



# Extracting accurate data from research papers

—  
Using Large Language Models (LLMs)

**Maciej P. Polak**, Dane Morgan  
Department of Materials Science and Engineering  
University of Wisconsin - Madison

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# Our approach to data extraction

- ❖ Break up papers into sentences and **classify**
  - *Does it contain relevant data?*
- ❖ **Extract** the data
  - By hand
  - Automatically – with **LLMs**
- ❖ **Accurate** extraction is possible:
  - ~90% precision and recall

# Our approach to data extraction

❖ **Problem:** high quality data needed for building machine learning models

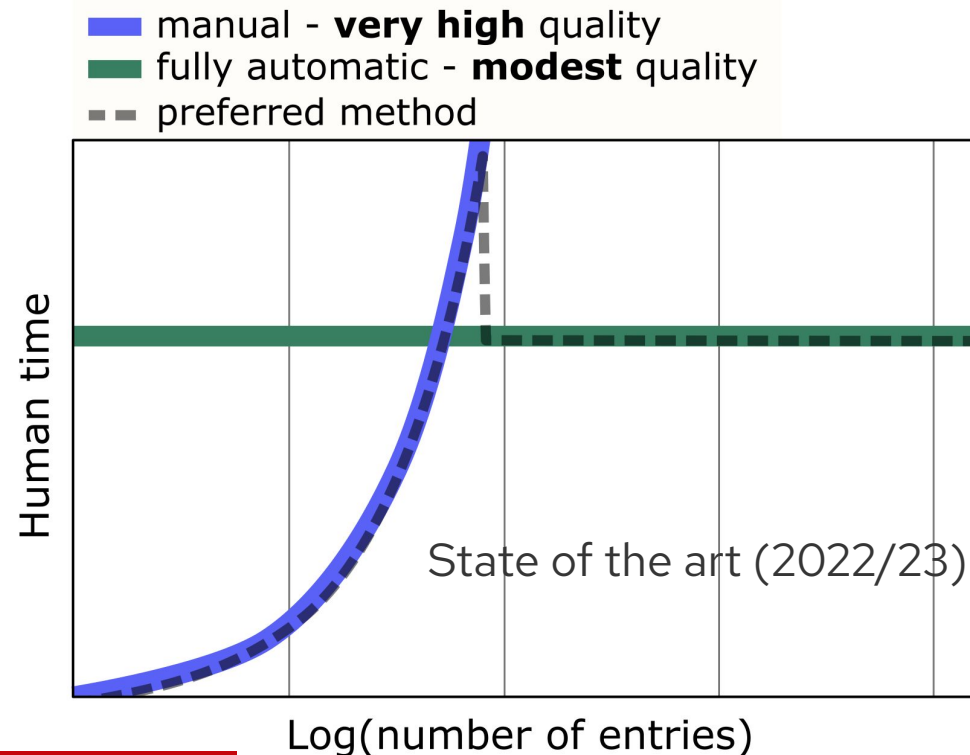
❖ **Solution:** extract data from research papers

