:
- **database verification**
  - **database updates**
  - **database enrichment**
  - **Building DBs from scratch**

# Original Research Goal: Fully Automated Database Curation via LLMs

## Classical DB curation via crowd sourcing:

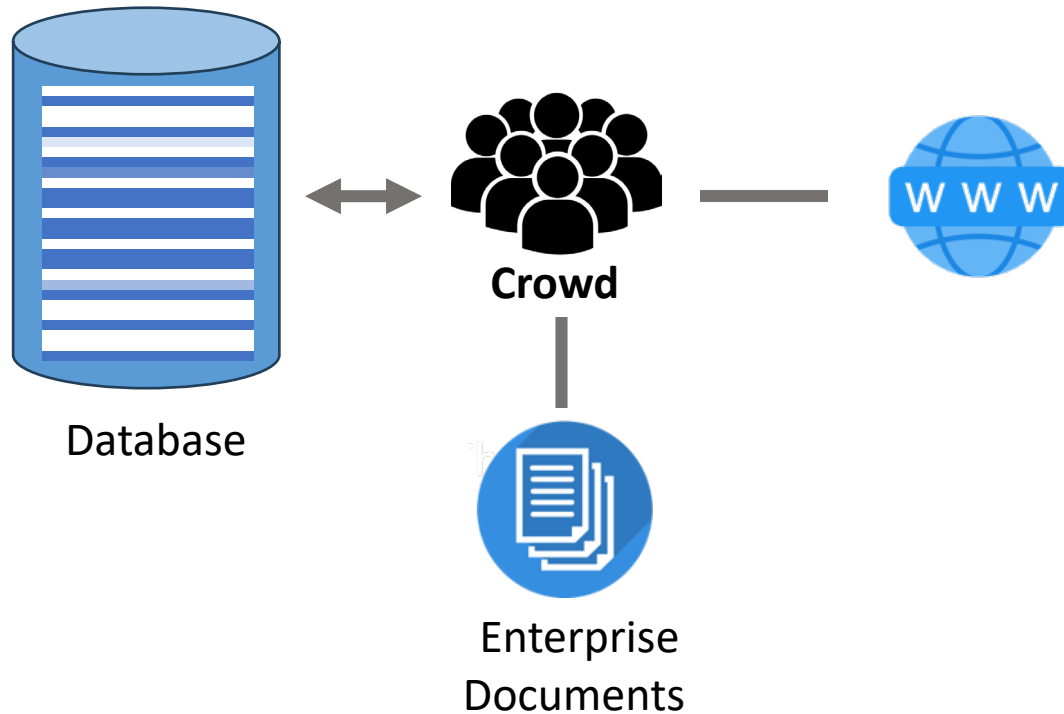


- For:
- **database verification**
  - **database updates**
  - **database enrichment**
  - **Building DBs from scratch**

Example:



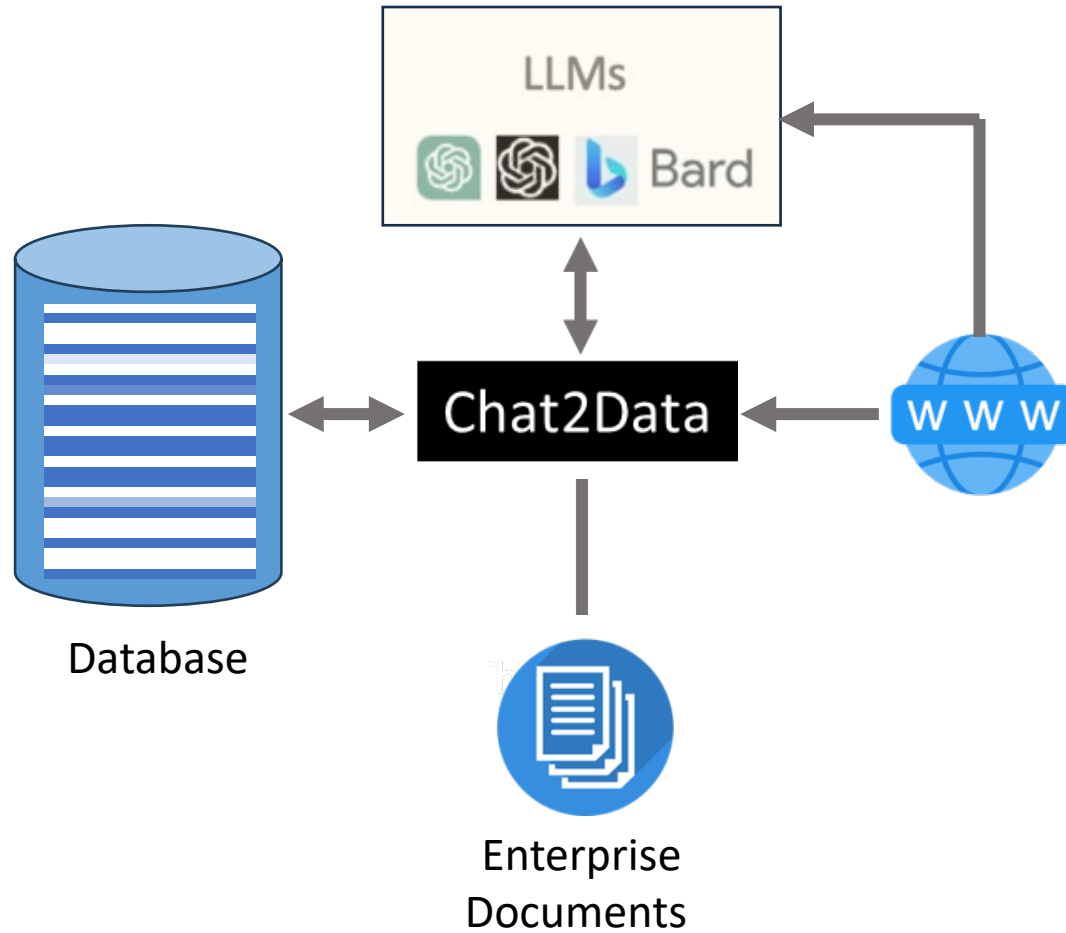
# Original Research Goal: Fully Automated Database Curation via LLMs



- For:
- database verification
  - database updates
  - database enrichment
  - Building DBs from scratch

***Database curation by humans is expensive, slow, and error prone.***

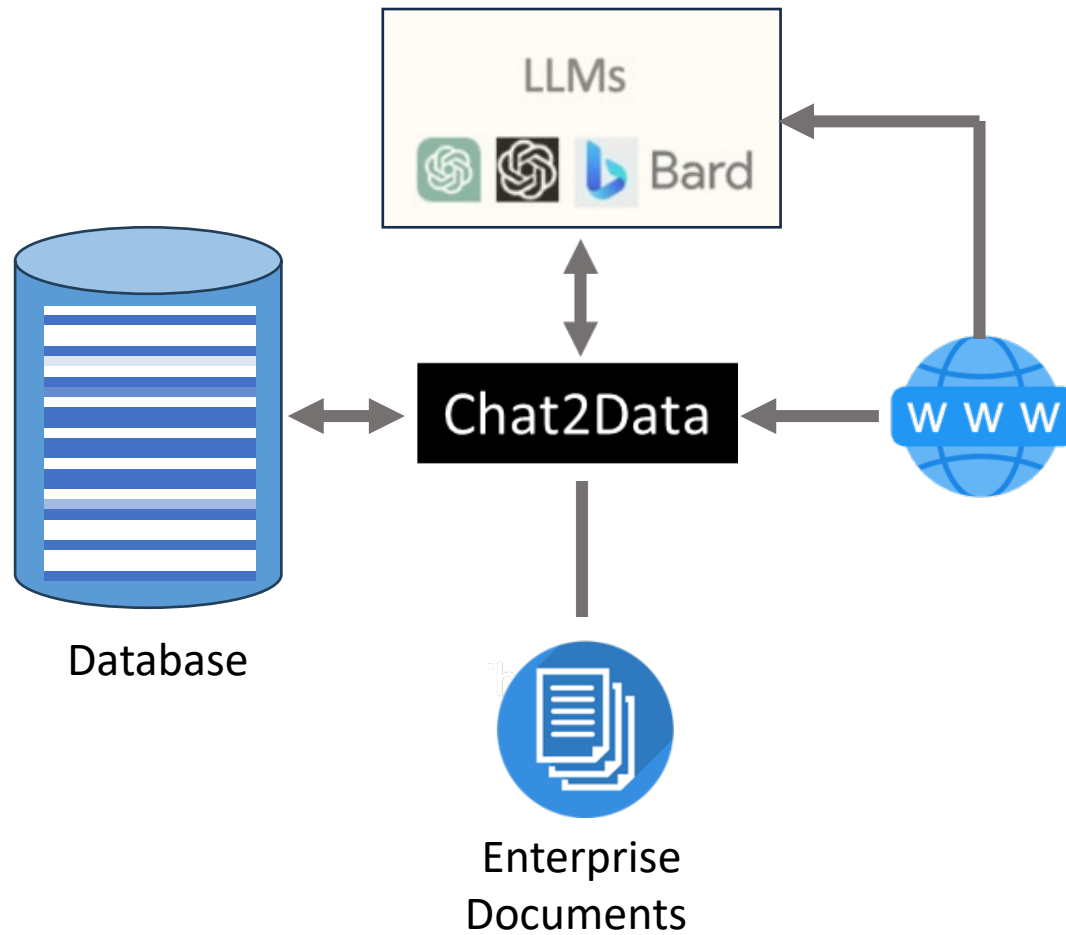
# Original Research Goal: Fully Automated Database Curation via LLMs



For:

- **database verification**
- **database updates**
- **database enrichment**
- **Building DBs from scratch**

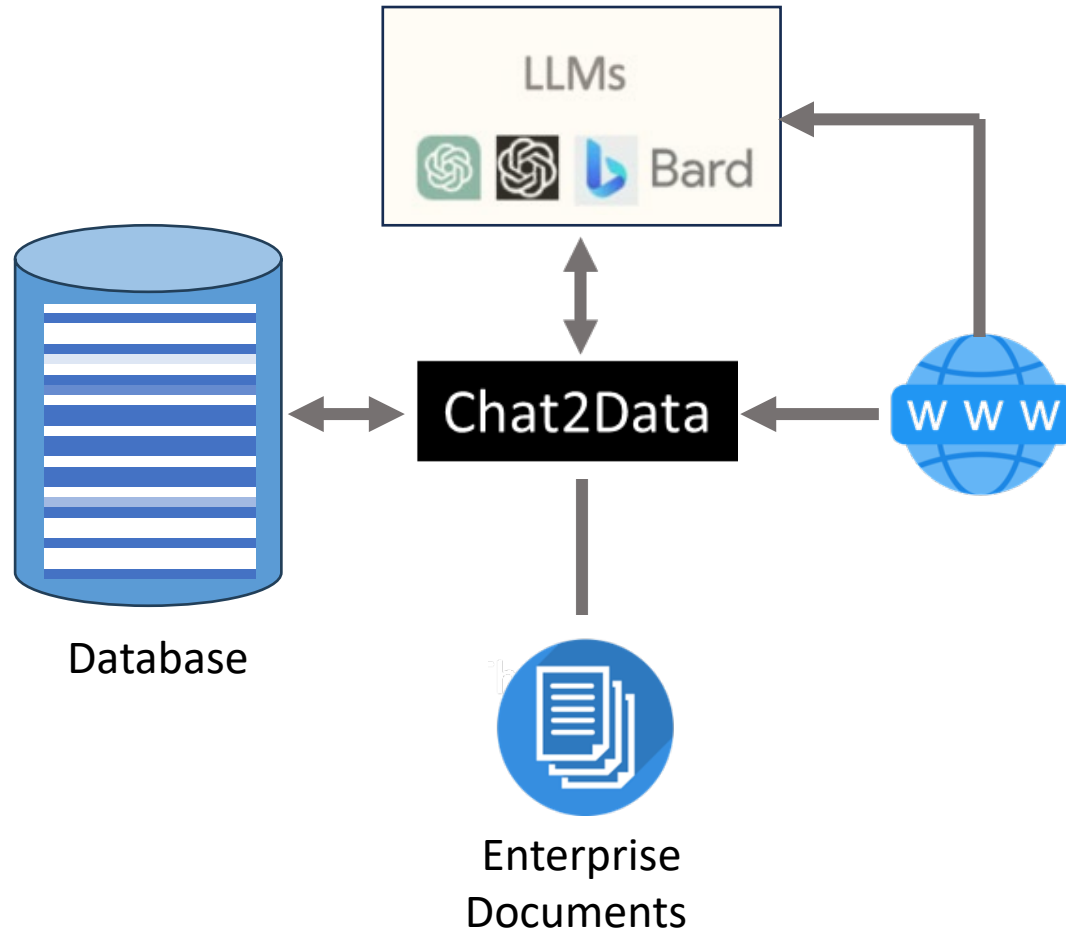
# The Chat2Data project: Fully Automated Database Curation via LLMs



For:

- **database verification**
- **database updates**
- **database enrichment**
- **Building DBs from scratch**

# Original Research Goal: Fully Automated Database Curation via LLMs



For:

- database verification
- database updates
- database enrichment
- Building DBs from scratch

***Our initial approach to simply prompting LLMs did not work: The LLMs made terribly many errors!***

# Major Problem with LLMs and Data: Truthfulness

- LLMs hallucinate by inventing facts or presenting them inappropriately.
- LLMs are biased and may propagate unfair statements.

