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Ontology Guided Large Language Model Pipeline for Structured Information Extraction from Battery Cell Datasheets

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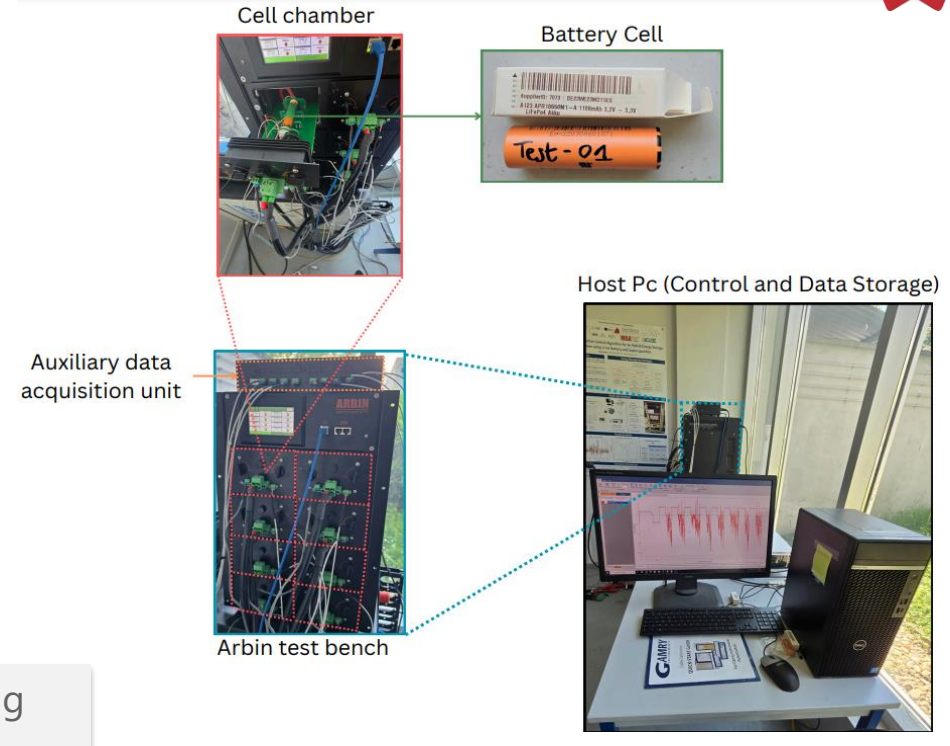
Context & Motivation

The Challenge

- Electric vehicles rely on battery cells as core energy-storage units
- Critical parameters needed: charging current, temperature range, voltage limits
- Datasheets often in PDF format, unstructured, multilingual (especially Chinese manufacturers)
- Information inconsistent, incomplete, or ambiguous across manufacturers



Key Problem: Manual extraction is time-consuming and error-prone. Automated extraction is essential for accurate battery modeling and testing.

Research Objectives

1
Automated Extraction Pipeline

2
Reduce LLM Hallucinations

3
Multi-language Support

Our Contributions

- **Dual-LLM pipeline** combining Chain-of-Thought (CoT) and few-shot prompting
- **Ontology-driven approach** to ensure structured, validated output
- **Scalable solution** for heterogeneous, multi-language datasheets

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Related Work: LLMs for Knowledge Extraction