- **Problems:**

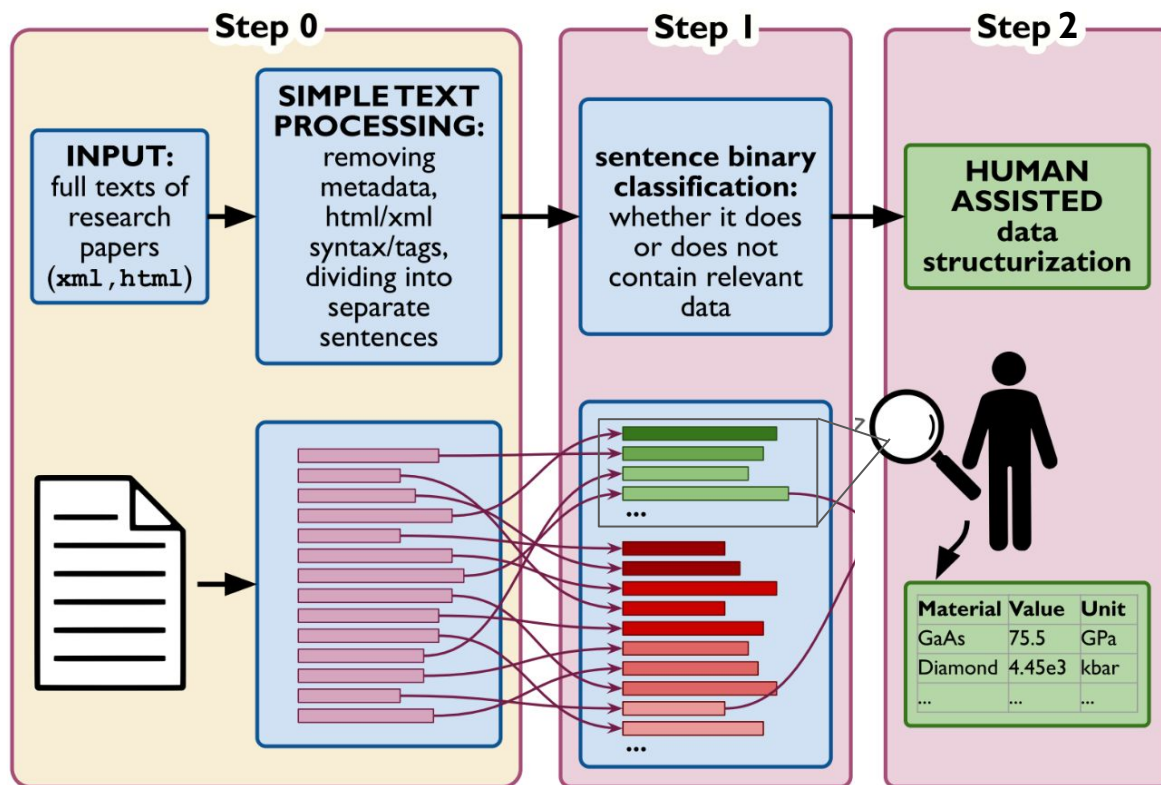
- low quality of automated data extraction
- too many papers to extract manually

