

Bridging Text Data and Graph Data: Towards Semantics and Structure-aware Knowledge Discovery

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Tutorial Website:



Estimated Timeline for This Tutorial

- Introduction: **15 mins (8:30 - 8:45 Bowen Jin)**
- Part I: Enhancing Text with Graph Structure: **45 mins (8:45 - 9:30 Sha Li)**
- Part II: Graph Mining with Large Language Models: **45 mins (9:30 - 10:15 Bowen Jin)**
- Break: **15 mins (10:15 - 10:30)**
- Part III: Text Mining with Structured Information: **45 mins (10:30 - 11:15 Yu Zhang)**
- Part IV: Summary & Looking Forward: **15 mins (11:15 – 11:30 Bowen Jin)**

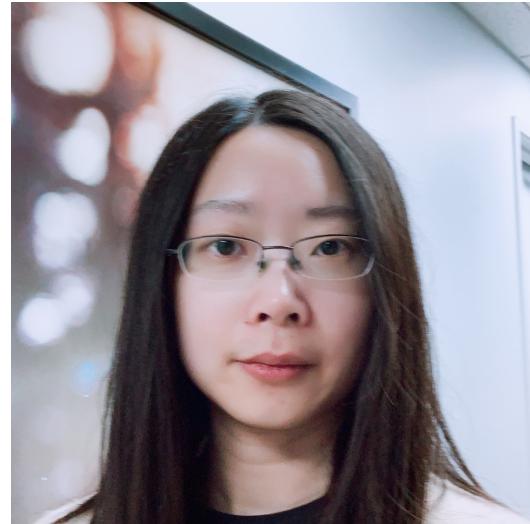
About Instructors



- ❑ Bowen Jin
- ❑ Ph.D. Candidate @ UIUC
- ❑ Apple PhD Fellowship (2024)



- ❑ Yu Zhang
- ❑ Ph.D. Candidate @ UIUC
- ❑ Dissertation Completion Fellowship (2023)
- ❑ Yunni and Maxine Pao Memorial Fellowship (2022)



- ❑ Sha Li
- ❑ Ph.D. Candidate @ UIUC



- ❑ Jiawei Han
- ❑ Michael Aiken Chair Professor @ UIUC
- ❑ ACM SIGKDD Innovation Award Winner (2024)

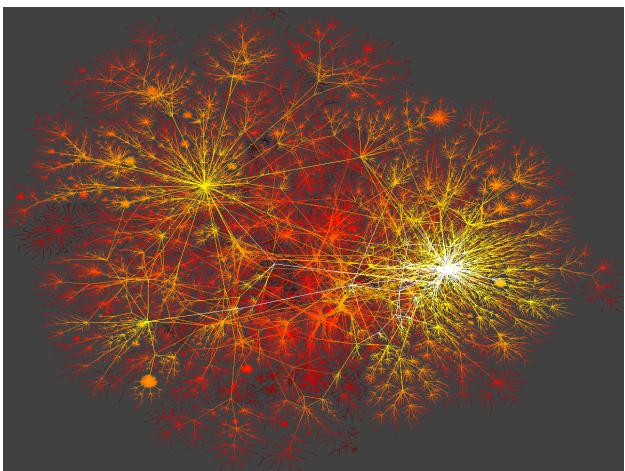
Over 80% of Big Data is Text Data

- Ubiquity of big unstructured, text data
 - **Big Data**: Over 80% of our data is from text (e.g., news, papers, social media): unstructured/semi-structured, noisy, dynamic, inter-related, high-dimensional, ...
- How to mine/analyze such big data systematically?
 - **Text Representation** (i.e., computing vector representations of words/phrases/sentences)
 - **Basic Structuring** (i.e., phase mining & transforming unstructured text into structured, typed entities/relationships)
 - **Advanced Structuring**: Discovering Hierarchies/taxonomies, exploring in multi-dimensional space

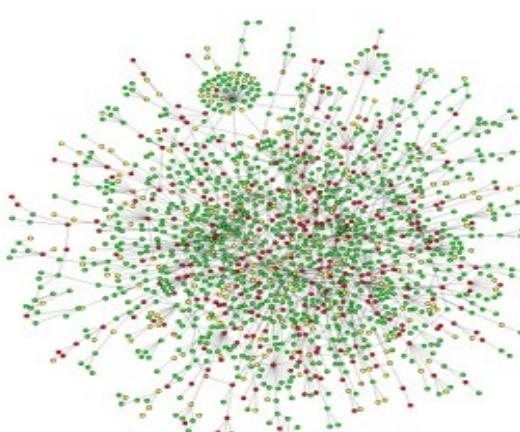


Graphs are Ubiquitous

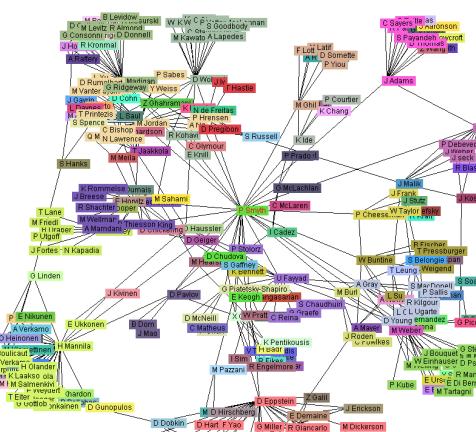
- ❑ Graphs and substructures: Chemical compounds, visual objects, circuits, XML
 - ❑ Biological networks
 - ❑ Bibliographic networks: DBLP, ArXiv, PubMed, ...
 - ❑ Social networks: Facebook >100 million active users
 - ❑ World Wide Web (WWW): > 3 billion nodes, > 50 billion arcs
 - ❑ Cyber-physical networks



