

Applications of LLMs in Library Information Organization



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Research focus: AI-driven methods and systems responsive to information needs

- Computational linguistics
- Human-centered artificial intelligence
- LLM applications
- Crisis informatics

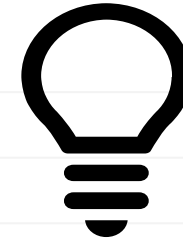
Jinyu Liu is a PhD student of Data Science in college of information at University of North Texas.

Research focus: development of AI-driven applications and system.

- Computational linguistics
- Question and answering
- Multimodal LLMs
- LLM applications



Learning Objectives



- Understand the foundational concepts and background of large language models (LLMs).
- Explore the application of LLMs in library information organization tasks, including classification and subject analysis.
- Understand LLMs training strategies, such as few-shot learning, fine-tuning, and Chain-of-Thought reasoning.
- Learn to apply LLMs in subject analysis by structuring outputs to meet user needs.

Outline

- AI in Library Information Organization
- Foundations of LLM Training
- Case Demonstration: LLMs for Subject Analysis

01

AI in Library Information Organization *

Gauging Library Needs for AI-Assisted Cataloging

Library Information Organization: the **established methods libraries have historically used to arrange, describe, and provide access to information resources** (books, journals, media, etc.) so that users can efficiently find and use them.

- In the future, can all knowledge objects be in digital format?



Gauging Library Needs for AI-Assisted Cataloging

Traditional Classification System: Retain <-> Abandon?

- Do we still need classification code and subject terms to describe knowledge objects?
- Retrieve information with better AI systems?



Gauging Library Needs for AI-Assisted Cataloging

Retrieve Information with AI systems?

Can you recommend a book with content to say that it is human intuition to put information in different category and are comfortable with that.

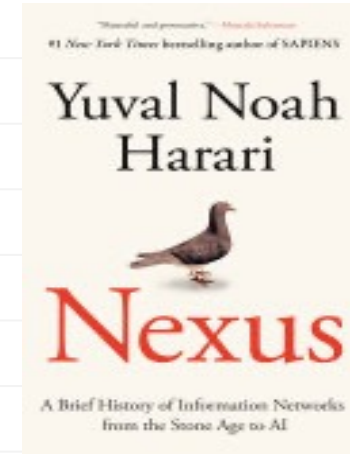
Yes! There are several books in cognitive psychology, philosophy, and information science that explore the idea that **categorization is a fundamental aspect of human intuition and comfort with information**. Here are a few strong recommendations:

Classic Cognitive Science

- **George Lakoff – *Women, Fire, and Dangerous Things: What Categories Reveal About the Mind***
A landmark book showing how humans naturally categorize the world. Lakoff argues that categorization is not just logical but grounded in human experience and intuition—our minds are wired to create and rely on categories.
- **Eleanor Rosch (collected works, but summarized in many texts on categorization and prototypes)**
Rosch pioneered the concept of *prototype theory*—that humans intuitively form categories around "best examples" rather than strict definitions, which feels natural and comfortable to us.

Information & Organization

- **Umberto Eco – *Kant and the Platypus: Essays on Language and Cognition***
Eco examines how humans instinctively categorize strange or ambiguous things (like a platypus) and why categories are central to how we process meaning.
- **Geoffrey Bowker & Susan Leigh Star – *Sorting Things Out: Classification and Its Consequences***
This book looks at classification systems (in science, medicine, and bureaucracy) and argues that categorization is not only natural but also socially powerful. It reflects our intuition but also shapes how we see the world.



Philosophy & Human Nature

- **Aristotle – *Categories*** (ancient but foundational)
Aristotle's work shows one of the earliest systematic arguments that humans instinctively organize the world into types and subtypes. Many modern discussions of categorization build on this lineage.
- **Steven Pinker – *The Stuff of Thought***
Pinker discusses how humans intuitively carve reality into categories through language and thought, suggesting it's part of our evolutionary toolkit.

👉 If you want **one book that explicitly argues "humans intuitively categorize information and are comfortable doing so"**, Lakoff's *Women, Fire, and Dangerous Things* is probably the clearest, most cited, and most accessible starting point.

Would you like me to also suggest some **shorter, more practical readings** (e.g., from information science or design research) that frame categorization as a natural human intuition in everyday contexts, not just theory-heavy books?

Gauging Library Needs for AI-Assisted Cataloging

Is AI needed in library information organization?