- **Solution:**

- use language models to extract data from research papers

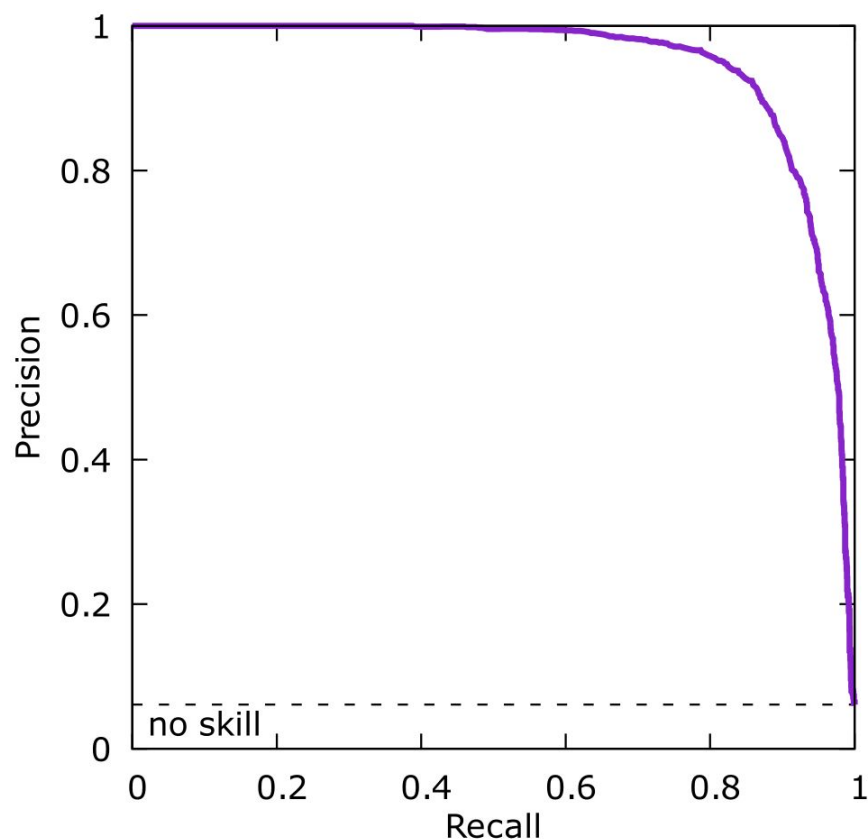
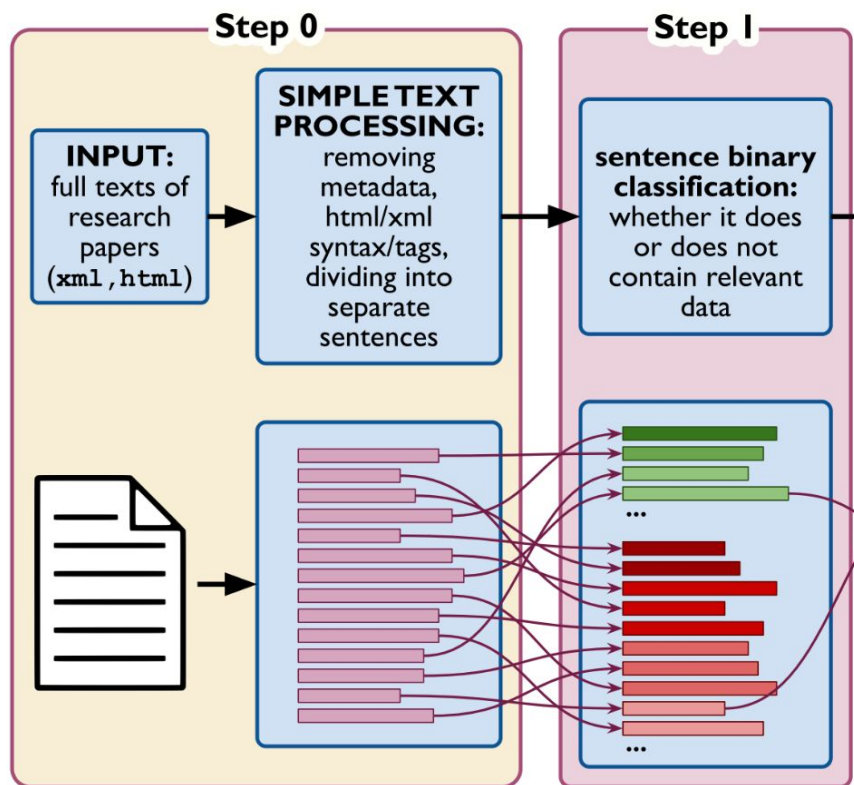