World-Wide Web



Yeast protein interaction network



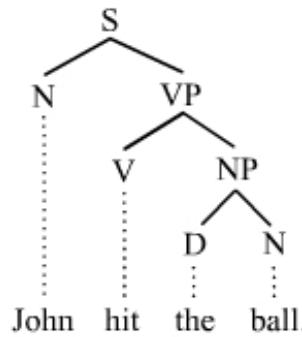
Co-author network



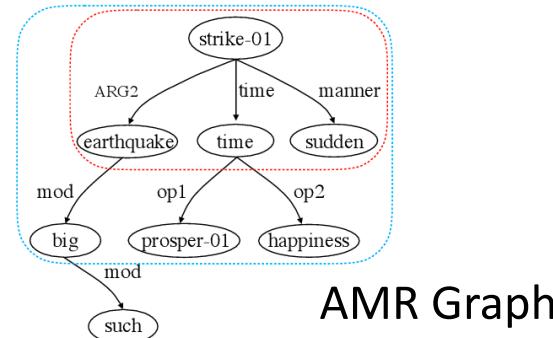
Social network sites

Text & Graph often appears simultaneously

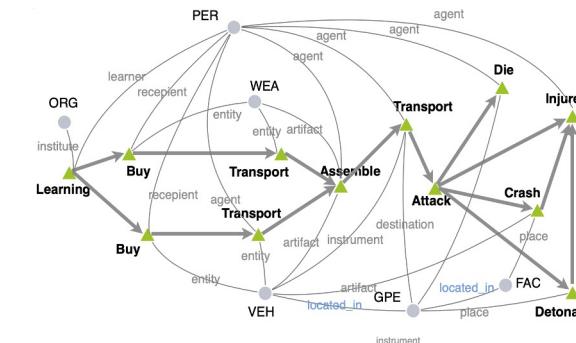
- Text sequence can be modeled as graph (AMR, information extraction, ...).



Constituency
parsing Graph



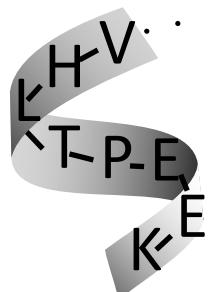
AMR Graph



IE Graph

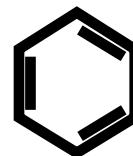
- Graphs are associated with text information.

Protein Graphs

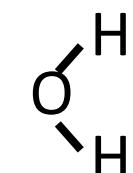


"Myoglobin holds oxygen in muscles."

Molecule Graphs

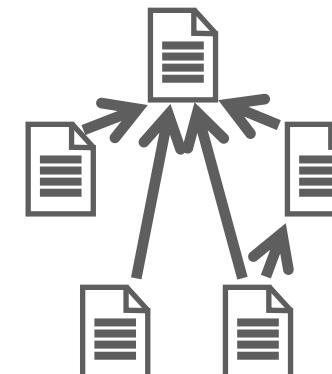


"Benzene is toxic"

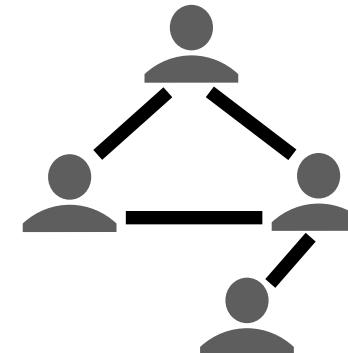


"Water is less toxic"