Successes

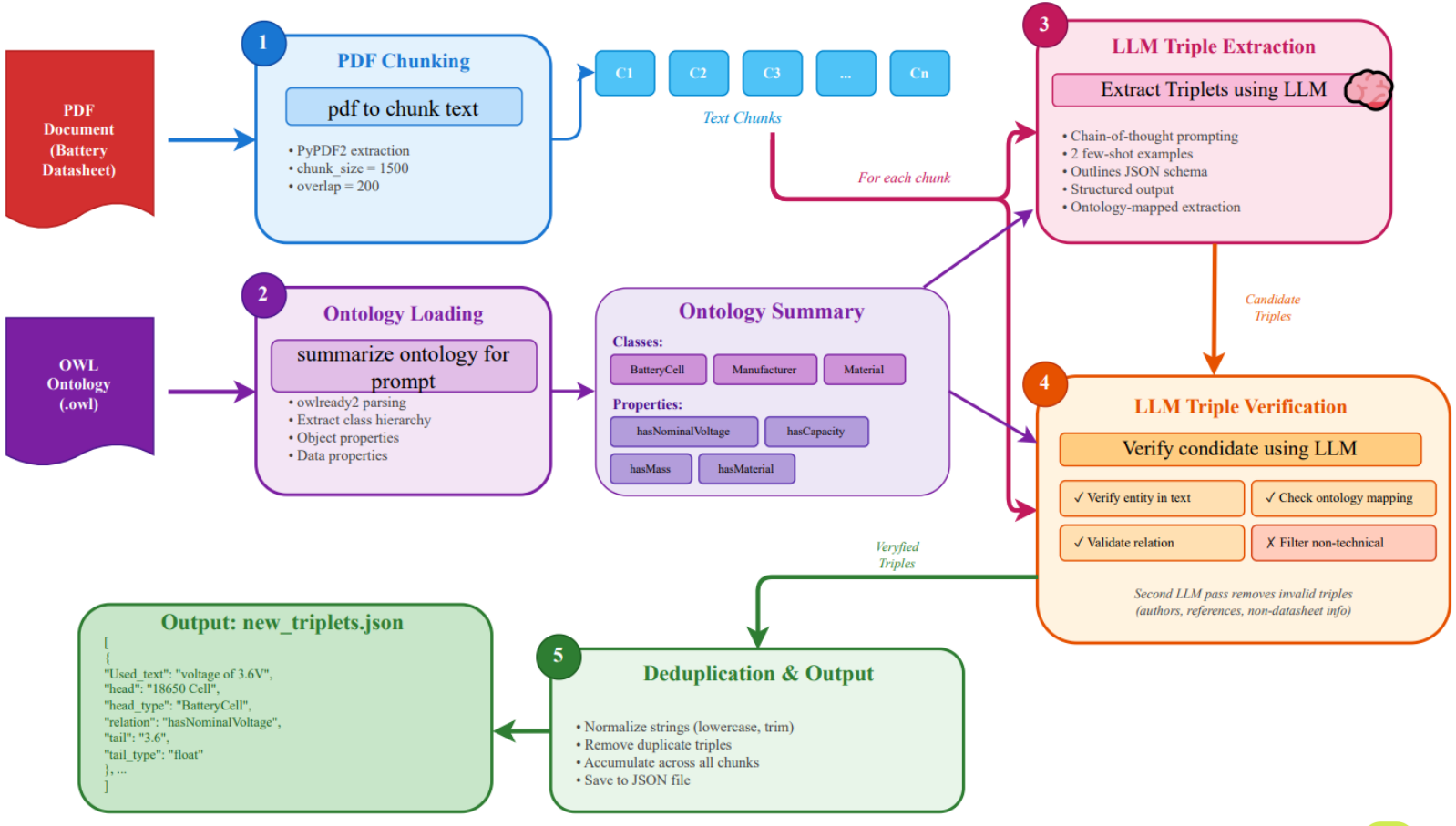
- LLMs outperform traditional NLP for entity/relation extraction
- Zero-shot KG construction from scientific papers
- Domain-specific extraction in materials science