- What about the cataloging of increasing amounts of books and dissertations?
 - What about the large amount of foreign resources, like books, journals?
 - What about enriched description with subject headings for existing knowledge objects?
-

Use AI to:

- Collaboratively work with librarians
 - Enhance the traditional library information organization work
 - Automate work that can be done by AI and put more time to research and innovations
-

Aims and Questions

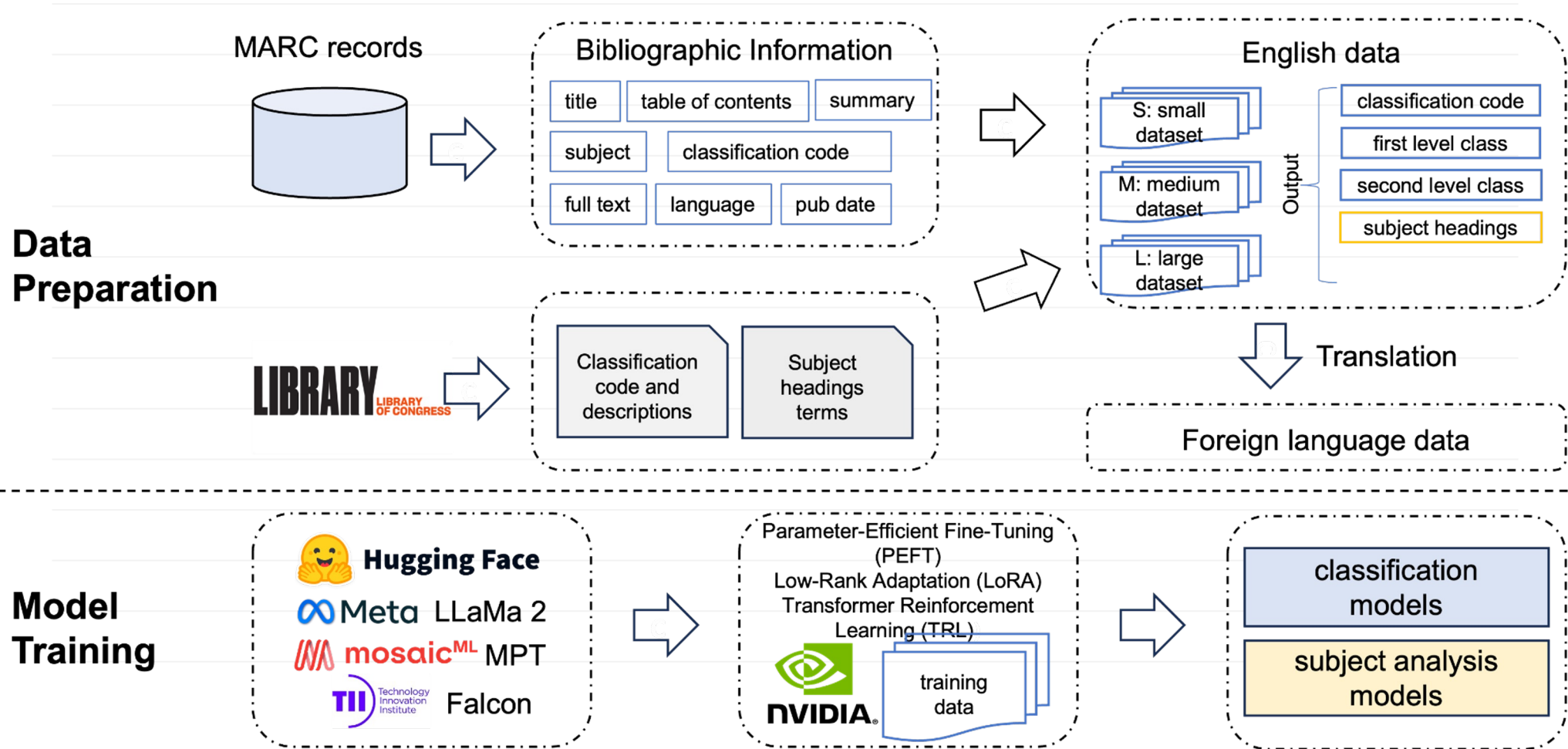
Aim

- Create a synergy by combining the capability of AI with the expertise of catalogers, to empower catalogers to be efficient and accurate.
-