Academic Networks

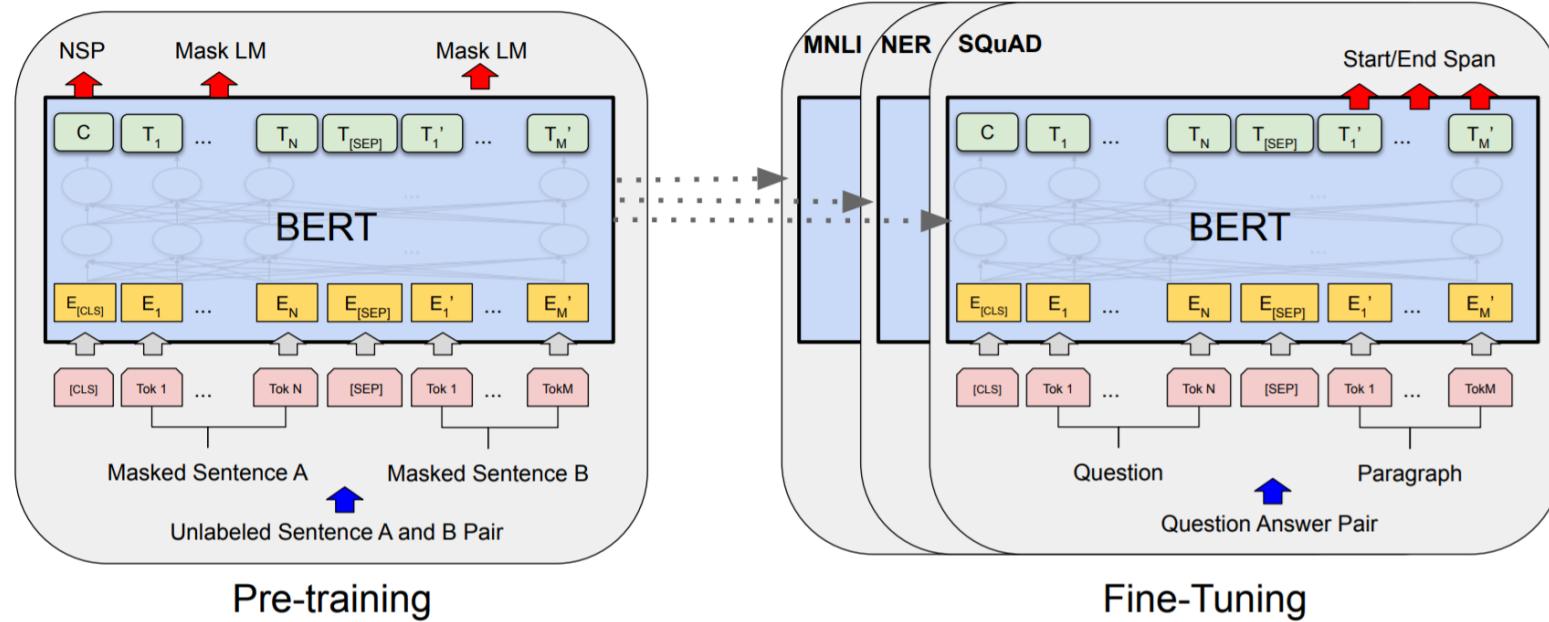


Social Networks



Foundation for Text Analysis: (Large) Language Models

- Language models are pre-trained on large-scale general-domain corpora to learn universal/generic language representations that can be transferred to downstream tasks via fine-tuning