# Using (L)LMs for sentence classification



**Data triplet:**  
Material, Value, Unit

# Using (L)LMs for sentence classification



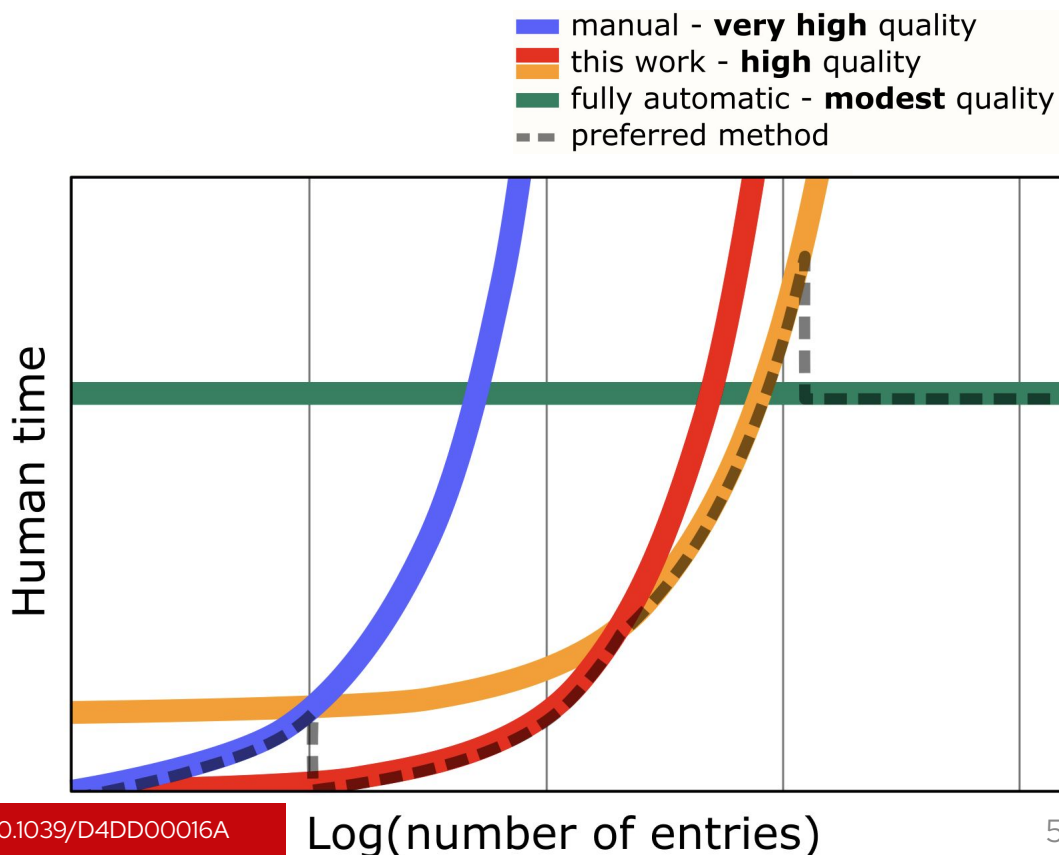


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## Flexible, model-agnostic method for materials data extraction from text using general purpose language models

Maciej P. Polak, \* Shrey Modi,  Anna Latosinska, Jinming Zhang, Ching-Wen Wang, Shaonan Wang, Ayan Deep Hazra and Dane Morgan\*

- ❖ Extremely simple
- ❖ Needs minimal resources
- ❖ Almost no coding required
- ❖ Used to develop the most complete and largest to date database of critical cooling rates of metallic glasses





# Automate data structurization with LLMs

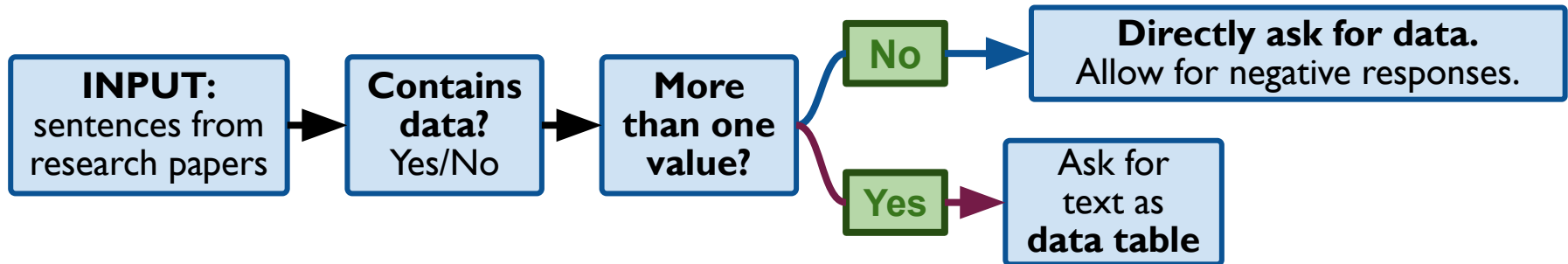


Using **GPT-4**:

- ~90% recall
- ~30% precision



# Automate data structurization with LLMs

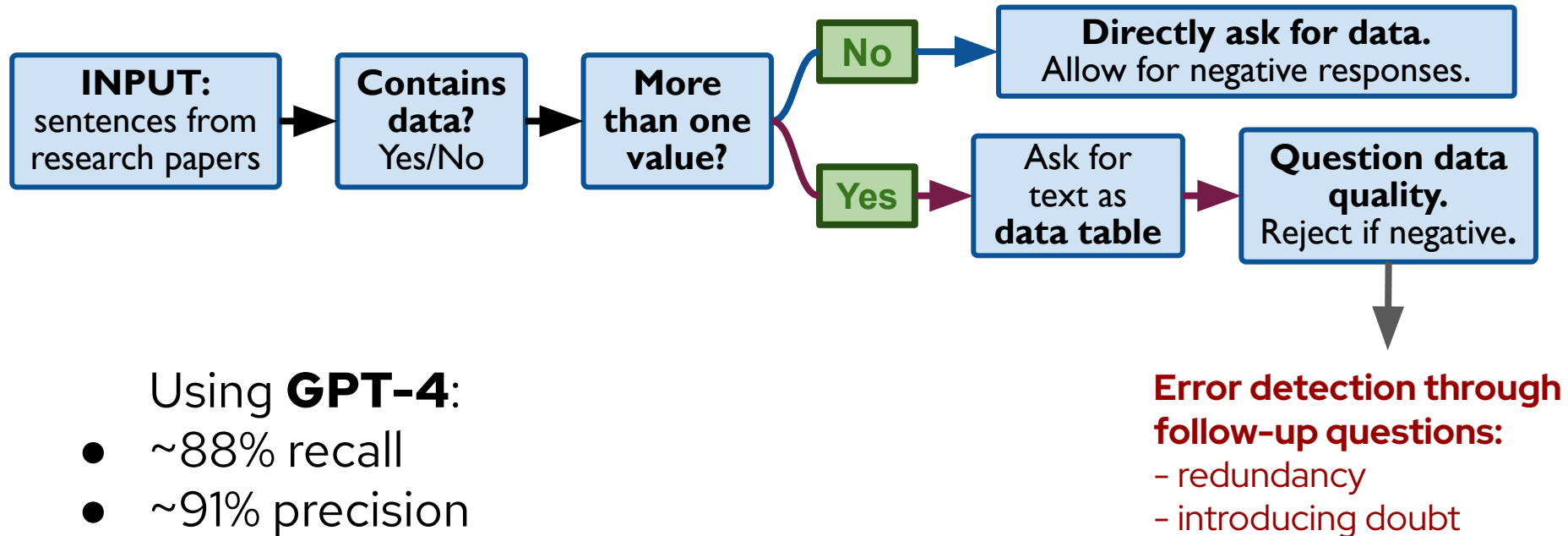


Using **GPT-4**:

- ~98% recall
- ~42% precision



# Automate data structurization with LLMs

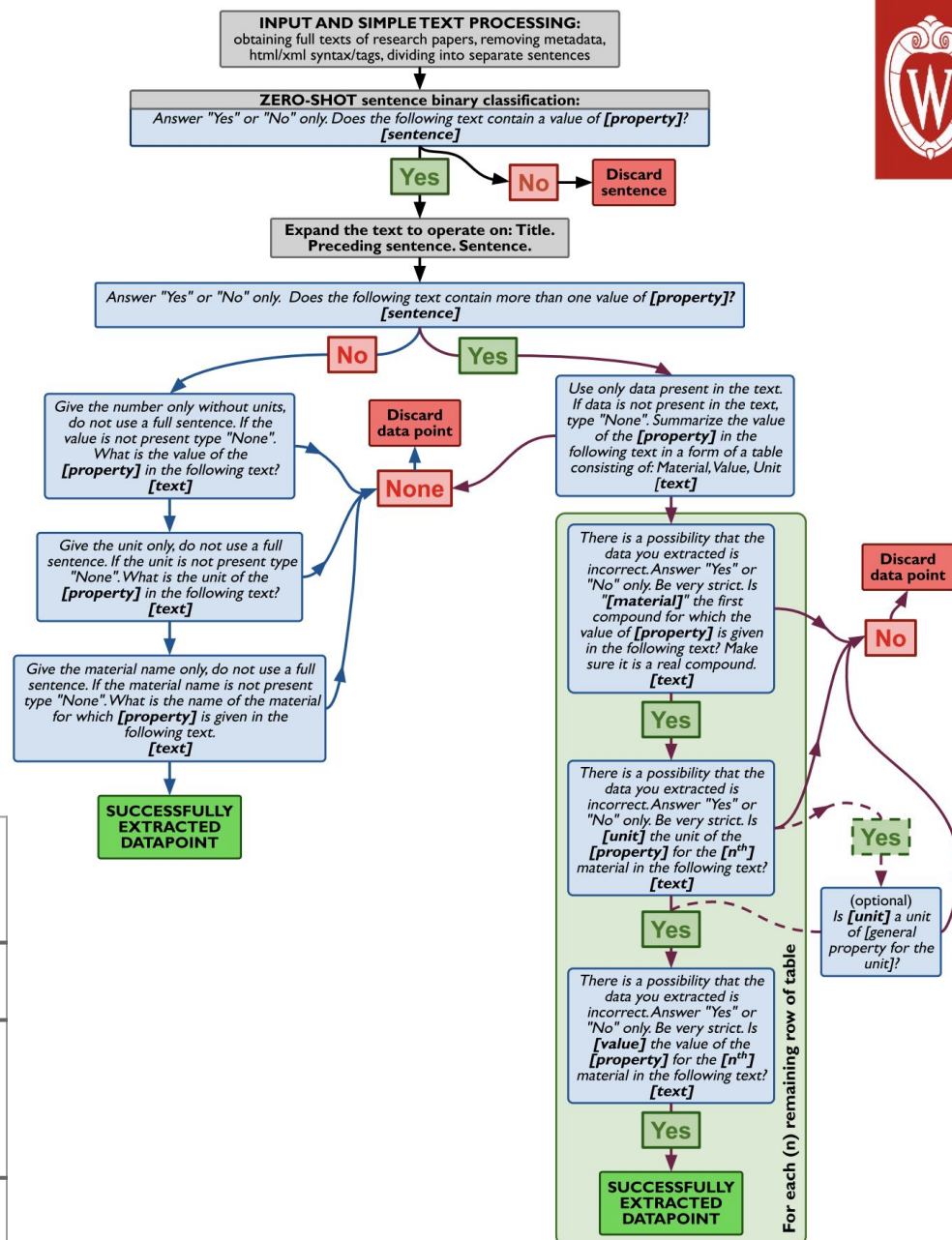




# ChatExtract

a workflow consisting of a series of engineered conversational prompts to a large language model (LLM), and actions based on the model's responses, with error detection.

	Precision (%)	Recall (%)
ChatExtract (GPT4)	90.8	87.7
Chain-of-thought (GPT4) (ChatExtract without error-detection)	42.7	98.9
Previous non LLMs	<50%	<50%