Research Questions

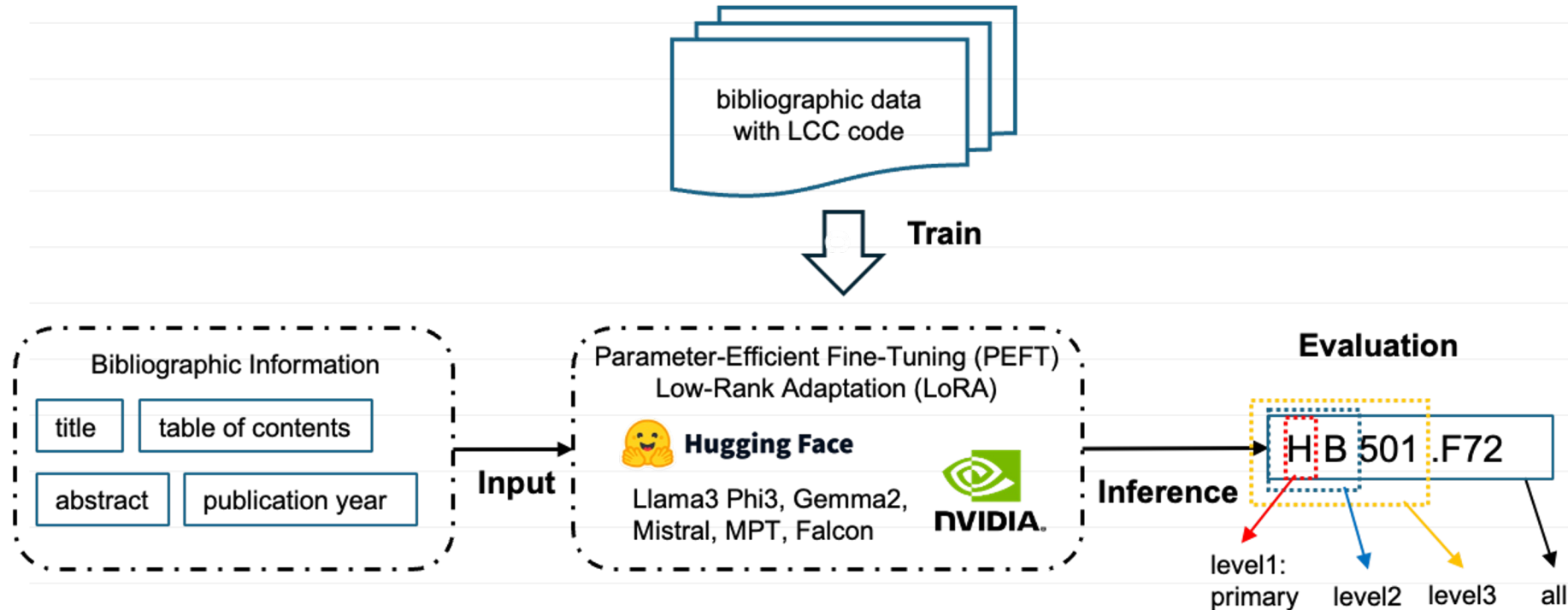
- How can LLM-based models be developed to generate accurate cataloging results, particularly classification and subject analysis, for both English and foreign language resources?
 - How can AI models be integrated into cataloging procedures to assist librarians?
-

Train LLMs for Cataloging Tasks



LLMs for Book Classification Tasks using LCCS

Explore how LLMs can be applied to predict the classification code of a book automatically.



LLMs Applied in Subject Analysis

Generate accurate LCSH subject headings with Large Language Models (LLMs) with metadata fields

Assuming that you are a professional cataloger in a library, please assign several subject headings to a book by selecting from the list of candidate Library of Congress subject headings based on the book's title and abstract. Return the selected subject headings in JSON format without explanatory text.

Title: ``{{Title}}``

Abstract: ``{{Abstract}}``

Candidate Library of Congress subject headings:``
{{candidate_words}}
``

Benefits and Challenges

Benefits: 

Automation Efficiency

Improved Discovery

Multilingual Support

User Interaction

Challenges: 