Challenges

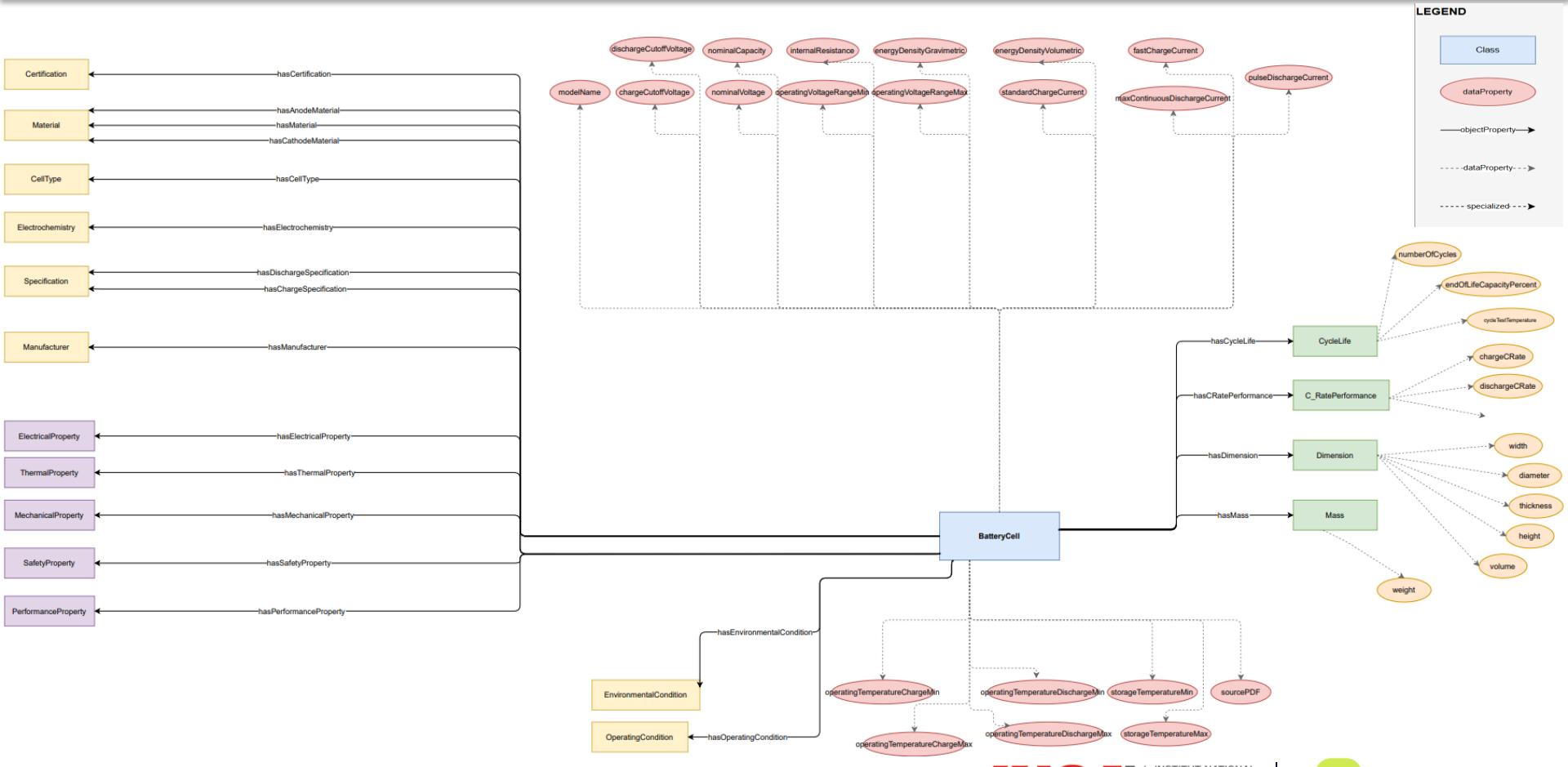
- **Hallucinations:** plausible but incorrect outputs
- Inconsistent entity resolution
- Semantic duplication
- Technical terminology handling

Our Solution: Hybrid approach combining LLM extraction + ontology-guided verification

Methodology: Three-Component Pipeline



Component 1: Battery Cell Ontology



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Component 1: Battery Cell Ontology

Q#	Competency Question	Answerable?	Explanation
1	What is the manufacturer of a specific battery cell?	Yes	Use `hasManufacturer` linking `BatteryCell` to `Manufacturer`.
2	What is the model name of a battery cell?	Yes	Use `hasModelName` of `BatteryCell`.
3	What is the nominal voltage and capacity of a battery cell?	Yes	Use `hasNominalVoltage` and `hasNominalCapacity`.
4	What is the internal resistance of a battery cell?	Yes	Use `hasInternalResistance`.
5	What is the charge and discharge cutoff voltage?	Yes	Use `hasChargeCutoffVoltage` and `hasDischargeCutoffVoltage`.
6	What is the operating voltage range?	Yes	Use `hasOperatingVoltageRangeMin` and `hasOperatingVoltageRangeMax`.
7	What is the standard and fast charge current?	Yes	Use `hasStandardChargeCurrent` and `hasFastChargeCurrent`.
8	What is the max continuous and pulse discharge current?	Yes	Use `hasMaxContinuous DischargeCurrent` and `hasPulseDischargeCurrent`.
9	What are the operating temperatures for charge and discharge?	Yes	Use `hasOperatingTemperature ChargeMin/Max` and `hasOperatingTemperature DischargeMin/Max`.
10	What are the storage temperature limits?	Yes	Use `hasStorageTemperatureMin` and `hasStorageTemperatureMax`.
11	What are the physical dimensions of a battery cell?	Yes	Use `Dimension` class with `hasDiameter`, `hasWidth`, `hasHeight`, `hasThickness`, `hasLength`, `hasVolume`.
12	What is the weight of a battery cell?	Yes	Use `Mass` class with `hasWeight`.