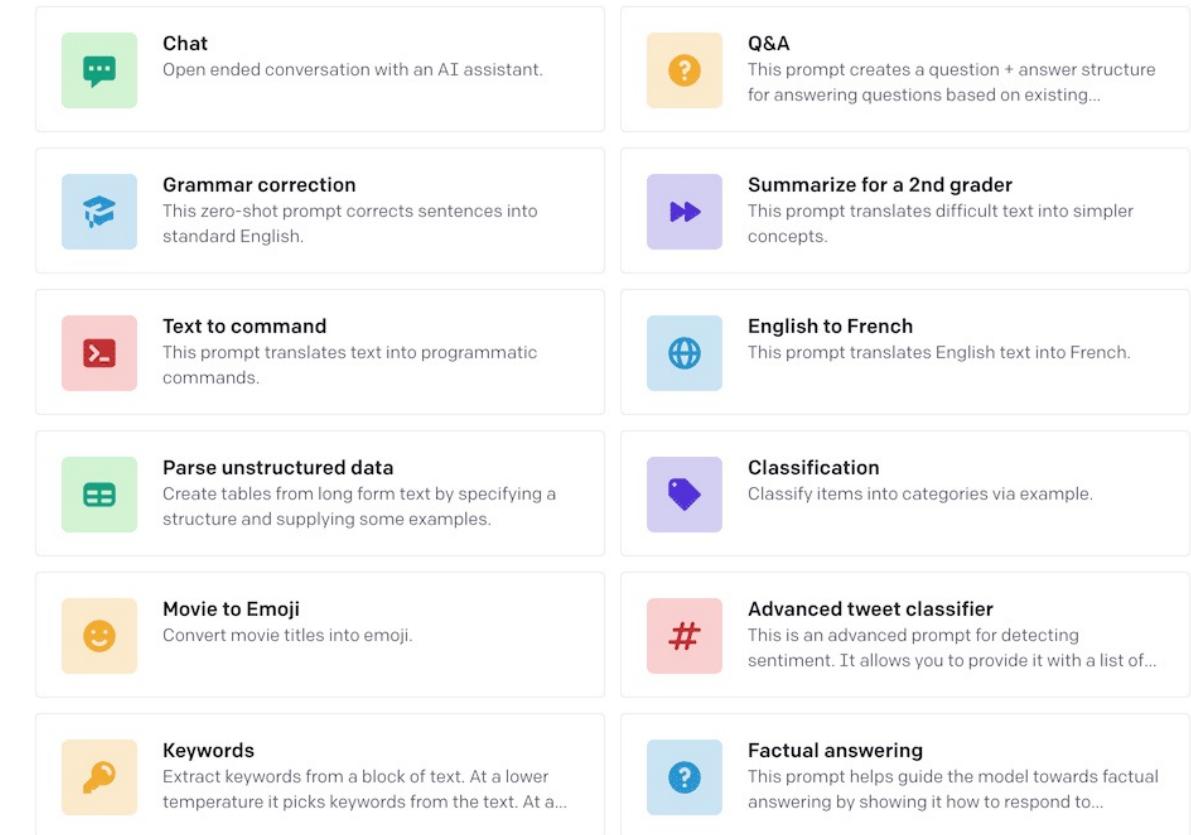
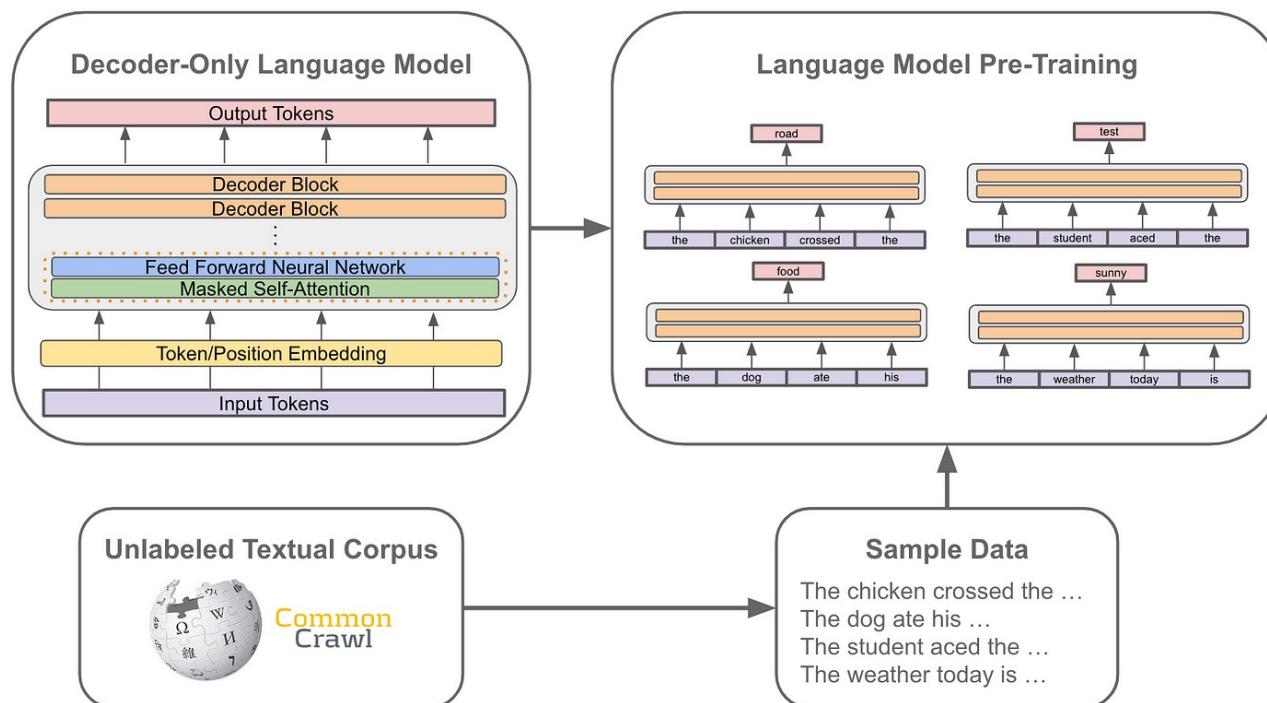


Unsupervised/Self-supervised;
On large-scale general domain corpus

Task-specific supervision;
On target corpus

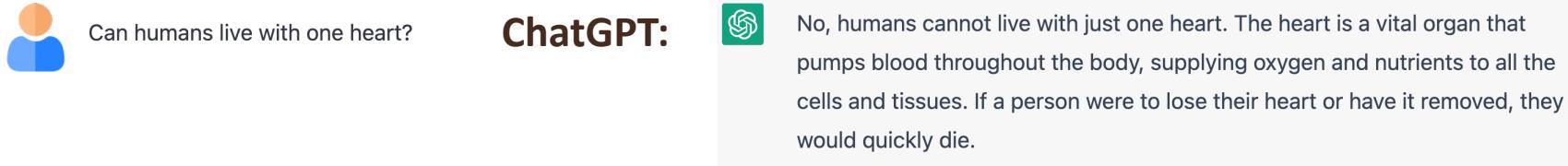
Generative Large Language Models: The GPT Series

- ❑ GPT models: Large language models (LLMs) trained for text generation
- ❑ Applicable to a wide range of tasks