Accuracy & Consistency

Bias & Hallucination

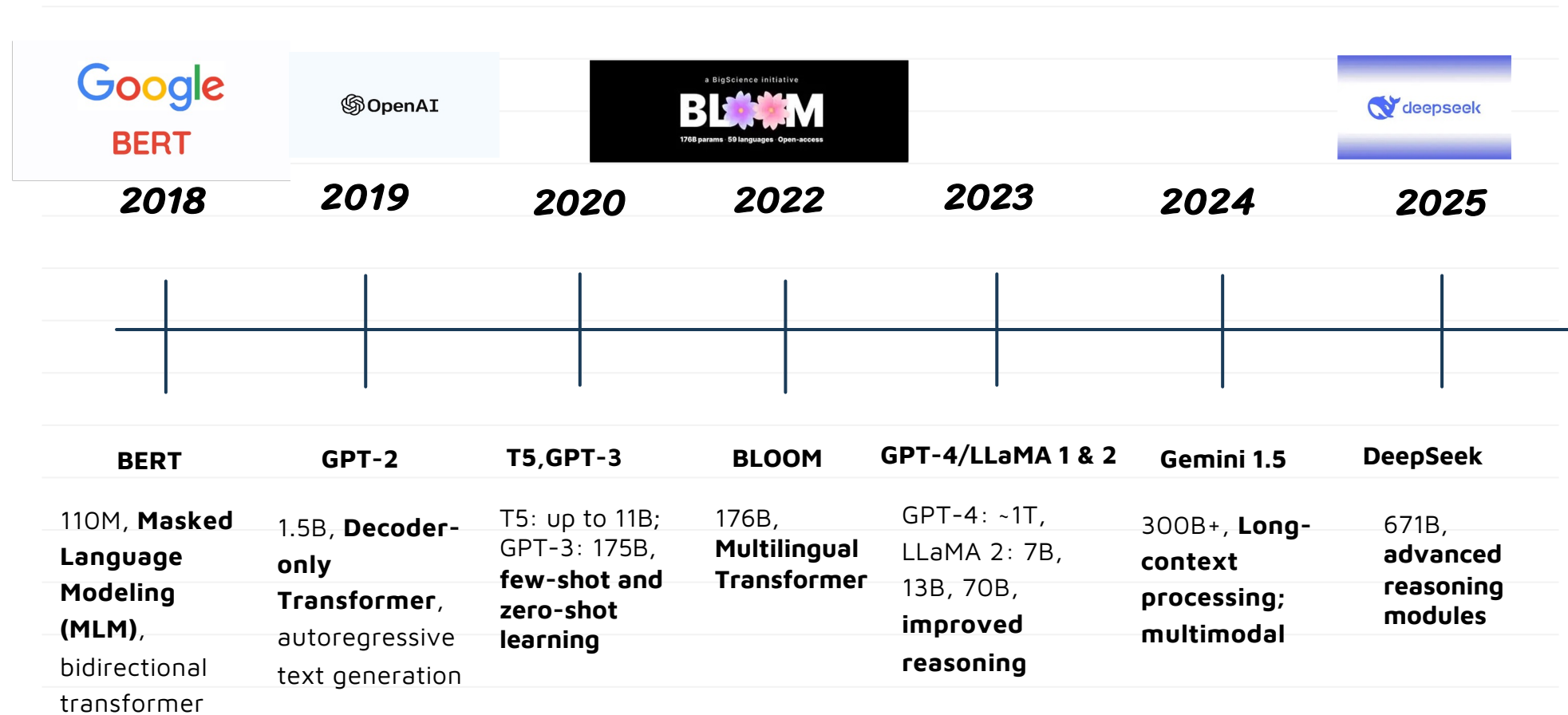
Data Privacy

Maintenance Cost

02

Foundations of LLM Training *

Milestones in LLM Evolution



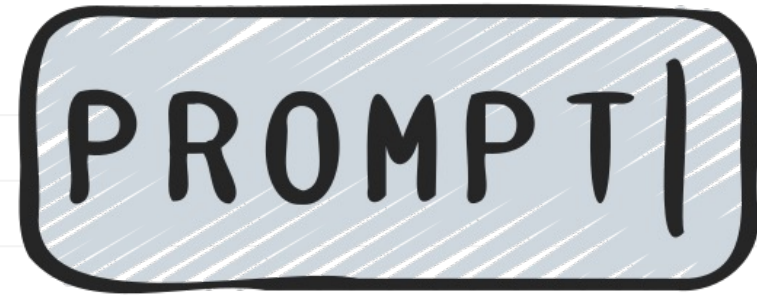
Some “tricks” in LLMs

How to make LLMs good at domain-specific tasks?

- Prompt engineering
- Few-shot learning
- Chain-of-thought reasoning
- Fine-tuning
- Post-editing



Prompt Engineering



- “Prompt Engineering” is refine the input we give to an LLM so that it produces the desired output.
- This includes choosing the right wording, structure, and context.

Basic Prompt:

Assign a subject heading to this book

Result: *"Climate change"*

VS

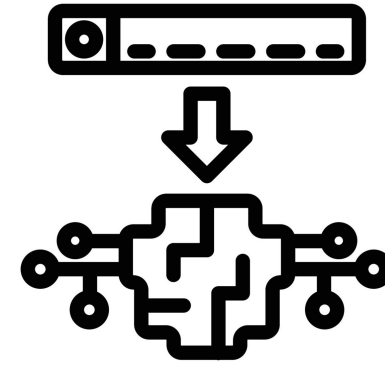
Refined Prompt:

“You are a professional librarian. Read the following book description and assign the most accurate Library of Congress Subject Headings, including broader and narrower terms where appropriate.

Result:

Climate change—Agricultural aspects
Agriculture—Environmental aspects
Sustainable agriculture—Adaptation

What is “Prompt”?