## ***“Psychoanalysis” of ChatGPT: Reasons why LLMs may hallucinate and make other mistakes***

- Information Compression, loss & mistaken “reconstruction”
- Missing “introspection”: The LLM often does not know what it knows or does not know.
- Adoption of wrong Web content
- Training Bias: Missing domains or topics in training data/ training corpora,
- Statistical bias and/or unfairness due to improper generalizations of statistics
- Wrong ordering of results
- “laziness”, imprecision, and/or saving resources
- Inaccuracies and logical inconsistencies across multiple prompts.
- .....

# Information Compression, loss & mistaken “reconstruction”



*List 5 publications by Georg Gottlob on query rewriting and data exchange*



# Information Compression, loss & mistaken “reconstruction”



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Gottlob, G., & Schwentick, T. (2004). Rewriting ontological queries into small nonrecursive datalog programs. KR 2004.

Barceló, P., Gottlob, G., & Pichler, R. (2014). Logical foundations of relational data exchange. ACM SIGLOG News, 1(1), 2-13.

Dalvi, N., Gottlob, G., & Kikot, S. (2012). Query rewriting for Horn-SHIQ plus rules. In Proceedings of the Twenty-Sixth AAAI Conference on AI

Gottlob, G., Orsi, G., & Pieris, A. (2014). Query rewriting and optimization for ontological databases. ACM Trans. on Database Systems 25.

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## Correct Citations:

Pablo Barceló. Logical foundations of relational data exchange, ACM SIGMOD Record, 2009

T. Eiter, M. Ortiz, M. Simkus, T.K. Tran & G. Xiao. Query rewriting for Horn-SHIQ plus rules. Proc. AAAI 2012

40% wrong  
How embarrassing!

# Information Compression, loss & mistaken “reconstruction”

Now with GPT 4o



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A paper with this title does not exist!

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90% wrong!

FORBES &gt; BUSINESS

BREAKING

# Lawyer Used ChatGPT In Court —And Cited Fake Cases. A Judge Is Considering Sanctions

**Molly Bohannon** Forbes Staff*I cover breaking news.*[Follow](#)

Jun 8, 2023, 02:06pm EDT

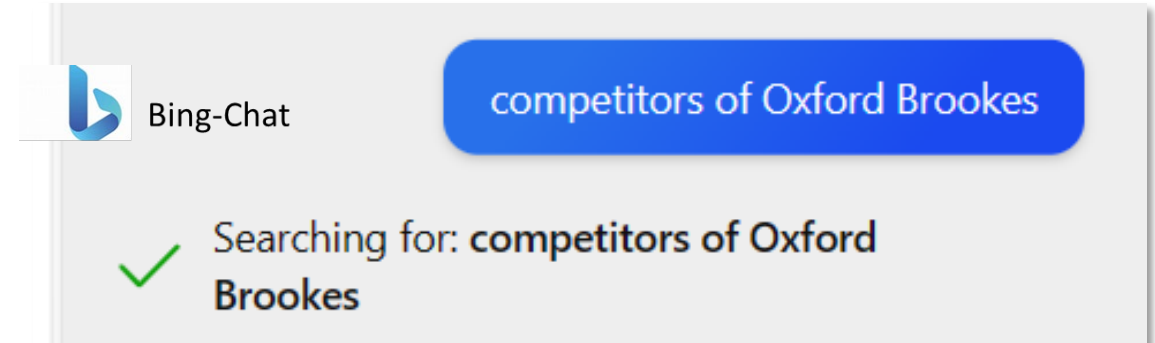
Updated Jun 8, 2023, 03:42pm EDT



**TOPLINE** The lawyer for a man suing an airline in a routine personal injury suit used ChatGPT to prepare a filing, but the artificial intelligence bot delivered fake cases that the attorney then presented to the court, prompting a judge to weigh sanctions as the legal community grapples with one of the first cases of AI “hallucinations” making it to court.

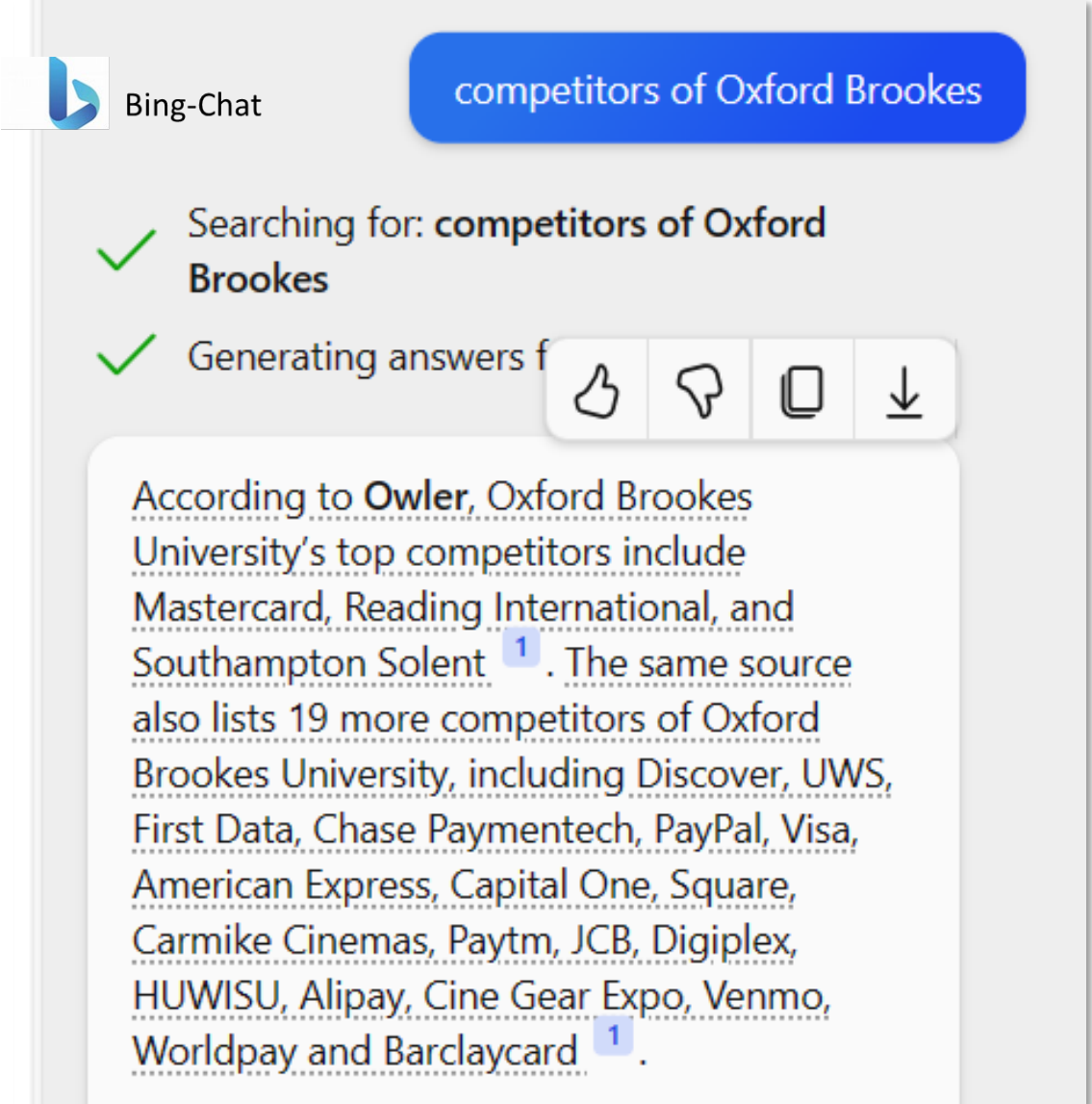
# Adoption of wrong Web content

- Previous example: GPT is not connected to the Web
- It can get worse: Wrong Web-data might be adopted



# Adoption of wrong Web content

- Previous example: GPT is not connected to the Web
- It can get worse: Wrong Web-data might be adopted



Bing-Chat

competitors of Oxford Brookes

✓ Searching for: **competitors of Oxford Brookes**

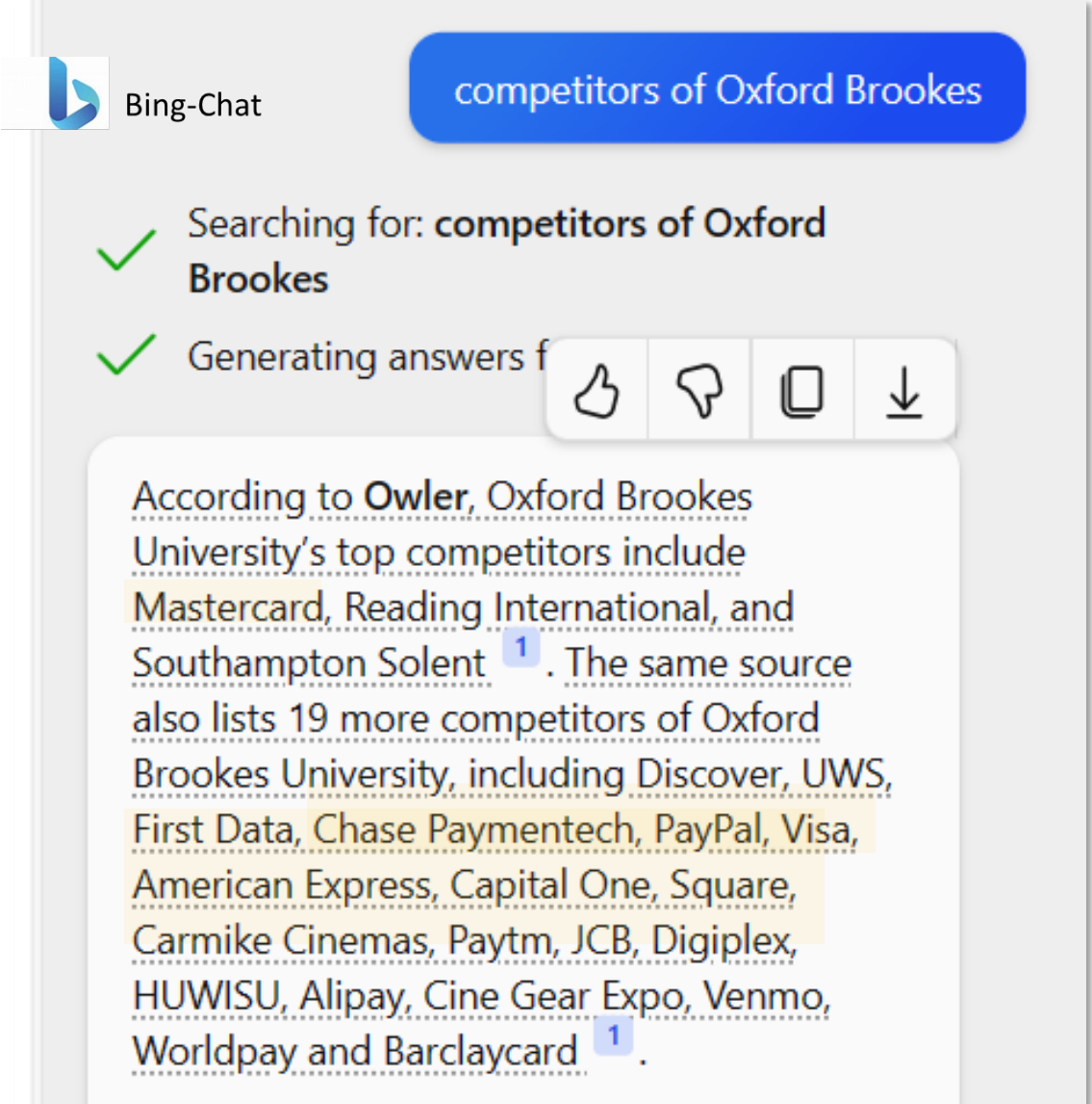
✓ Generating answers for

According to Owler, Oxford Brookes University's top competitors include Mastercard, Reading International, and Southampton Solent <sup>1</sup>. The same source also lists 19 more competitors of Oxford Brookes University, including Discover, UWS, First Data, Chase Paymentech, PayPal, Visa, American Express, Capital One, Square, Carmike Cinemas, Paytm, JCB, Digiplex, HUWISU, Alipay, Cine Gear Expo, Venmo, Worldpay and Barclaycard <sup>1</sup>.