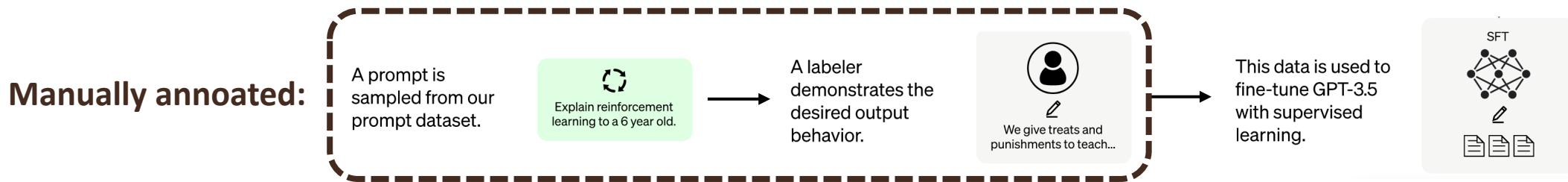


Challenges of Large Language Models

- ❑ Not factually guaranteed: May generate wrong information

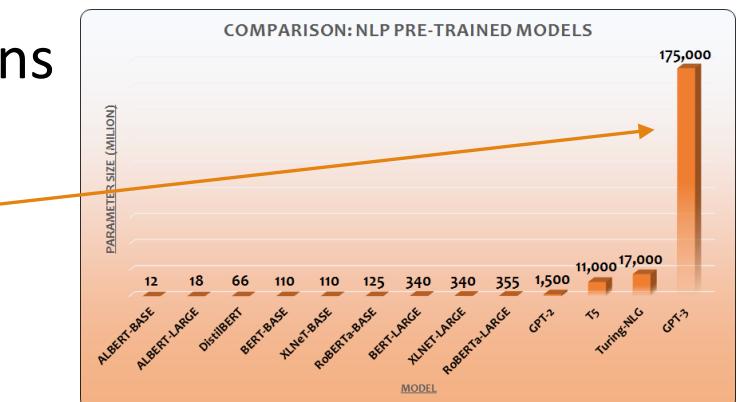


- ❑ Heavy supervision required: Trained on massive annotated data



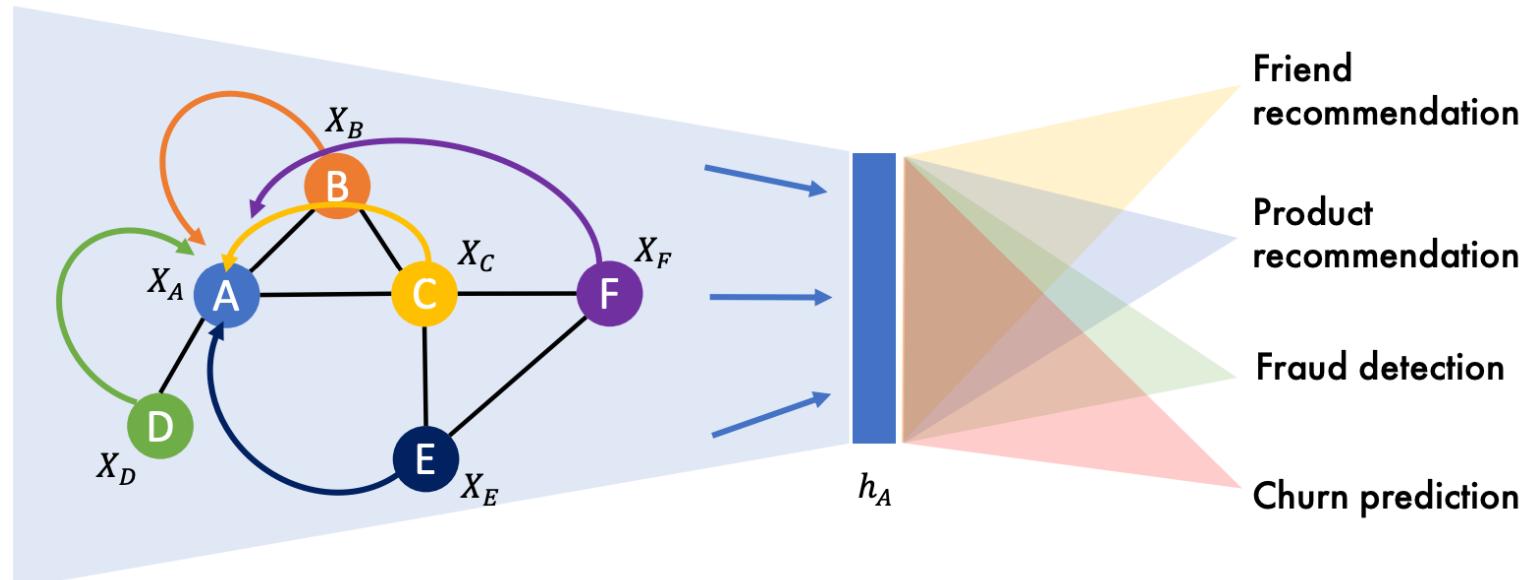
- ❑ Costly & Inefficient: Too large to be used in many applications

GPT3 has 175B parameters (ChatGPT/GPT-4 may have more!)