- A prompt works as the starting signal for LLM.
- When we type a prompt, the model converts your words into numerical representations (embeddings).
- It then predicts the next word step-by-step, guided by the context we provided, until the answer is complete.
- The quality, clarity, and structure of the prompt will directly influence the model’s output.

Why we need “Prompt”?



LLM outputs are context-sensitive—the way we ask is as important as what we ask. We use prompt for:

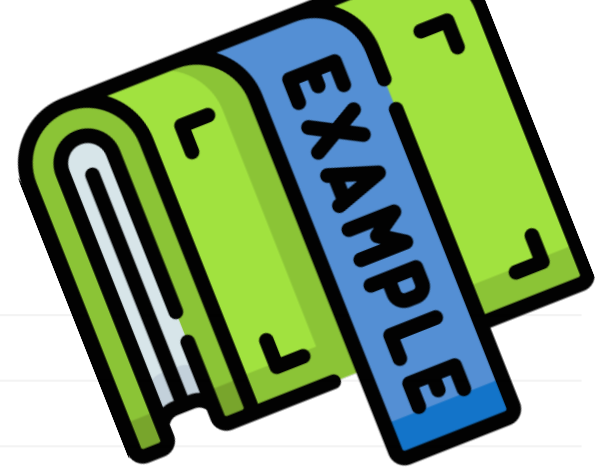
- Guide the model’s thinking
- Control the output format
- Improve accuracy and relevance

Few-Shot Learning



- Few-shot learning is teaching LLMs with a few examples.
- It allows LLM to learn a new task or desired output format using just a few examples(usually 3 to 5).
- The examples are directly put inside the prompt.
- Then the models will learn from the examples.

Few-Shot Learning Prompt



"You are a librarian. Assign the most accurate Library of Congress Subject Headings (LCSH) to each book description based on the given examples."

Example 1:

Description: "A detailed history of the Silk Road and its role in cultural exchange between East and West."

Subject Headings: Silk Road—History; Cultural relations—Asia—Europe

Example 2:...

Example 3:...

Now classify: Description: "A study of the economic and social impacts of climate change on rural farming communities."

Chain-of-Thoughts reasoning

- CoT is a strategy encourage model to generate intermediate reasoning steps before giving the final answer.
- Useful in complex tasks.
- Helps avoid “shortcut” answers.

Role: You are a professional cataloging librarian using LCSH.

Task: Assign the most accurate LCSH to the description **by reasoning in 5 passes**, each pass focusing on a different lens.

Do your full reasoning internally; output only short step summaries (≤8 words each) and the final headings.

Pass 1 – Topic/Domain: identify the central phenomenon or field.

Pass 2 – Entities/Scope: who/what is affected; place/time if explicit.

Pass 3 – Facets/Aspects: economic/social/technical/policy/etc. angles.

Pass 4 – Vocabulary Mapping: map to LCSH (BT/NT/RT if helpful).

Pass 5 – Quality Check: specificity, neutrality, and parallel structure.

Fine-tuning



- Fine-tuning is the process of continuing the training of LLM on a smaller, task-specific dataset.
- The goal is to adapt the model to perform a specific task better.
- Fine-tuning updates the model's weights and changes the model 'itself.
- Adjust the model's internal parameters using additional and domain-specific data.

Fine-tuning

Method	What it does?	Pros	Cons
Full Model Fine-tuning	Updates all model parameters on your dataset	Maximum adaptation; works for major domain shifts	Resource issues(GPU, memory, time), risk of overfitting
LoRA Fine-tuning (Low-Rank Adaptation)	Freezes most weights, adds small trainable adapter layers	Much faster & cheaper; less storage; can apply multiple LoRA modules for different tasks	Less flexible for domain changes

Fine-tuning vs Zero-shot

- Domain specialization
- Improve task performance
- Adapt tone/style
- Reduce irrelevant answers