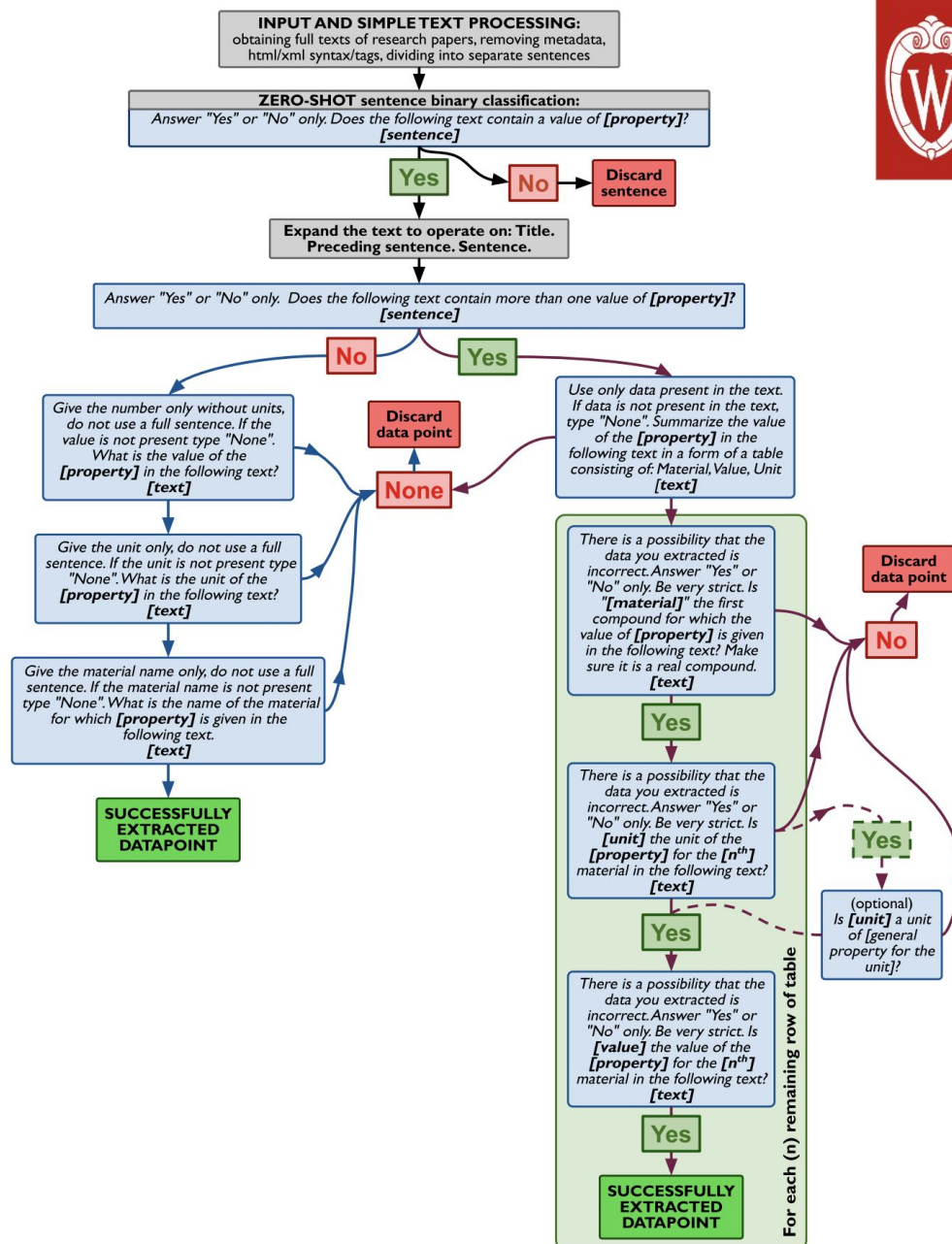
# ChatExtract

## Key concepts:

- Break up tasks into the simplest possible steps
- Strictly enforce output format
- Allow for negative answers
- When validating – be redundant, introduce doubt

## Benefits of our approach:

- Flexible and adaptable
- No need for deep understanding of data to be extracted





# Extracting accurate materials data from research papers with conversational language models and prompt engineering

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Maciej P. Polak<sup>1</sup>✉ & Dane Morgan<sup>1</sup>✉

Accepted: 5 February 2024

## Metallic Glass Critical Cooling Rates

- Returned 684 papers, 110,126 sentences.
- ChatExtract (GPT-4) extracted 721 values.
- Standardized version had 280 values (120 unique compounds), 1.5x previous databases.

## High-Entropy Alloy Yield Stress

- 4029 research papers, 840,431 sentences.
- ChatExtract extracted 8,961 values.
- Standardized version had 2416 values.
- Largest database up to date

## Performance

- Precision and Recall ~90%
- ~10m human time
- ~3h compute time (ChatGPT)
- ~0-2h Standardization