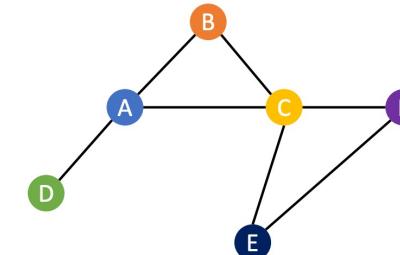
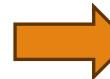
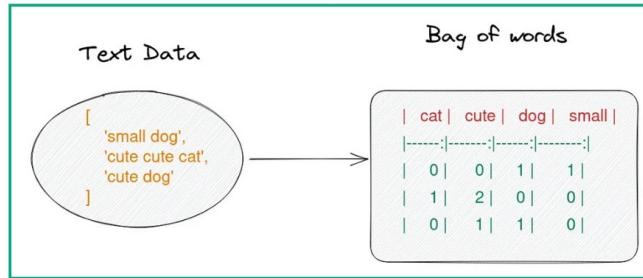
Foundation for Graph Analysis: Graph Neural Networks

- Graph Neural Network
- Propagation & Aggregation.
- Applied for various downstream tasks.

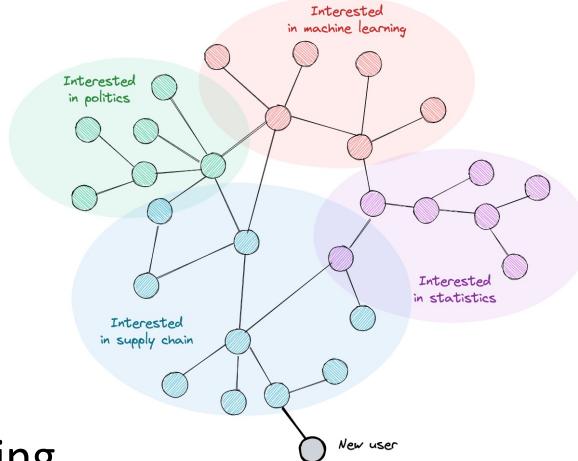


Challenges of Graph Neural Networks

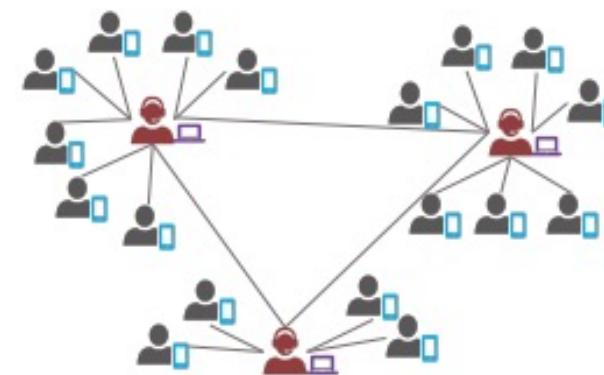
- ❑ Not able to capture rich contextualized text info with nodes/edges.
- ❑ Need to transfer to BOW features or context-free embeddings.



- ❑ Suffers from over-smoothing and heterophily issues.