# Adoption of wrong Web content

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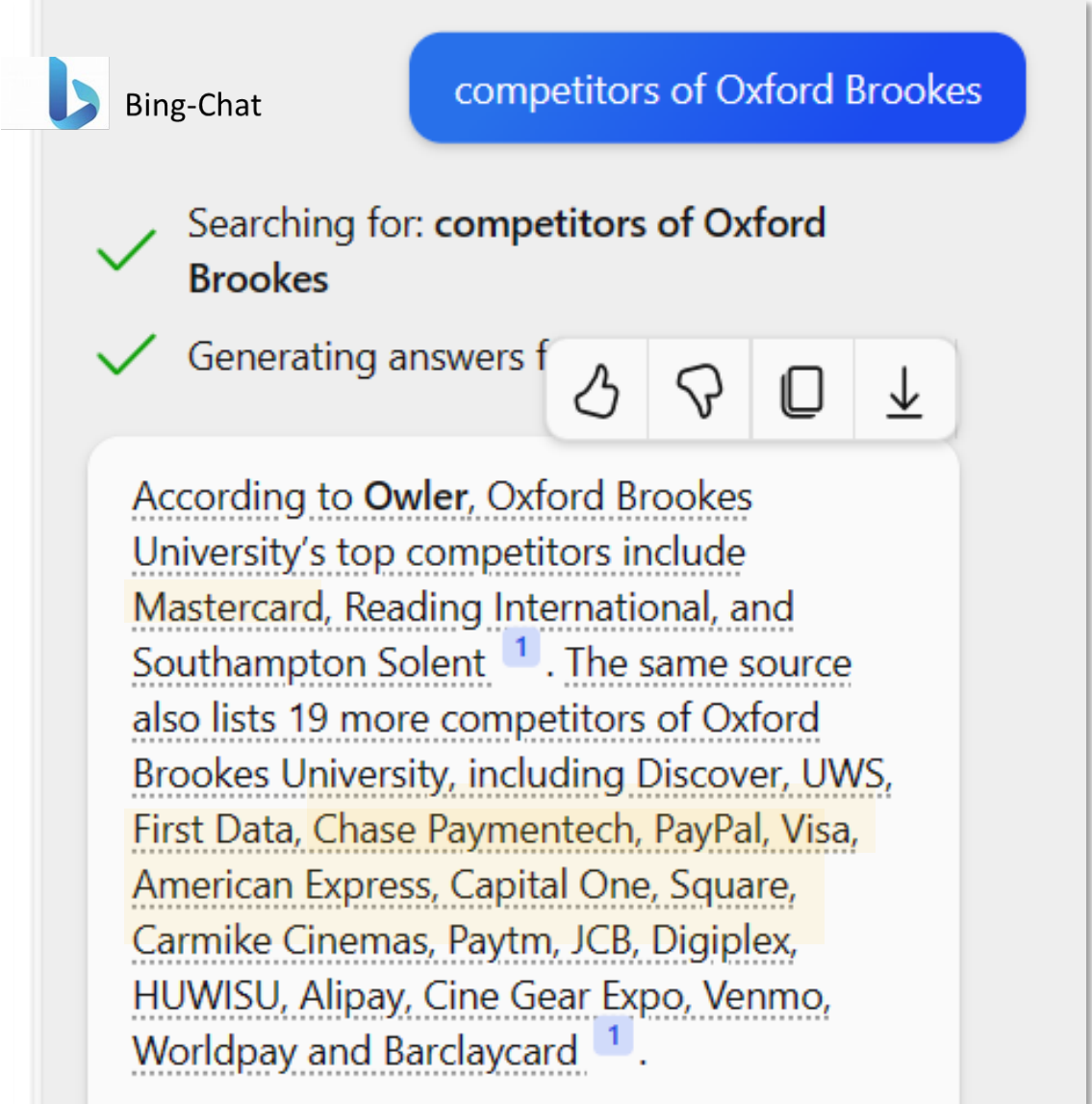


The screenshot shows a Bing-Chat interface. At the top left is the Bing-Chat logo. To its right is a blue button with the text "competitors of Oxford Brookes". Below the logo, there are two green checkmarks indicating the search process: "Searching for: competitors of Oxford Brookes" and "Generating answers for". To the right of the second checkmark is a row of four icons: a thumbs up, a thumbs down, a document, and a download arrow. Below these elements is a text box containing the following text: "According to Owler, Oxford Brookes University's top competitors include Mastercard, Reading International, and Southampton Solent <sup>1</sup>. The same source also lists 19 more competitors of Oxford Brookes University, including Discover, UWS, First Data, Chase Paymentech, PayPal, Visa, American Express, Capital One, Square, Carmike Cinemas, Paytm, JCB, Digiplex, HUWISU, Alipay, Cine Gear Expo, Venmo, Worldpay and Barclaycard <sup>1</sup>." The text is surrounded by a dotted border, and the source "Owler" is underlined.

# Adoption of wrong Web content

- Previous example: GPT is not connected to the Web
- It can get worse: Wrong Web-data might be adopted

*All errors made by crowdsourcing are now imported!  
That's actually what we wanted to avoid.*



The screenshot shows the Bing-Chat interface. At the top, the Bing-Chat logo is on the left, and a blue button with the text "competitors of Oxford Brookes" is on the right. Below the button, there are two green checkmarks indicating the search and answer generation status. The search query is "competitors of Oxford Brookes". The generated answer is a paragraph of text listing competitors of Oxford Brookes University, including Mastercard, Reading International, and Southampton Solent. The text is highlighted in yellow, and there are blue superscript "1" markers at the end of the first and last sentences. To the right of the answer, there are four icons: a thumbs up, a thumbs down, a document, and a download arrow.

Bing-Chat

competitors of Oxford Brookes

✓ Searching for: **competitors of Oxford Brookes**

✓ Generating answers for

According to **Owler**, Oxford Brookes University's top competitors include Mastercard, Reading International, and Southampton Solent <sup>1</sup>. The same source also lists 19 more competitors of Oxford Brookes University, including Discover, UWS, First Data, Chase Paymentech, PayPal, Visa, American Express, Capital One, Square, Carmike Cinemas, Paytm, JCB, Digiplex, HUWISU, Alipay, Cine Gear Expo, Venmo, Worldpay and Barclaycard <sup>1</sup>.

# Missing domains or topics in training data/training corpora

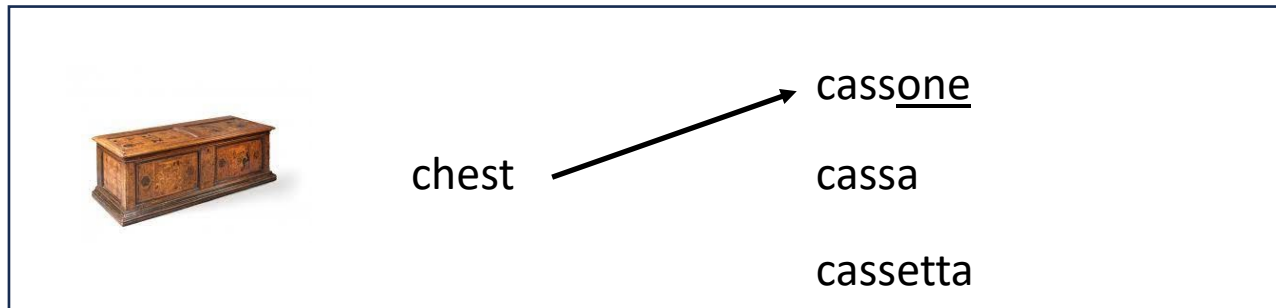
Imaginary scenario: LLM-translator trained on real estate & household concepts.

Has access to basic dictionary.

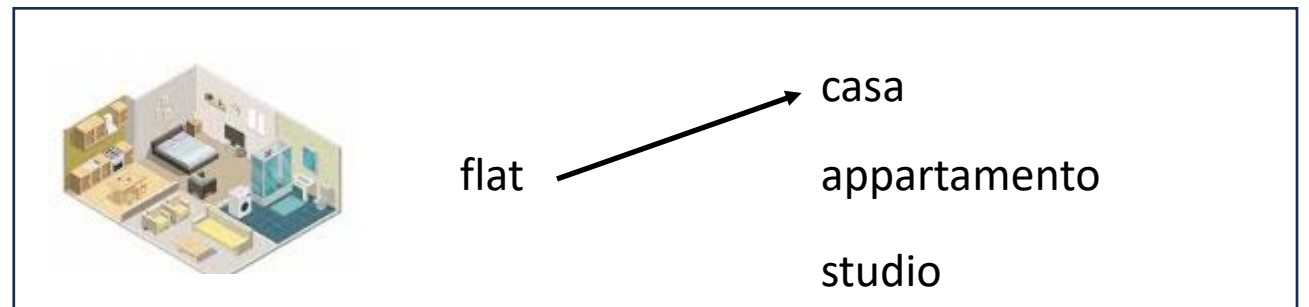
Does it also work in other contexts?

(example invented in honor of Maria-Gabriella Arru)

**Training example (generated statistically from training corpus):**



**Training example:**



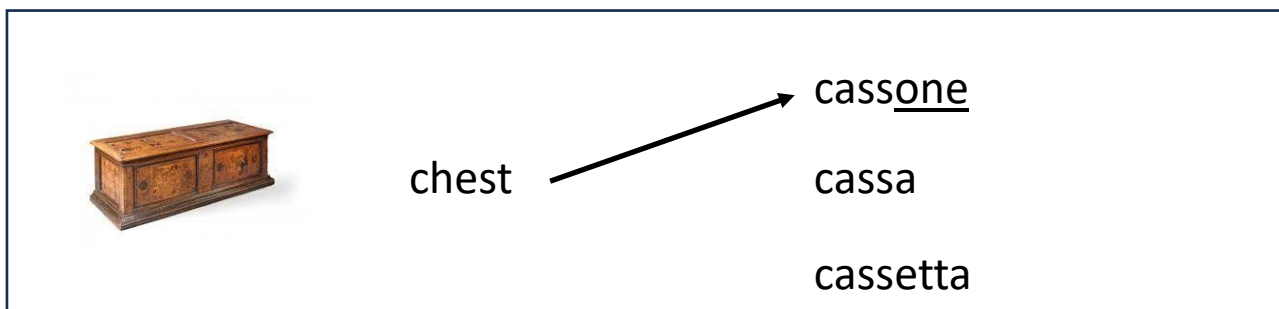
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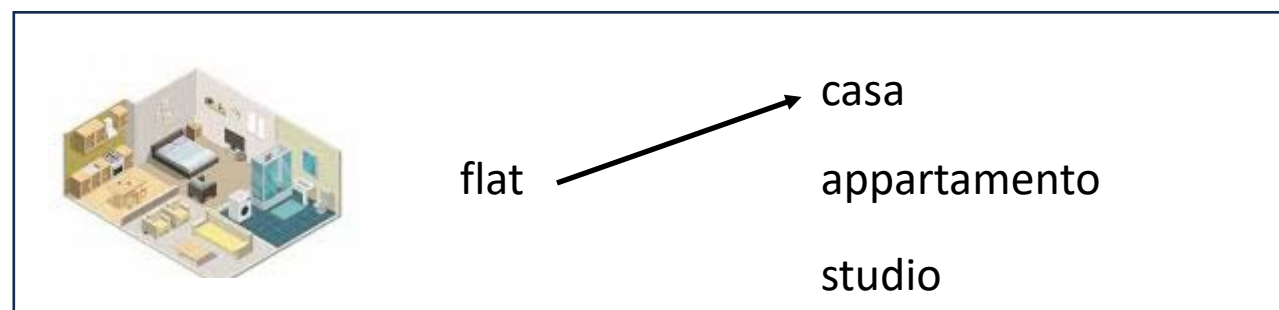
Has access to basic dictionary.

Does it also work in other contexts?

**Training example (generated statistically from training corpus):**




**Training example:**



# Missing domains or topics in training data/training corpora


Training example:



house → palazzo  
casa  
appartamento

etc...