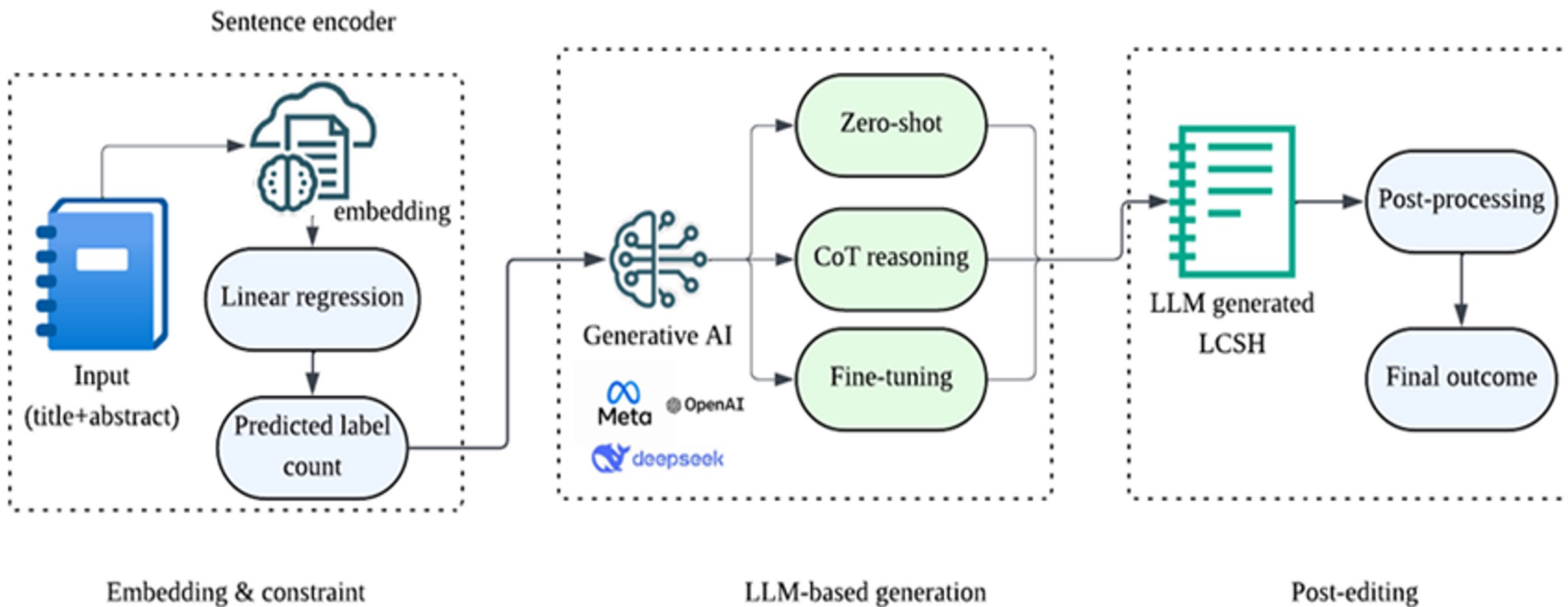
Fine Tuning

03

Case Demonstration



How we apply LLM in subject analysis?



Workflow



01

Input Preparation

02

Prompt dsign

03

Strategies in LLM

04

Evaluation

Input Preparation

- Build Metadata for LLM Input.

Raw Data Sources:

- Usually MARC records

Key fields: Title, Abstract/Summary, Author Info...



METADATA

Prompt design



- Be clear about the goal:

example: "Identify 3 Library of Congress Subject Headings for the following book summary."

- Provide context:

"You are a helpful assistant predicting Library of Congress Subject Headings (LCSH) for books."

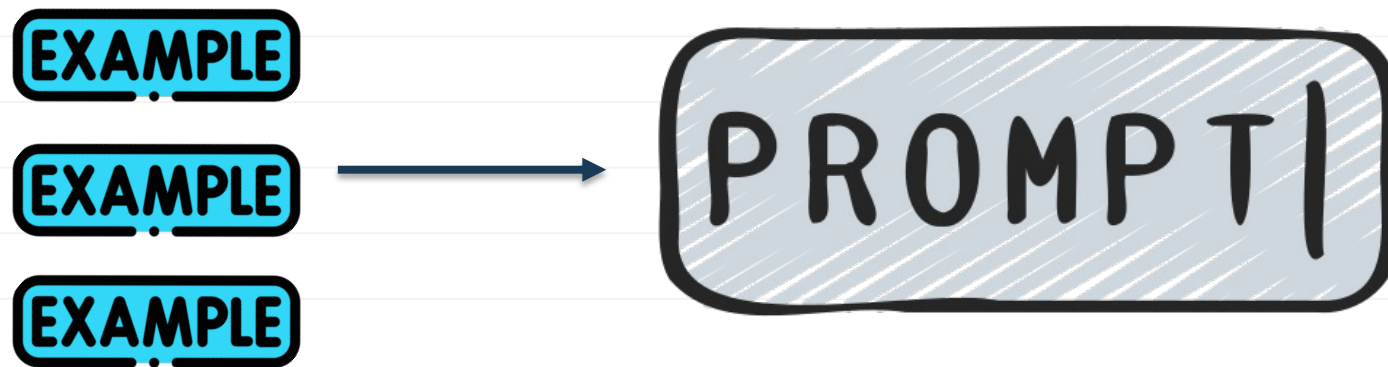
- Define the output format:

"Respond only with the predicted LCSH labels separated by commas."