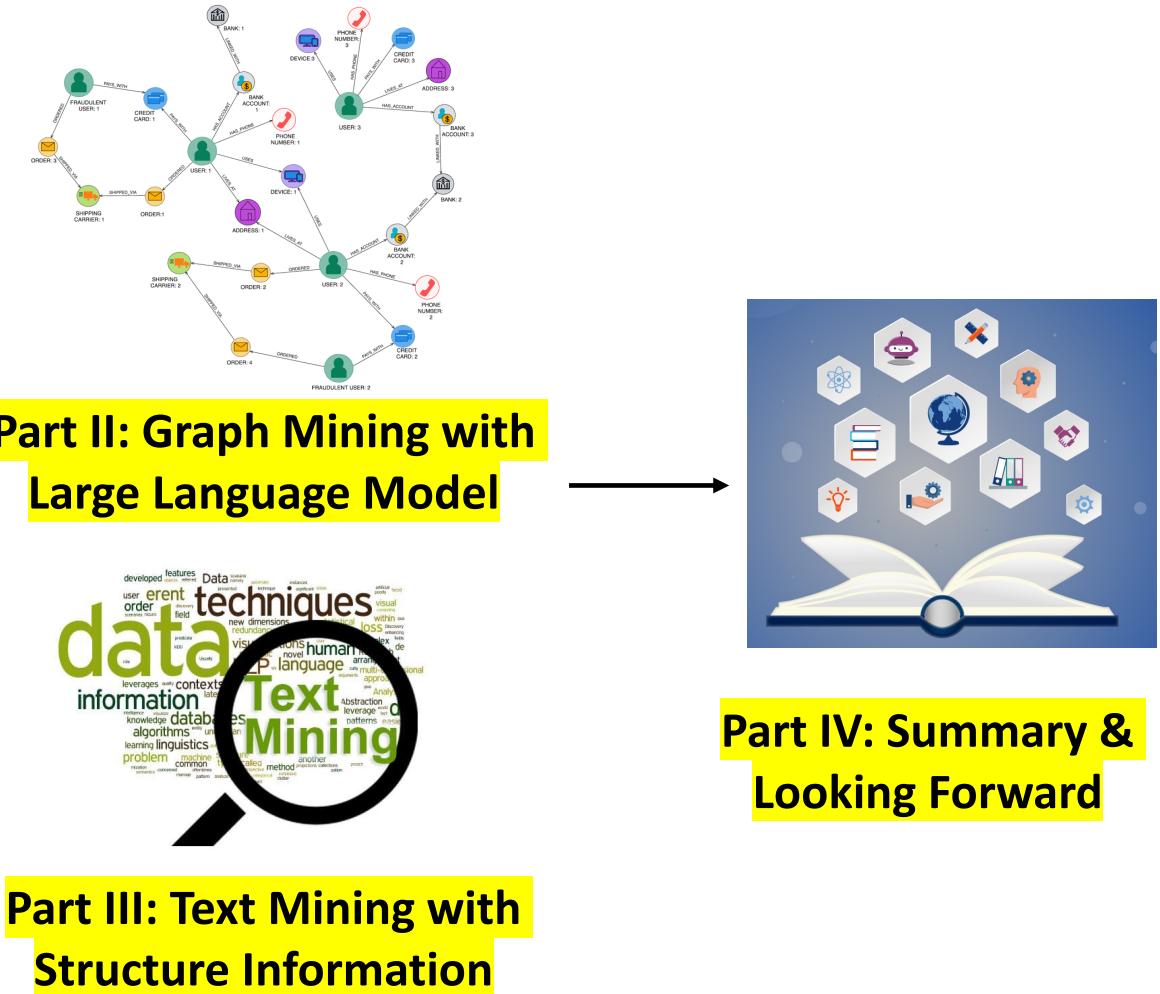
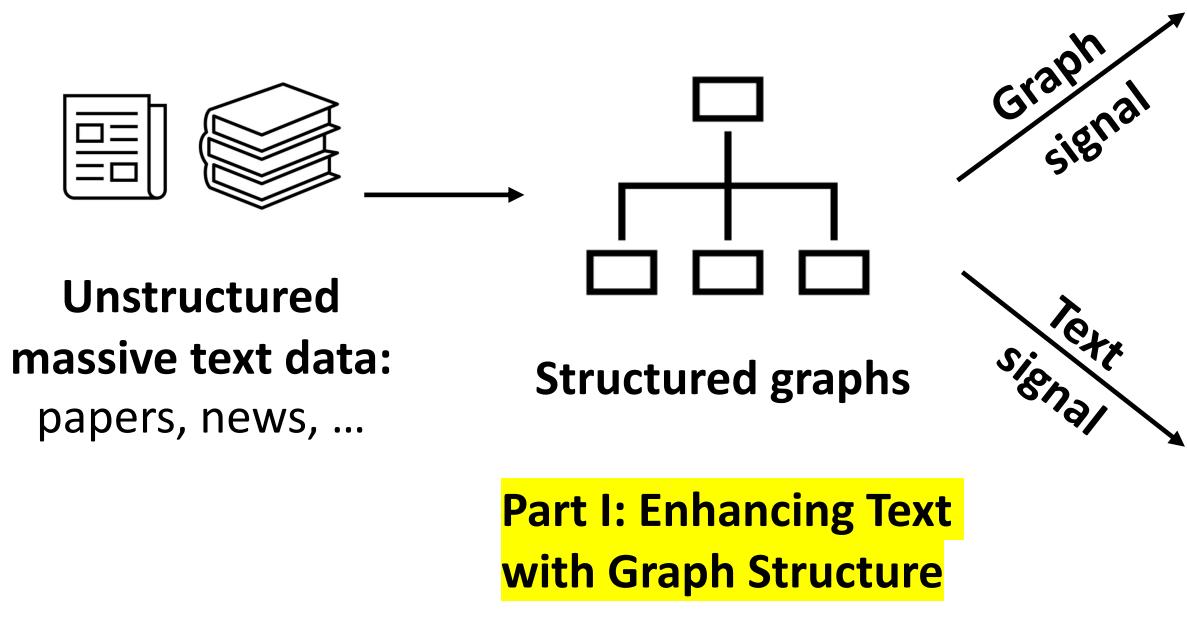
Over-Smoothing