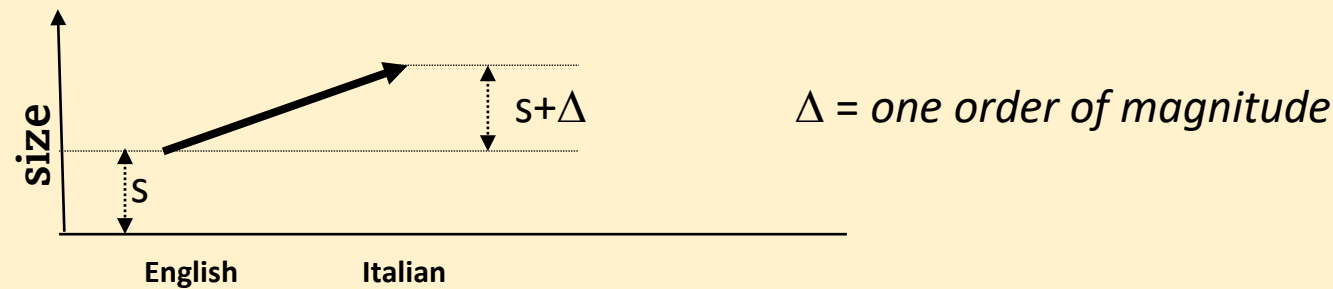
Apply system to translate concepts in real-estate domain



palace → reggia  
palazzo  
casa



The system has learnt the following “Italian translation vector” in the dimension “size”:

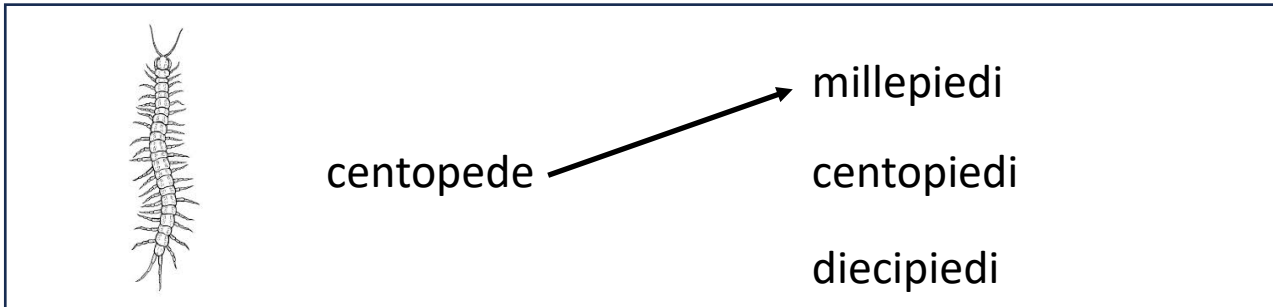


# Missing domains or topics in training data/training corpora

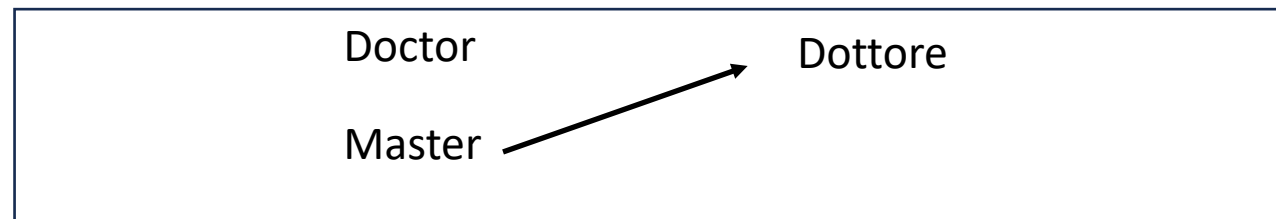
Let us now use this trained system to translate English → Italian in other domains.

Let's see the outcome...

## Domain of Entomology

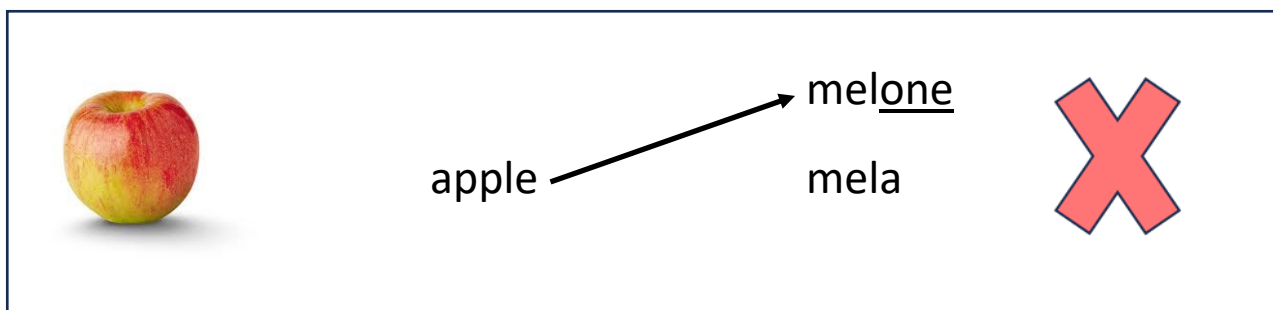


## Academic Domain



# Missing domains or topics in training data/training corpora

Domain “food”



# Wrong ordering of results



*List joint competitors of Birkbeck and Oxford Brookes regarding reputation*



Regarding reputation, some universities in the UK that could be considered joint competitors of Birkbeck College and Oxford Brookes University are:

1. University of Warwick
2. University of Bristol
3. University of Sheffield
4. University of Leeds
5. Univ. of Nottingham



# Wrong ordering of results



*List joint competitors of Birkbeck and Oxford Brookes regarding reputation*



Regarding reputation, some universities in the UK that could be considered joint competitors of Birkbeck College and Oxford Brookes University are:

1. University of Warwick 101-125
2. University of Bristol 81-90
3. University of Sheffield 126-150
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5. Univ. of Nottingham 151-175



# Wrong ordering of results



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Regarding reputation, some universities in the UK that could be considered joint competitors of Birkbeck College and Oxford Brookes University are:

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3. University of Sheffield 126-150
4. University of Leeds 101-125
5. Univ. of Nottingham 151-175



Birkbeck College	351-400
Oxford Brookes	601-800

 **MASSIVE GAP!**

# Inaccuracies and logical inconsistencies across prompts

For example, when determining the similarity score between “pen” and “marker”,



***Prompt 1:*** What's the **similarity score between “pen” and “marker”**, on a scale between 1 (lowest) and 10 (highest)?

**Prompt 1:** What's the **similarity score between “pen” and “marker”**, on a scale between 1 (lowest) and 10 (highest)?

**Answer 1:** [...] Based on a general semantic similarity between ‘pen’ and ‘marker’, I would assign a similarity score of **6 out of 10**.

**Prompt 1:** What's the **similarity score between “pen” and “marker”**, on a scale between 1 (lowest) and 10 (highest)?

**Answer 1:** [...] Based on a general semantic similarity between ‘pen’ and ‘marker’, I would assign a similarity score of **6 out of 10**.

**Prompt 2:** Please explain **which properties an object must have to have similarity score 9 with a pen**

**Prompt 1:** What's the **similarity score between “pen” and “marker”**, on a scale between 1 (lowest) and 10 (highest)?

**Answer 1:** [...] Based on a general semantic similarity between ‘pen’ and ‘marker’, I would assign a similarity score of **6 out of 10**.

**Prompt 2:** Please explain **which properties an object must have to have similarity score 9 with a pen**

**Answer 2:** [...]The object should be a **writing instrument that uses ink** or a similar fluid to make marks on paper or other surfaces. It should **have a slender, cylindrical shape that is easy to hold and manipulate**. It should have a **pointed tip that can be used to make precise marks or lines**. It should be **lightweight and portable**, making it easy to carry around and use in various situations. It should be **available in various colors or types of ink**, allowing users to **create different types of marks or highlight important information**. Objects such as pencils, quills, fountain pens, ballpoint pens, highlighters, sharpies, gel pens, felt-tip pens, chalk, and crayons are all writing instruments that share many of these properties [...].

**Prompt 1:** What's the **similarity score between “pen” and “marker”**, on a scale between 1 (lowest) and 10 (highest)?

**Answer 1:** [...] Based on a general semantic similarity between ‘pen’ and ‘marker’, I would assign a similarity score of **6 out of 10**.

**Prompt 2:** Please explain **which properties an object must have to have similarity score 9 with a pen**

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**Prompt 3:** Please list some examples of **objects that have a similarity score of 9 out of 10 with a pen**. Please do just make a comma-separated list of just the names of the objects, and do not use line-breaks in that list.



**Prompt 1:** What's the **similarity score between “pen” and “marker”**, on a scale between 1 (lowest) and 10 (highest)?

**Answer 1:** [...] Based on a general semantic similarity between ‘pen’ and ‘marker’, I would assign a similarity score of **6 out of 10**.

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**Prompt 3:** Please list some examples of **objects that have a similarity score of 9 out of 10 with a pen**. Please do just make a comma-separated list of just the names of the objects, and do not use line-breaks in that list.

**Answer 3:** Sure, here's a comma-separated list of objects that have a similarity score of 9 out of 10 with a pen: Pencil, Highlighter, **Marker**, Fountain pen, Ballpoint pen, Gel pen, [...]

**Prompt 1:** What's the **similarity score between “pen” and “marker”**, on a scale between 1 (lowest) and 10 (highest)?

**Answer 1:** [...] Based on a general semantic similarity between ‘pen’ and ‘marker’, I would assign a similarity score of **6 out of 10**.

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**Answer 2:** [...]The object should be a **writing instrument that uses ink** or a similar fluid to make marks on paper or other surfaces. It should **have a slender, cylindrical shape that is easy to hold and manipulate**. It should have a **pointed tip that can be used to make precise marks or lines**. It should be **lightweight and portable**, making it easy to carry around and use in various situations. It should be **available in various colors or types of ink**, allowing users to **create different types of marks or highlight important information**. Objects such as pencils, quills, fountain pens, ballpoint pens, highlighters, sharpies, gel pens, felt-tip pens, chalk, and crayons are all writing instruments that share many of these properties [...].

**Prompt 3:** Please list some examples of **objects that have a similarity score of 9 out of 10 with a pen**. Please do just make a comma-separated list of just the names of the objects, and do not use line-breaks in that list.

**Answer 3:** Sure, here's a comma-separated list of objects that have a similarity score of 9 out of 10 with a pen: Pencil, Highlighter, **Marker**, Fountain pen, Ballpoint pen, Gel pen, [...]

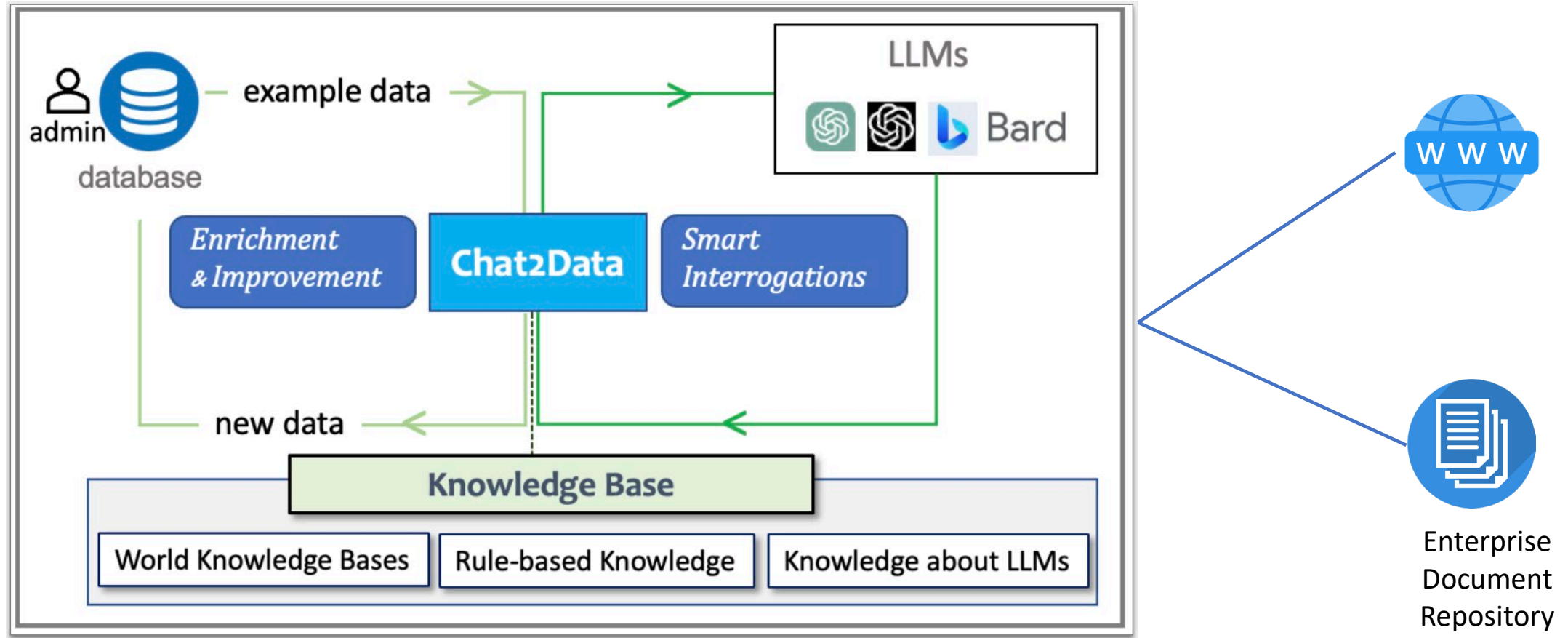


# How to get high-quality data from an LLM?

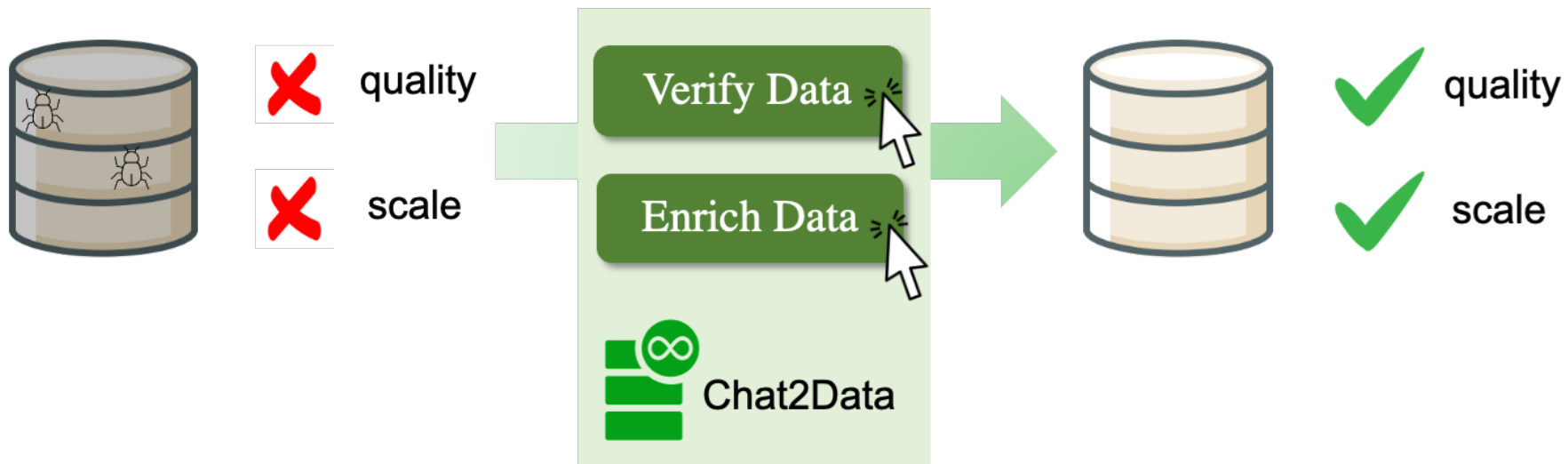
By an **automated prompt engineering** process that:

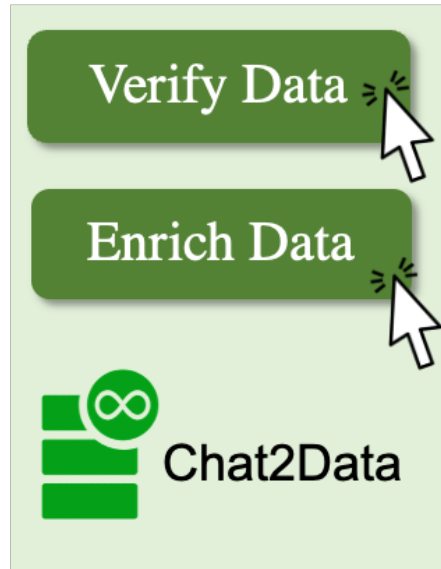
- generates **solutions examples**
- generates and issues “**chain-of thought**” prompts
- generates and issues “**food-for-thought**” prompts
- performs **problem decompositions**
- asks for **main criteria** and their weights
- Asks for **exceptions**
- performs a **consistency analysis** (logical co-pilot)
- performs **list-digging prompts**
- **Imports relevant knowledge** from the Web into the context (RAG)
- Uses **knowledge and rules**
- .....

# Chat2Data Project



- generation of new datasets
- enrichment of existing databases
- verification of data records in a DB
- update of data & null values





## Vision



for **any** data types and domains  
for **any** data storage paradigms  
(e.g., **Knowledge Graphs**)

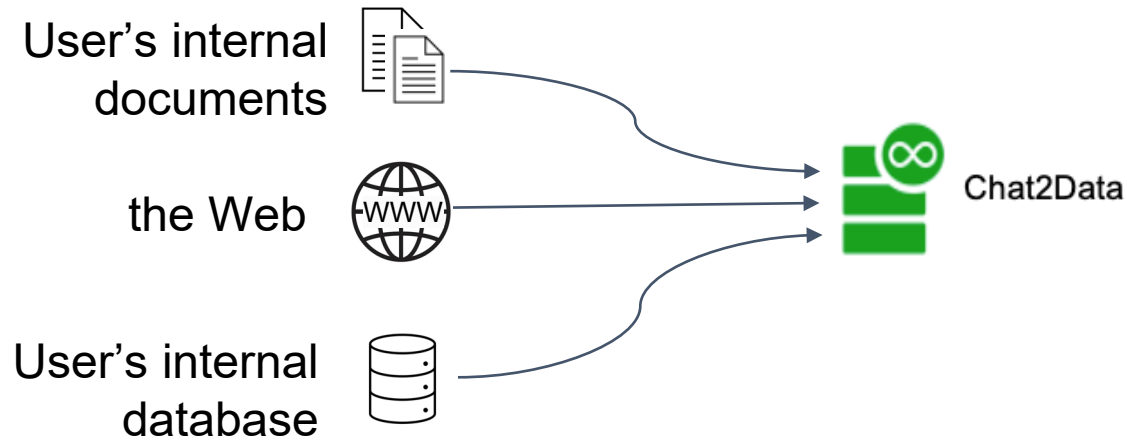


**without any** human effort

Automated

Efficient

Accurate



Fully automatic:

- generation of new datasets
- enrichment of existing databases
- verification of data records in a DB
- update of data & null values
- ... ..

**Chat2Data** seamlessly integrates with the Web, the user's internal document repositories, or databases to automatically perform a wide range of data perfection tasks.

## Recall: LLMs make mistakes

### Example.

**[Prompt]:** List ten competitors to Zenjob.

Zenjob is a personal service provider for part-time jobs that automatically connects companies to part-time job seekers so that both get exactly what they are looking for.

**[GPT-4]:**

1. StudentJob ✓
2. JobUFO ✗ *platform for creating video application*
3. Staffbase ✗ *internal communication platform*
4. Templafy ✗ *document generation tool*
5. ....
6. ....



**Observation:** Advanced prompting like **Chain-Of-Thoughts**, can also make errors, in intermediate steps and in the final results.

[Prompt] List competitors to Zenjob. To solve this problem, please think step by step:

1. List all the important criteria that determine the competitor relationship between two companies in the industry Zenjob operates in.
2. List possible candidate competitors to Zenjob.
3. According to each criterion, score each candidate based on that criterion.
4. Finally, aggregate these scores to generate a final score. Rank these candidates based on the final score. Return those highly ranked ones.

This prompt has explicitly explained how to find competitors of Zenjob step by step.

[GPT-4]

#### **Step 5: Rank Based on Total Score**

1. Coople, JobToday, Staffy, BlueCrew (Tied) - 39
2. Side - 37
3. GigNow & Catapult (Tied) - 35
4. Instahire - 34

**Results:** Based on the hypothetical scores, Coople, JobToday, Staffy, and BlueCrew emerge as the closest competitors to Zenjob.

#### **Incorrect answers:**

##### **Wrong Geographic Presence:**

- Coople
- Instahyre
- BlueCrew

##### **Wrong Market Segment:**


- Staffy

Based on previous observations, we faced two research problems:

? **Problem I:**  
How to properly guide LLMs to  
accomplish complicated data verification  
or enrichment tasks?

? **Problem II:**  
How to ensure the correctness of  
LLM's answers at each sub-step of the  
whole workflow?

# Example Database (starting point)

 Data verification and enrichment using LLMs.

## Competitors

focal entity	related entity
Zenjob	Cocople
Zenjob	JobUFO
Imagga	
FoodCheri	
Oxford Brookes University	Mastercard
MediSafe	Pear Therapeutics
HELLO! Magazine	Who What Wear
Iveda	FLIR Systems
Roku	BMG
Blue Nile	De Beers
Lightspeed Systems	McAfee
Dr Falk Pharma	Novartis
Telus	Rogers
CurrencyFair	TransferGo

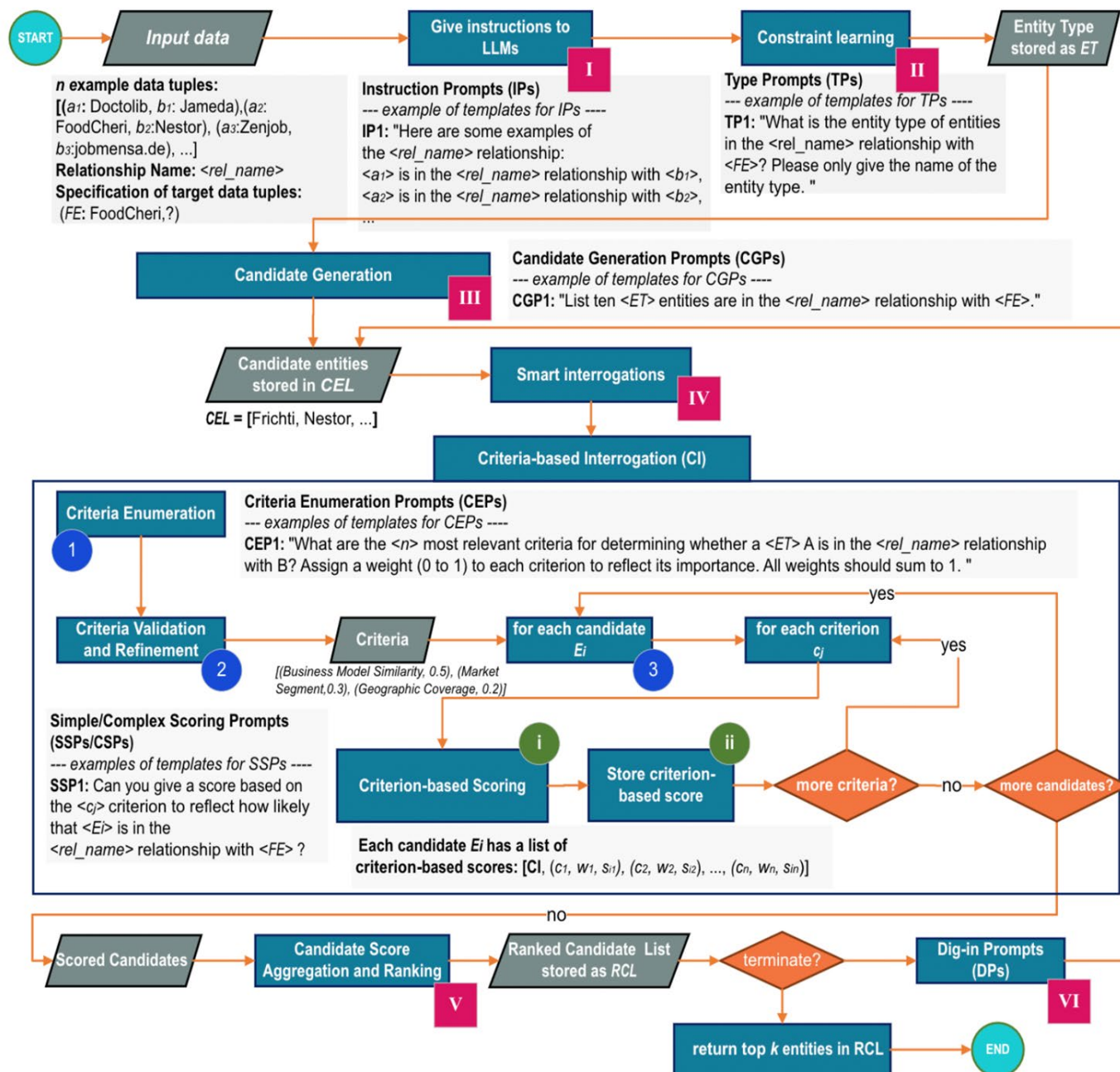
VERIFY DATAENRICH DATA

Smart InterrogationsGraphExplanations

### Smart Interrogations Workflow

The Smart Interrogations workflow will be displayed here.

## Data Generation



An example workflow for **enriching** a binary-relation table.

The whole problem is decomposed into sub-problems. Each sub-problem is solved by a sub-process that properly utilizes LLMs.

Let's have a look at real workflows generated by our **Chat2Data** system.

**Verification** of the tuple (Coople, Zenjob) in the competitors relation:

Is Coople a competitor of Zenjob?

**Use GPT to understand what the data relation is about.**

**Retrieve GPT's knowledge about the competitors relationship.**

**Regarding each criterion, generate a score for Coople.**

## Use GPT to understand what the data relation is about.

### Main Prompt:

Here are example tuples of a data relation:

---

(Zenjob, Coople)  
(Zenjob, JobUFO)  
(Oxford Brookes University, Mastercard)  
(MediSafe, Pear Therapeutics)  
(HELLO! Magazine, Who What Wear)  
(Iveda, FLIR Systems)  
(Roku, BMG)  
(Blue Nile, De Beers)

---

Please generate a phrase to describe this data relation.

[See Full Prompt](#)


 **gpt-3.5-turbo:** [answer]competitors[/answer]

## Retrieve GPT's knowledge about the competitors relationship.

### Main Prompt:

Please generate three most important criteria that determine whether or not entities are in the competitors relationship.

[See Full Prompt](#)

 **gpt-3.5-turbo:** [answer][('Geographic Presence', 'Target Customer or Audience Base', 'Product or Service Offerings')][answer]



## Regarding each criterion, generate a score for Coople.

### Main Prompt:

Task Instruction:

In order to determine whether or not Zenjob and Coople are in direct competitors

relationship, we need to consider the key factor of Geographic Presence. Use YOUR CURRENT KNOWLEDGE of Zenjob and Coople regarding

Geographic Presence.