Component 2: Extraction LLM with CoT & Few-Shot

Prompting Strategy

- **Chain-of-Thought (CoT):** Step-by-step reasoning guidance
- **Few-shot examples:** Sample triples showing desired output format
- **Ontology summary:** Classes and properties in prompt (not full OWL)
- **Rules:** Process sentence-by-sentence, normalize entities, translate to English

Why this approach?
CoT + few-shot significantly improves extraction without model fine-tuning, while keeping token usage manageable

Component 2: Extraction LLM with CoT & Few-Shot

You are a battery datasheet information extraction model. Your task is to extract **only technical datasheet information** such as: - Electrical specifications: nominal voltage, capacity, charge/discharge limits, internal resistance - Mechanical specifications: dimensions, mass - Materials & components: electrodes, separators, electrolytes - Cell type / chemistry

RULES:

1. Process the text sentence by sentence.
2. Map each entity to a class from the ontology dictionary.
3. Use only valid relations (object/data properties) from the ontology.
4. Normalize entity names to full canonical identifiers.
5. Return ONLY triples aligned with the ontology and found in the text. Output format: JSON array of objects with keys: "Used_text", "head", "head_type", "relation", "tail", "tail_type"

Ontology dictionary (classes and relations):
{ontology_summary}
Few-shot examples:
{examples_str}
Text to analyze:
{chunk_text}

Extraction Example

Input Text Chunk

"The 18650 lithium-ion cell has a nominal voltage of 3.6V and a nominal capacity of 3000mAh."

Extracted Triple (JSON format)


```
{ "Used_text": "The 18650 lithium-ion cell has...",
"head": "18650 LithiumIonCell",
"head_type": "BatteryCell",
 "relation": "hasNominalVoltage",
"tail": "3.6",
 "tail_type": "float" }
```

Component 3: Validation LLM as Judge

Validation Criteria

- **Ontology compliance:** head_type, tail_type, relation must exist in ontology
- **Text grounding:** Information must be present in source chunk
- **Format validation:** Correct JSON structure with required keys
- **Content filtering:** Only technical datasheet information retained

Result: Reduces hallucinations, and non-datasheet content (authors, references, etc.)

Component 3: Verification LLM (Judge)

You are an expert validator for battery datasheet information. Your task is to strictly validate candidate triples.

RULES:

1. Keep only triples that describe **technical datasheet information**: - Electrical properties: voltage, capacity, charge/discharge limits, internal resistance - Mechanical properties: dimensions, mass - Materials & components: electrodes, electrolytes, separators - Cell type / chemistry
2. Verify that each entity exists in the text chunk.
3. Verify ontology alignment: head_type, tail_type, relation must exist in ontology.
4. Ignore all non-battery content (authors, references, journals, etc.)

Output ONLY a JSON array of objects with keys: "Used_text", "head", "head_type", "relation", "tail", "tail_type"

Candidate triples:
{candidates}
Text chunk:
{chunk_text}
Ontology dictionary:
{ontology_summary}
Return ONLY the JSON array of validated datasheet triples.

Experiments: Setup & Models

Tested Models (5 Lightweight LLMs)

- Qwen/Qwen2-7B-Instruct
- mistralai/Mistral-7B-Instruct-v0.3
- meta-llama/Llama-3.1-8B-Instruct
- Qwen/Qwen3-8B
- openai/gpt-oss-20b

Evaluation

- 5 PDFs from major manufacturers
- Same LLM for extraction & verification(Manual validation of extracted triples
- Strict criteria: no incomplete sentences, errors, or duplicates

Results: Extracted vs Validated Triples

Model	P1	P2	P3	P4	P5
Qwen2-7B	34 / **19**	117 / **30**	70 / **13**	62 / **25**	70 / **17**
Mistral-7B	7 / **1**	41 / **6**	26 / **1**	13 / **0**	18 / **0**
Llama-3.1-8B	26 / **5**	120 / **20**	76 / **16**	68 / **13**	66 / **13**
Qwen3-8B	56 / **29**	157 / **20**	81 / **23**	83 / **31**	69 / **23**
gpt-oss-20b	12 / **7**	46 / **7**	21 / **5**	19 / **2**	20 / **3**

Format: Total Extracted / **Validated**

Key Findings

Performance Insights

- **Best performers:** Qwen3-8B and Qwen2-7B-Instruct (most validated triples)
- **Significant variance:** Model choice critically impacts extraction quality
- **Validation effectiveness:** Filters out ~50-70% of raw extractions
- **Recent models win:** Newer architectures show better structural consistency

Conclusion & Future Directions

✓ Achievements

- Effective ontology-driven pipeline
- Reduced hallucinations via dual-LLM verification
- Multi-language support demonstrated
- No fine-tuning required

→ Future Work

- Automated evaluation metrics
- Extended ontology coverage
- Integration with knowledge graphs

Code available: github.com/BatIE-OGLLM

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