Strategies to increase performance

Few-shot learning:

Directly put a few example in the prompt.

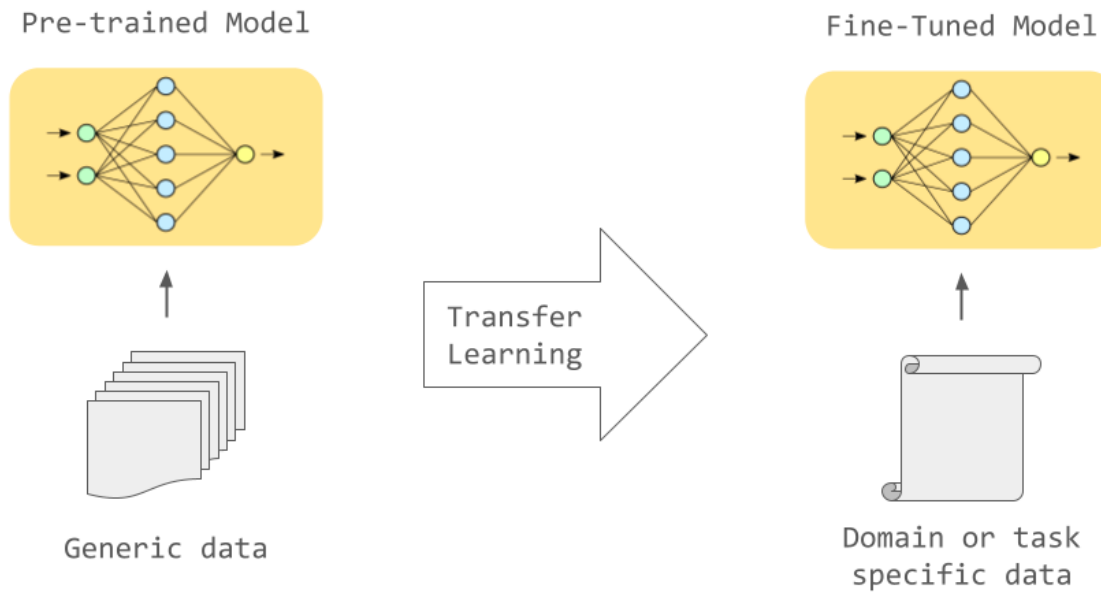


competition at
the prison car

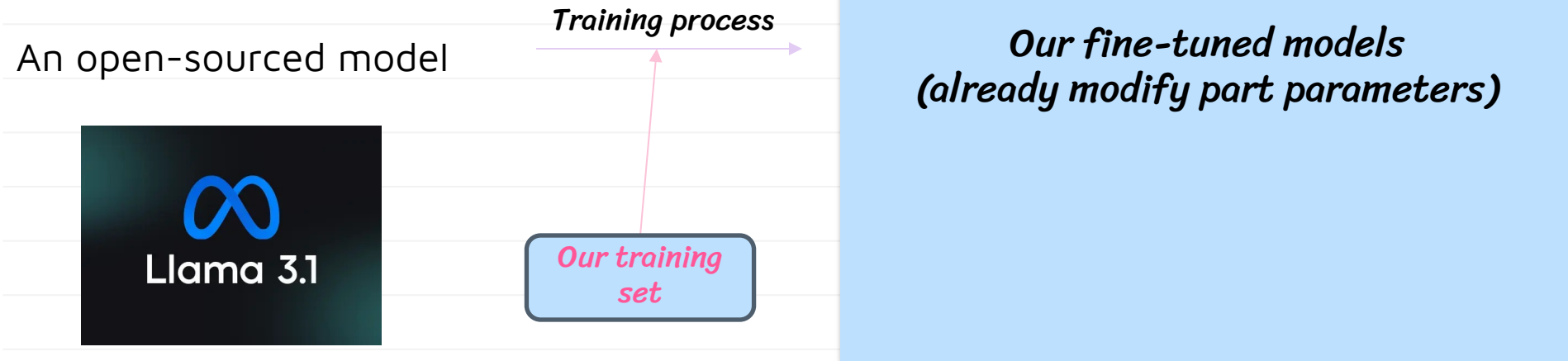


Strategies to increase performance

Fine-tuning:



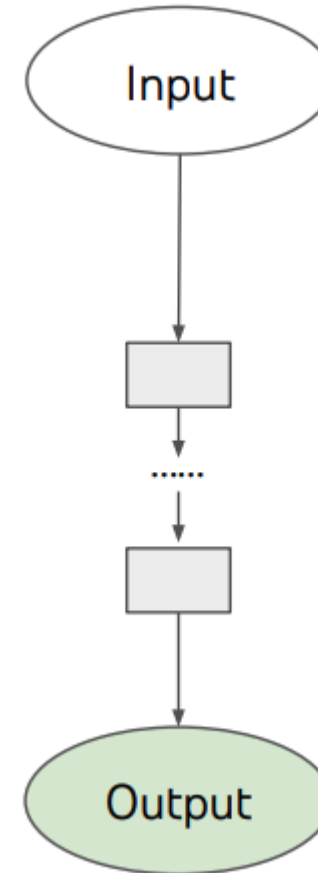
Strategies to increase performance



Strategies to increase performance

Chain-of-thought reasoning:

Refine the prompt by step-by-step reasonings.