Analyze whether or not Zenjob and Coople have overlap Geographic Presence.

Your answer should be one of the following:

['highly overlap', 'some overlap', 'different'].

[Few-shot examples have been omitted.] [See Full Prompt](#)




**gpt-3.5-turbo:** Zenjob mainly operates in Germany, with a presence in several German cities such as Berlin, Hamburg, Munich, and Frankfurt, among others. Coople operates in the United Kingdom and Switzerland. Their Geographic Presence is different, as Zenjob operates in Germany while Coople operates in the United Kingdom and Switzerland. Thus, the answer is [Answer]different[/Answer].

**Main Prompt:**  
Task Instruction:

In order to determine whether or not Zenjob and Coople are in direct competitors relationship, we need to consider the key factor of Product or Service Offerings.  
Use YOUR CURRENT KNOWLEDGE of Zenjob and Coople regarding Product or Service Offerings.  
Analyze whether or not Zenjob and Coople have overlap Product or Service Offerings.

Your answer should be one of the following:  
['highly overlap', 'some overlap', 'different'].  
[Few-shot examples have been omitted.] [See Full Prompt](#)

 **gpt-3.5-turbo:** Zenjob and Coople both operate in the gig economy and offer temporary staffing solutions. They connect businesses with flexible workers for various industries such as retail, hospitality, and events. While both companies have a similar focus on temporary staffing, their specific product or service offerings may differ in terms of features, pricing, and target markets. Without detailed knowledge of their specific offerings, it is difficult to determine the extent of overlap. However, based on their shared focus on temporary staffing, it can be concluded that Zenjob and Coople have [Answer]some overlap[/Answer] in their product or service offerings.

**Main Prompt:**

Task Instruction:

In order to determine whether or not Zenjob and Coople are in direct competitors

relationship, we need to consider the key factor of Target Customer or Audience Base.

Use YOUR CURRENT KNOWLEDGE of Zenjob and Coople regarding Target Customer or Audience Base.

Analyze whether or not Zenjob and Coople have overlap Target Customer or Audience Base.

Your answer should be one of the following:

['highly overlap', 'some overlap', 'different'].

[Few-shot examples have been omitted.] [See Full Prompt](#)



**gpt-3.5-turbo:** Zenjob and Coople are both platforms that connect businesses with temporary workers. They both target businesses and individuals looking for temporary staffing solutions. Their

Target Customer or Audience Base has a high degree of overlap, as they cater to the same market and offer similar services. Thus, the answer is [Answer]highly overlap[/Answer]

### Explanations

- **Criterion:** Geographic Presence

**Analysis:** Zenjob mainly operates in Germany, with a presence in several German cities such as Berlin, Hamburg, Munich, and Frankfurt, among others. Coople operates in the United Kingdom and Switzerland. Their Geographic Presence is different, as Zenjob operates in Germany while Coople operates in the United Kingdom and Switzerland. Thus, they are not competitors.

- **Criterion:** Product or Service Offerings

**Analysis:** Zenjob and Coople both operate in the gig economy and offer temporary staffing solutions. They connect businesses with flexible workers for various industries such as retail, hospitality, and events. While both companies have a similar focus on temporary staffing, their specific product or service offerings may differ in terms of features, pricing, and target markets. Without detailed knowledge of their specific offerings, it is difficult to determine the extent of overlap.

- **Criterion:** Target Customer or Audience Base

**Analysis:** Zenjob and Coople are both platforms that connect businesses with temporary workers. They both target businesses and individuals looking for temporary staffing solutions. Their Target Customer or Audience Base has a high degree of overlap, as they cater to the same market and offer similar services.

## **Enrichment** of the the competitors relation:

Which companies are competitors of Iveda?

**Use GPT to understand what the data relation is about.**

**Retrieve GPT's knowledge about the competitors relationship.**

**Generate candidates that are in the considered relationship with the focal entity.**

**Regarding each criterion, generate a score for each candidate.**

**Note that,**

all the prompts previously shown are **simple prompts**, intended to illustrate our workflows.

In reality, **using these simple prompts is not sufficient**, as they can lead to mistakes in the intermediate results of each sub-step



**Example:** simple prompt used in a sub-step leads to incorrect answer.

**Prompt:**

In order to determine whether or not Zenjob and Coople are in direct competitors relationship, we need to consider the key factor of Geographic Presence.  
Use YOUR CURRENT KNOWLEDGE of Zenjob and Coople regarding Geographic Presence.  
Analyze whether or not Zenjob and Coople have overlap Geographic Presence.

Your answer should be one of the following:  
['highly overlap', 'some overlap', 'different'].

ChatGPT's answer is incorrect, because Zenjob and Coople targets customers in **different countries**.



**ChatGPT**

As of my last update in January 2022, both Zenjob and Coople primarily operate in Europe, with a focus on Germany and Switzerland. While they may have some overlap in geographic presence, particularly in these regions, they also target different markets and have different strengths in certain cities or regions. Therefore, I would categorize their geographic presence as having "some overlap."

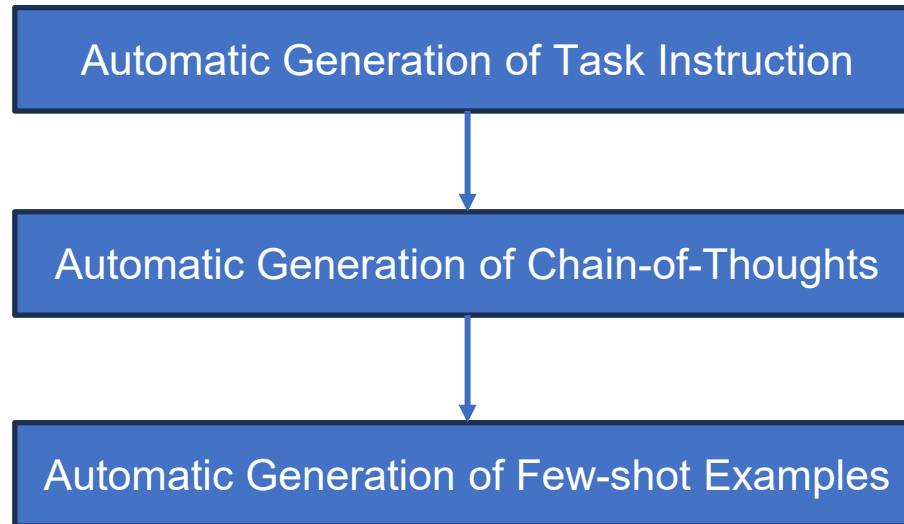
That's why we need to solve problem II:

**?** **Problem II:**  
How to ensure the correctness of LLM's  
answers at each sub-step of the whole  
workflow?



## Our Solution:

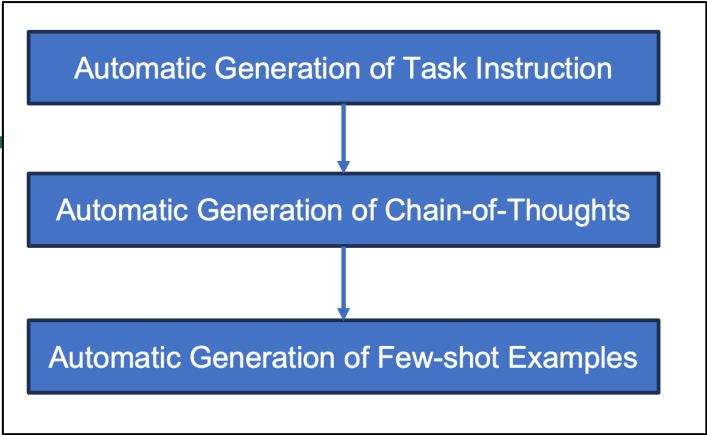
automatic generation of  
high-quality prompts  
for each sub-step in our  
workflow



Original Simple Prompt:

In order to determine whether or not Zenjob and Coople are in direct competitors relationship, we need to consider the key factor of Geographic Presence. Use YOUR CURRENT KNOWLEDGE of Zenjob and Coople regarding Geographic Presence. Analyze whether or not Zenjob and Coople have overlap Geographic Presence.

Your answer should be one of the following:  
['highly overlap', 'some overlap', 'different'].



Final Prompt:

Considering the criterion of 'Geographic Presence,' evaluate the extent of overlap between Zenjob and Coople. To do this, assess the geographic regions where both companies operate and determine the level of similarity or divergence. Provide a score indicating the likelihood of them being competitors based on their geographic presence. Use the following scale: 'highly overlap' if they operate extensively in the same regions, 'some overlap' if there are common areas but also distinctions, and 'different' if their geographic focus is largely distinct.

To complete this task, you may follow the following steps:

1. Identify the primary operating regions of Zenjob and Coople
2. Assess the level of similarity in the geographic regions where Zenjob and Coople operate
3. Determine the extent of overlap: Consider whether Zenjob and Coople operate extensively in the same regions or if there are differences in their target markets and geographic focus.
4. Evaluate the commonalities and distinctions.
5. Provide a score indicating the likelihood of competition based on their geographic presence

Some Examples are:

Q:  
focal entity: McDonald's, candidate competitor: KFC  
criterion: Geographic Presence

A:  
McDonald's has a geographic presence across countries and cities worldwide. KFC also has a geographic presence across countries and cities worldwide. Its Geographic Presence are almost the same with McDonald's, i.e., both have a geographic presence across countries and cities worldwide. Thus, the answer is [Answer]highly overlap[/Answer]

[more examples are omitted ]

Q:  
focal entity: Zenjob, Candidate competitor: Coople  
criterion: Geographic Presence


A:

## In summary, Chat2Data features:

- (1) decomposing a complicated problem into sub-tasks, and
- (2) using automatically generated high-quality prompts to ensure the quality of each sub-task.

## Evaluations on Competitors Dataset

Domain	Recall	Precision	Negative Predictive Value	Specificity	Accuracy	F-Score
Chat2Data	0.74	0.76	0.8	0.83	0.79	0.75
COT prompting (GPT4)	0.63	0.64	0.65	0.66	0.65	0.63
+Few-shot prompting (GPT4)	0.71	0.72	0.71	0.71	0.72	0.71



Prompts carefully crafted by human experts are used. These methods reflect the best results that human experts can achieve using advanced prompting techniques.

# Evaluations on Similar Products Dataset

Domain	Recall	Precision	Negative Predictive Value	Specificity	Accuracy	F-Score
Chat2Data	0.94	0.82	0.91	0.75	0.86	0.88
COT prompting (GPT4)	0.69	0.47	0.48	0.27	0.48	0.56
+Few-shot prompting (GPT4)	0.71	0.49	0.55	0.32	0.51	0.58

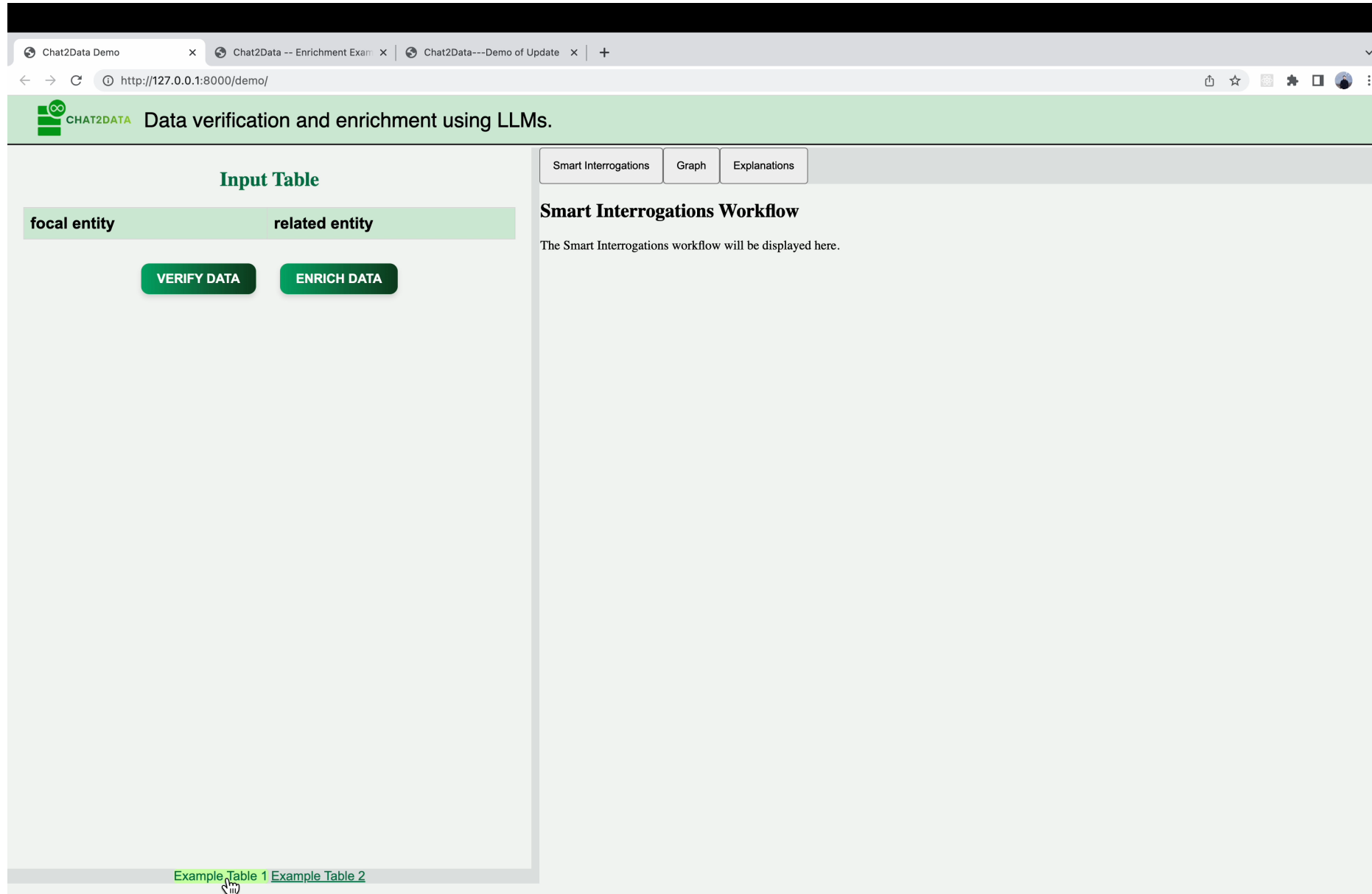
# Key Evaluation Metrics for Classification Models

METRIC	DEFINITION
Recall	The proportion of true positives correctly identified by the model.
Precision	The proportion of positive results that are true positives.
Negative Predictive Value	The proportion of true negatives correctly identified among all negative predictions.
Specificity	The proportion of true negatives correctly identified by the model.
Accuracy	The proportion of all correct predictions (both true positives and true negatives) made by the model.
F-score	The harmonic mean of Precision and Recall, balancing the two metrics.

# DEMO VIDEOS

Long online video: <https://www.unlimidata.com/intro>

The next two pages contain (links to) short videos.



LINK TO VIDEO: <https://www.dropbox.com/scl/fi/8d2b3r3zpmg4eyu1j9waf/demos-1-and-2-and-3.mp4?rlkey=5ubpy6mpt66hqr5kt1y989iac&dl=0>



tax

Generate Error Detection Rules

TaxpayerID	FirstName	LastName	Gender	AreaCode	Phone	City	State	Zip
1	John	Doe	Male	415	555-0123	San Francisco	CA	94102
2	Jane	Smith	Female	415	555-0456	Oakland	CA	94612
3	Bob	Johnson	Male	212	555-0789	New York	NY	10019
4	Alice	Williams	Female	305	555-0123	Miami	FL	33101
5	Chris	Davis	Male	212	555-0987	New York	NY	10019
6	Emily	Taylor	Female	213	555-1122	Los Angeles	CA	90015
7	David	Wilson	Male	305	555-0123	Miami	FL	33101
8	Olivia	Lee	Female	415	555-0456	San Francisco	CA	94102
9	James	Moore	Male	718	555-1212	Brooklyn	NY	11201
10	Sophia	Brown	Female	202	555-1234	Washington	DC	20005
11	Michael	Garcia	Male	510	555-6789	Berkeley	CA	94704
12	Isabella	Jones	Female	718	555-4321	Brooklyn	NY	11201
13	Ethan	Miller	Male	312	555-5678	Chicago	IL	60616
14	Madison	Wilson	Female	312	555-8765	Chicago	IL	60616
15	Aiden	Martinez	Male	305	555-7890	Miami	FL	33101
16	Abigail	Anderson	Female	415	555-0147	San Francisco	CA	94102
17	Joshua	Thomas	Male	415	555-0198	Oakland	CA	94612
18	Sophie	Hernandez	Female	305	555-1122	Miami	FL	33101
19	Ella	Lopez	Female	212	555-2222	New York	NY	10019
20	Noah	Hall	Male	212	555-3333	New York	NY	10019
21	William	Scott	Male	510	555-4444	Fremont	CA	94538
22	Chloe	Young	Female	510	555-5555	Fremont	CA	94538
23	Liam	Mendez	Male	213	555-6666	Los Angeles	CA	90015
24	Charlotte	Clark	Female	213	555-7777	Los Angeles	CA	90015
25	Lucas	Perez	Male	212	555-8888	New York	NY	10019
26	Mia	Ramirez	Female	312	555-9999	Chicago	IL	60616
27	Jack	Roberts	Male	312	555-0000	Chicago	IL	60616

Description: **### Dataset Overview**

This dataset contains individual tax records, blending synthetic and real data elements to represent the financial and personal demographics of taxpayers. It is designed for analysis and modeling purposes, particularly in understanding tax liabilities and exemptions.

**### Column Descriptions**

- **\*\*TaxpayerID\*\***: A unique identifier for each taxpayer within the dataset, ensuring anonymity and unique representation for data processing.
- **\*\*FirstName\*\***: The first name of the taxpayer, representing the personal aspect of the dataset.
- **\*\*LastName\*\***: The last name of the taxpayer, used in conjunction with the first name for full identification in data analysis.
- **\*\*Gender\*\***: The taxpayer's gender, typically categorized as male or female. This demographic detail can be used for various analytical insights.
- **\*\*AreaCode\*\***: The telephone area code for the taxpayer's primary residence, indicative of geographical distribution and potentially correlating with tax-related statistics.
- **\*\*Phone\*\***: The taxpayer's telephone number, combined with the area code for full contact detail.
- **\*\*City\*\***: The city in which the taxpayer resides, important for regional tax analysis and demographic studies.
- **\*\*State\*\***: The state where the taxpayer lives, represented by a state abbreviation (e.g., NY for New York, CA for California). This is critical for understanding state-specific tax implications.
- **\*\*Zip\*\***: The postal zip code of the taxpayer's residence, useful for precise location-based analysis and regional tax norms.
- **\*\*MaritalStatus\*\***: Indicates the marital status of the taxpayer (e.g., single, married), which is a significant factor in tax calculations and exemptions.

Trigger Rule

LINK TO VIDEO: <https://www.dropbox.com/scl/fi/hicncf923pywae5jnc7gz/demo-4-rule-generation.mp4?rlkey=mizyeq345iy3d9i810eju8jov&dl=0>

So far, we have seen the basic ideas of Chat2Data.  
Now, let's explore some **advanced features**.

# Innovative Prompts

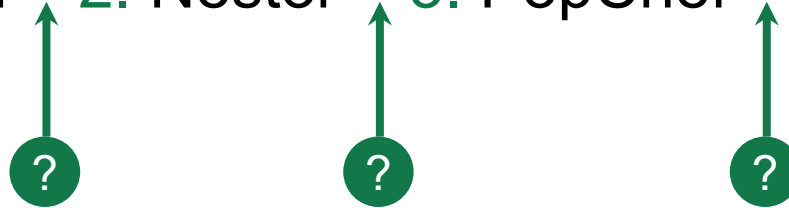
- Data Intelligence Prompts
- Problem Deconstruction Prompts
- LLM Certainty Assessment Prompts
  - + novel weights-learning method;
  - + new fuzzy aggregation method [LSG22]
- List re-ordering prompts
- List “Dig-in” prompts
- Knowledge-based logical consistency checks

[LSG22] Matthias Lanzinger, Stefano Sferrazza , Georg Gottlob: MV-Datalog+-: Effective Rule-based Reasoning with Uncertain Observations. Theory Pract. Log. Program. 22(5): 678-692 (2022)

# “Dig-in” prompts

Assume that, at some stage, the Chat2Data has discovered the following top competitors of FoodCheri :

[ 1. Frichti 2. Nestor 3. PopChef 4. ... ... ]



What is missing ?

## Example:

Find competitors C of FoodCheri to be ranked between Nestor and PopChef regarding their competitive proximity to FoodCheri because they are:

- (i) to a lesser degree competing with FoodCheri than Nestor and
- (ii) to a higher degree competing with FoodCheri than PopChef.

## LOGIC CO-PILOT

similarity\_score(pen,marker,6)

**Prompt 1:** What's the **similarity score between "pen" and "marker"**, on a scale between 1 (lowest) and 10 (highest)?

**Answer 1:** [...] Based on a general semantic similarity between 'pen' and 'marker', I would assign a similarity score of **6 out of 10**.

**Prompt 2:** Please explain **which properties an object must have to have similarity score 9 with a pen**

**Answer 2:** [...]The object should be a **writing instrument that uses ink** or a similar fluid to make marks on paper or other surfaces. It should **have a slender, cylindrical shape that is easy to hold and manipulate**. It should have a **pointed tip that can be used to make precise marks or lines**. It should be **lightweight and portable**, making it easy to carry around and use in various situations. It should be **available in various colors or types of ink**, allowing users to **create different types of marks or highlight important information**. Objects such as pencils, quills, fountain pens, ballpoint pens, highlighters, sharpies, gel pens, felt-tip pens, chalk, and crayons are all writing instruments that share many of these properties [...].

**Prompt 3:** Please list some examples of **objects that have a similarity score of 9 out of 10 with a pen**. Please do just make a comma-separated list of just the names of the objects, and do not use line-breaks in that list.

**Answer 3:** Sure, here's a comma-separated list of objects that have a similarity score of 9 out of 10 with a pen: Pencil, Highlighter, **Marker**, Fountain pen, Ballpoint pen, Gel pen, [...]

similarity\_score(pen,marker,9)

## LOGIC CO-PILOT

similarity\_score(pen,marker,6)

### Knowledge:

similarity\_score (X,Y,Z) &  
similarity\_score (X,Y,Z') &  
 $Z \leftrightarrow Z' \rightarrow \perp$

similarity\_score(pen,marker,9)



**Prompt 1:** What's the **similarity score between "pen" and "marker"**, on a scale between 1 (lowest) and 10 (highest)?

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## LOGIC CO-PILOT

similarity\_score(pen,marker,6)

similarity\_score(pen,marker,9)

### Knowledge:

similarity\_score (X,Y,Z) &

similarity\_score (X,Y,Z') &

$Z \leftrightarrow Z' \rightarrow \perp$

### Reasoner:

Theorem Prover or  
CSP solver, or LLM

### Actions:

Make further prompting  
Depending on discovered  
Inconsistency.

→ Logic-Based Automated  
Prompt Engineering

**Prompt 1:** What's the **similarity score between "pen" and "marker"**, on a scale between 1 (lowest) and 10 (highest)?

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## LOGIC CO-PILOT

similarity\_score(pen,marker,6)

similarity\_score(pen,marker,9)

### Knowledge:

similarity\_score (X,Y,Z) &

similarity\_score (X,Y,Z') &

$Z \leftrightarrow Z' \rightarrow \perp$

### Reasoner:

Theorem Prover or  
CSP solver, or LLM

### Actions:

Make further prompting  
Depending on discovered  
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→ Logic-Based Automated  
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**Answer 1:** [...] Based on a general semantic similarity between 'pen' and 'marker', I would assign a similarity score of **6 out of 10**.

**Prompt 2:** Please explain **which properties an object must have to have similarity score 9 with a pen**

**Answer 2:** [...]The object should be a **writing instrument that uses ink** or a similar fluid to make marks on paper or other surfaces. It should **have a slender, cylindrical shape that is easy to hold and manipulate**. It should have a **pointed tip that can be used to make precise marks or lines**. It should be **lightweight and portable**, making it easy to carry around and use in various situations. It should be **available in various colors or types of ink**, allowing users to **create different types of marks or highlight important information**. Objects such as pencils, quills, fountain pens, ballpoint pens, highlighters, sharpies, gel pens, felt-tip pens, chalk, and crayons are all writing instruments that share many of these properties [...].

**Prompt 3:** Please list some examples of **objects that have a similarity score of 9 out of 10 with a pen**. Please do just make a comma-separated list of just the names of the objects, and do not use line-breaks in that list.

**Answer 3:** Sure, here's a comma-separated list of objects that have a similarity score of 9 out of 10 with a pen: Pencil, Highlighter, **Marker**, Fountain pen, Ballpoint pen, Gel pen, [...]

*Huge opportunities for Neuro-Symbolic AI!*



# Neuro-symbolic AI (loosely coupled)

LEFT BRAIN

SYMBOLIC REASONING


SLOW THINKING  
(Kahneman)

**LOGIC CO-PILOT**

similarity\_score(pen,marker,6)

**Knowledge:**  
similarity\_score (X,Y,Z) &  
similarity\_score (X,Y,Z') &  
 $Z \diamond Z' \rightarrow \perp$

similarity\_score(pen,marker,9)



Prompt 1: What's the similarity score between "pen" and "marker", on a scale between 1 (lowest) and 10 (highest)?

Answer 1: [...] Based on a general semantic similarity between 'pen' and 'marker', I would assign a similarity score of 6 out of 10.