Strategies to increase performance

```
# Round 1
assistant_first_round = generate_step([
    {"role": "user", "content": f"Title: {title}\nAbstract: {abstract}"},
    {"role": "user", "content": f"Predict exactly {n} Library of Congress Subject Headings (LCSH) labels. Respond only with the predicted LCSH labels separated by commas."},
])

# Round 2
assistant_second_round = ""
if assistant_first_round:
    assistant_second_round = generate_step([
        {"role": "user", "content": f"Title: {title}\nAbstract: {abstract}"},
        {"role": "user", "content": f"Current LCSH labels: {assistant_first_round}"},
        {"role": "user", "content": f"Predict {2*n} additional Library of Congress Subject Headings (LCSH) labels. Respond only with the predicted LCSH labels separated by commas."},
    ])

# Round 3
assistant_third_round = ""
if assistant_second_round:
    assistant_third_round = generate_step([
        {"role": "user", "content": f"Title: {title}\nAbstract: {abstract}"},
        {"role": "user", "content": f"Current LCSH labels: {assistant_second_round}"},
        {"role": "user", "content": f"Predict as many additional Library of Congress Subject Headings (LCSH) labels as possible. Respond only with the predicted LCSH labels separated by commas."},
    ])
```

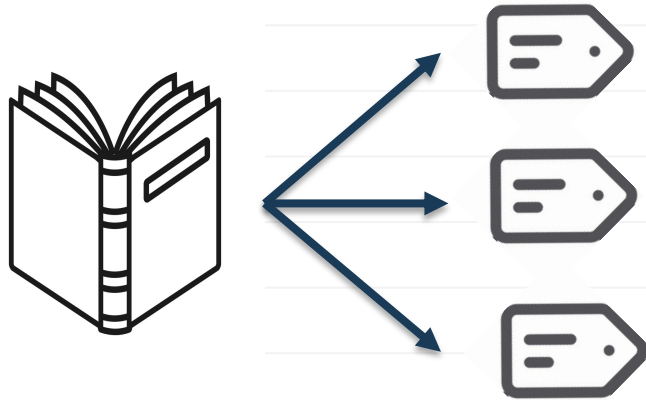
Frist round

Second round

Last round

Evaluation Metrics in Subject Analysis

- LCSH prediction is a multi-label classification task.
- Each book/doc may match multiple labels.



Evaluation Metrics in Subject Analysis

Metric	Measures	Meaning
Precision	Correct predicted labels / total predicted labels	Avoids "hallucinated" or noisy terms
Recall	Correct predicted labels / total true labels	Measures coverage
F1-score	Harmonic mean of precision and recall	Overall balance of correctness and coverage

Evaluation Metrics in Subject Analysis

Key Metrics Used:

- Precision: When it says 1 how often is it right

$$\# \text{ TP} / (\# \text{ TP} + \# \text{ FP})$$

- Accuracy: What fraction does it get right

$$\# (\text{TP} + \# \text{ TN}) / \# \text{ Total}$$

- Recall: What fraction of 1s does it get right

$$\# \text{ TP} / (\# \text{ TP} + \# \text{ FN})$$

prediction			
actual		1	0
	1	3	2
	0	3	2

prediction			
actual		1	0
	1	True positive	False Negative
	0	False Positive	True Negative

Evaluation Metrics in Subject Analysis



Title: museum rhetoric : building civic identity in national spaces

Abstract: examines the role of museums in promoting cultural heritage and national identity...

Predict LCSH: Nationalism and collective memory, **Nationalism**, Civic improvement, **Cultural property**, Museum exhibits, Collective memory, Civic engagement, Communication in museology, **Museums**, Identity (Psychology), National characteristics, Group identity, Public spaces, **Rhetoric**

Original LCSH: **museums; national museums; rhetoric; nationalism**; cultural property

Evaluation Metrics in Subject Analysis

Recall: 0.8 (4/5)

Precision: 0.29 (4/14)

F1-score: 0.43 $[(2 * 0.8 * 0.29) / (0.8 + 0.29)]$



Thank you!



Do you have any questions?