Prompt 2: Please explain which properties an object must have to have similarity score 9 with a pen

Answer 2: [...] The object should be a writing instrument that uses ink or a similar fluid to make marks on paper or other surfaces. It should have a slender, cylindrical shape that is easy to hold and manipulate. It should have a pointed tip that can be used to make precise marks or lines. It should be lightweight and portable, making it easy to carry around and use in various situations. It should be available in various colors or types of ink, allowing users to create different types of marks or highlight important information. Objects such as pencils, quills, fountain pens, ballpoint pens, highlighters, sharpies, gel pens, felt-tip pens, chalk, and crayons are all writing instruments that share many of these properties [...].

Prompt 3: Please list some examples of objects that have a similarity score of 9 out of 10 with a pen. Please do just make a comma-separated list of just the names of the objects, and do not use line-breaks in that list.

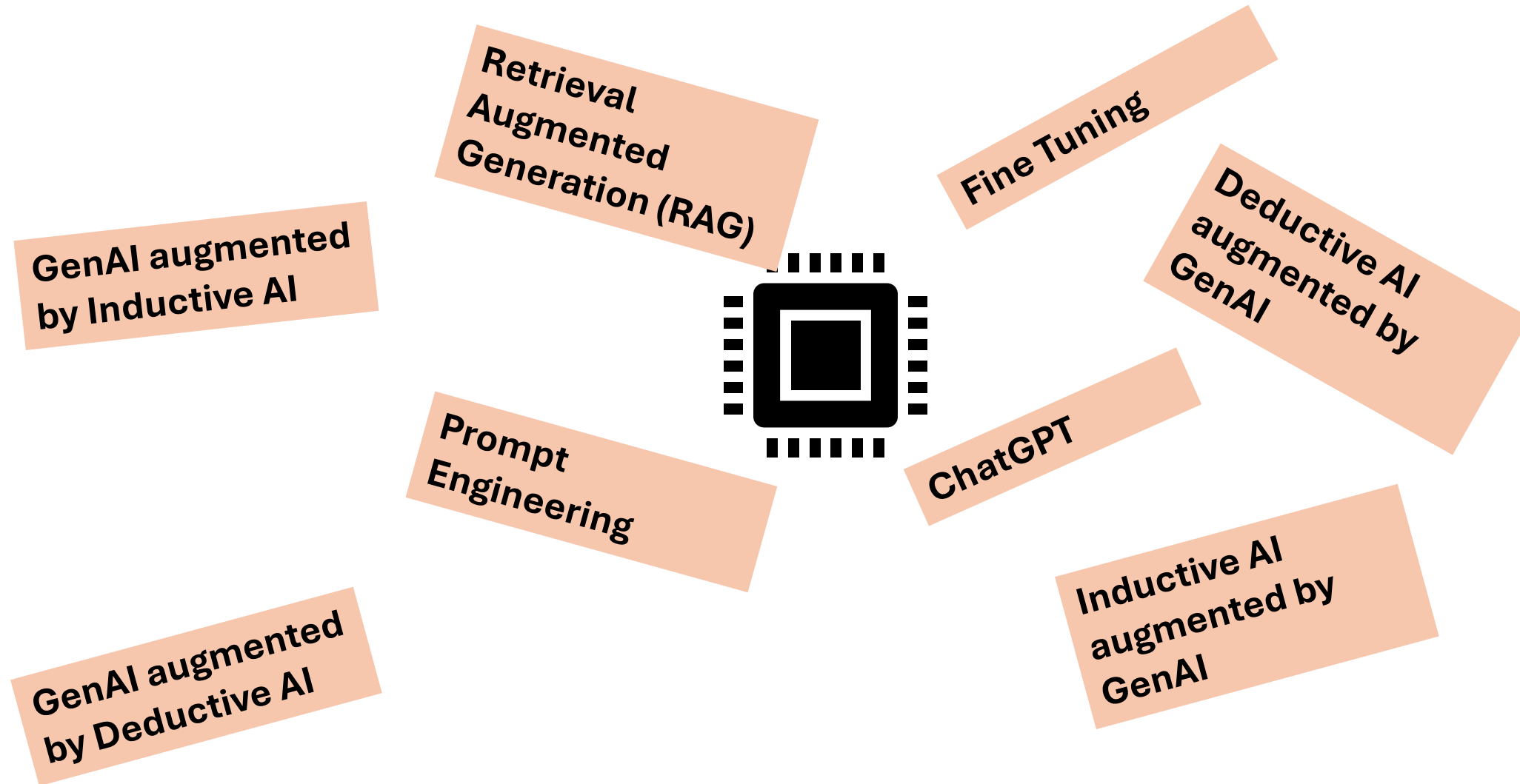
Answer 3: Sure, here's a comma-separated list of objects that have a similarity score of 9 out of 10 with a pen: Pencil, Highlighter, Marker, Fountain pen, Ballpoint pen, Gel pen, [...]

RIGHT BRAIN

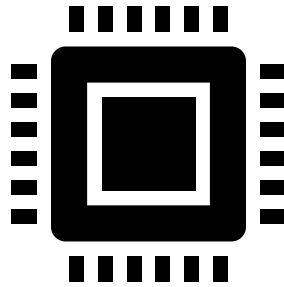
SUB-SYMBOLIC REASONING

FAST THINKING  
(Kahneman)

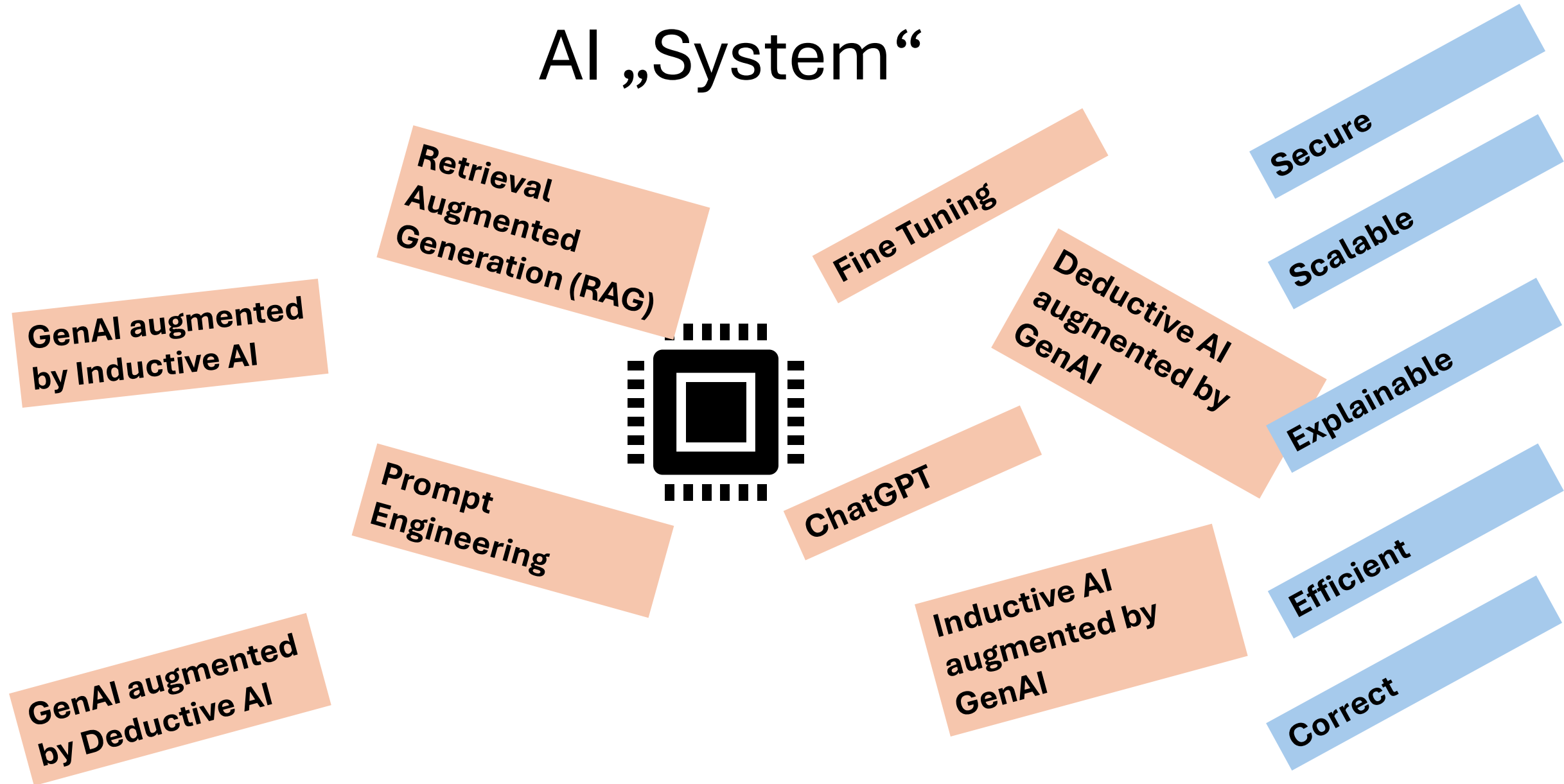
# AI „System“



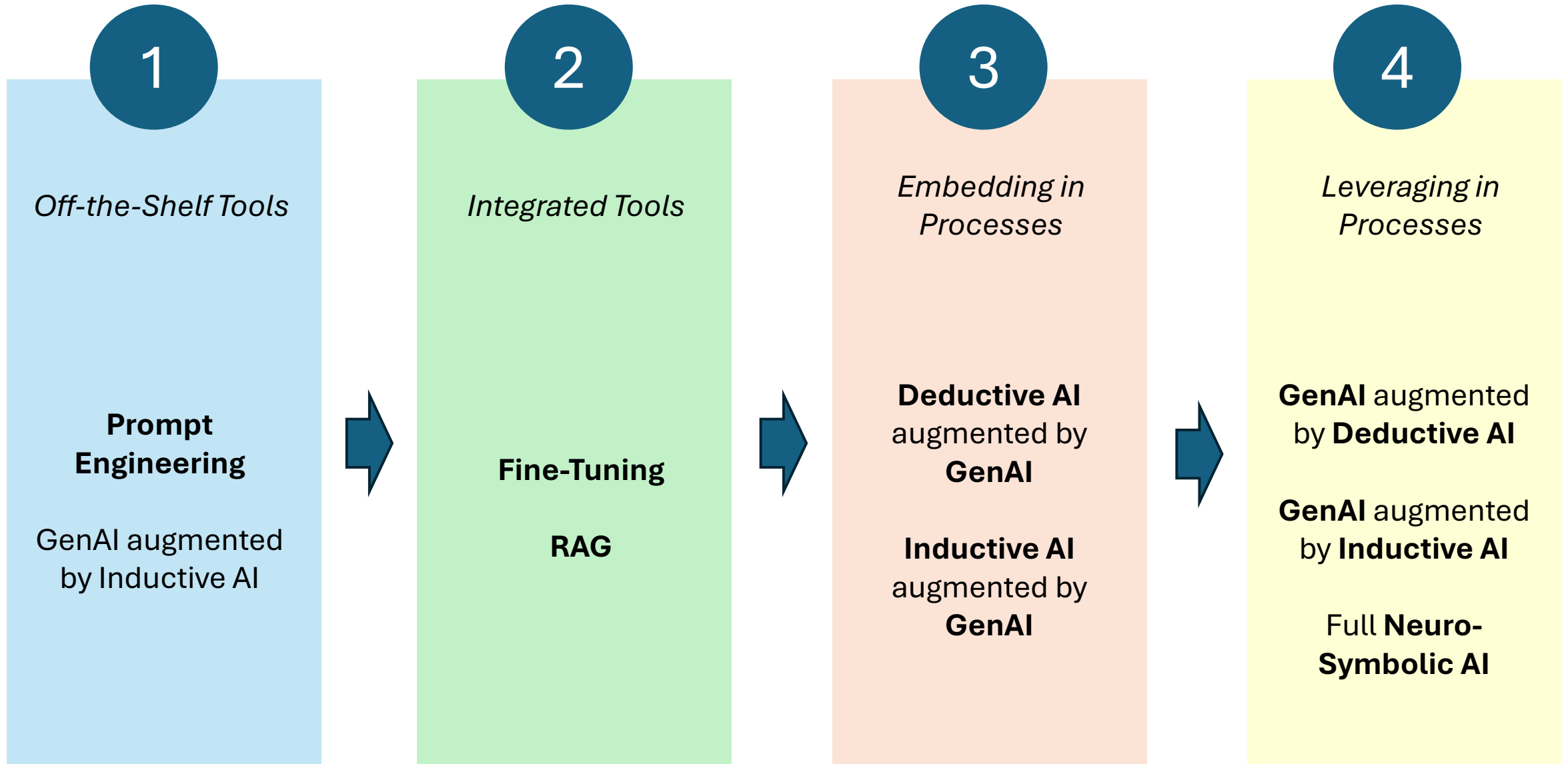
# AI „System“



# AI „System“



# Enterprises need a principled approach towards tools and methods towards neurosymbolic AI



Thank You