Heterophilic Graph

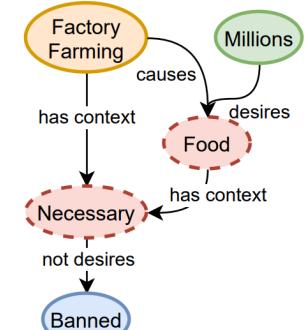
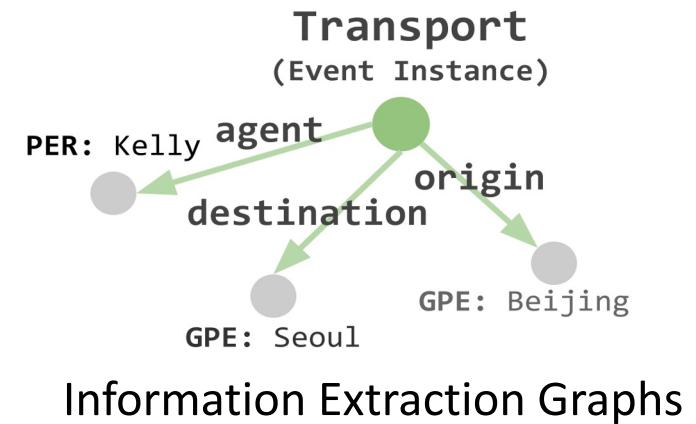
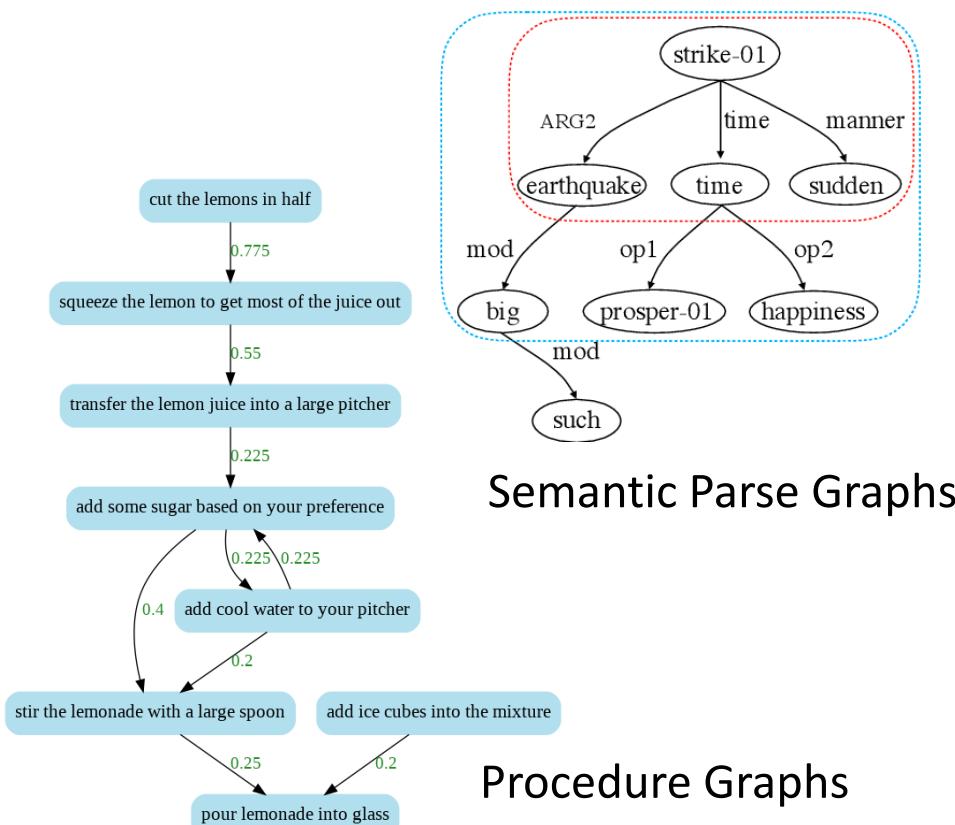
Bridging Text Data and Graph data

❑ Towards Semantics and Structure-aware Knowledge Discovery



Overview of Enhancing Text with Graph Structure

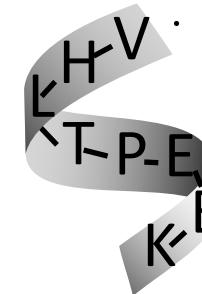
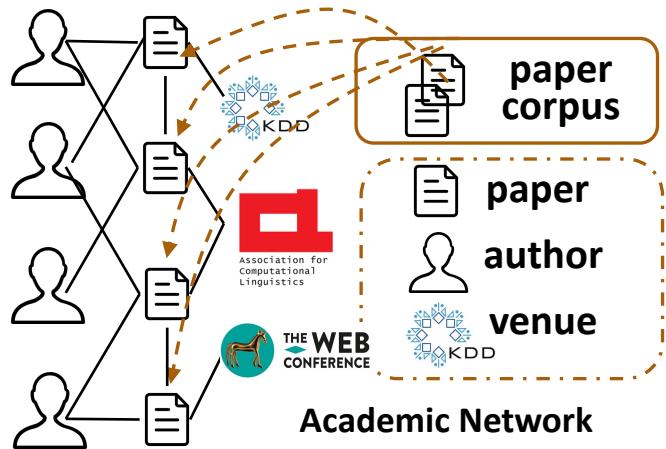
- Text can be converted to (or augmented with) graph structures at various different levels
- How should we perform the conversion and when is it useful?



Reasoning Graphs

Overview of Graph Mining with Large Language Models

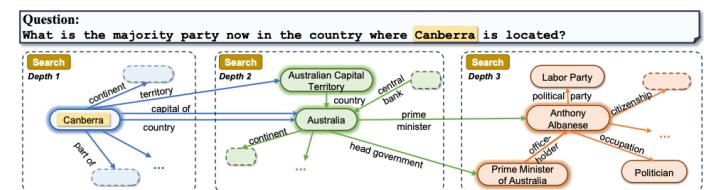
- In real world, text and graph appears simultaneously.
 - Text data are associated with rich structure information in the form of graphs.
 - Graph data are captioned with rich textual information.



Protein Graphs

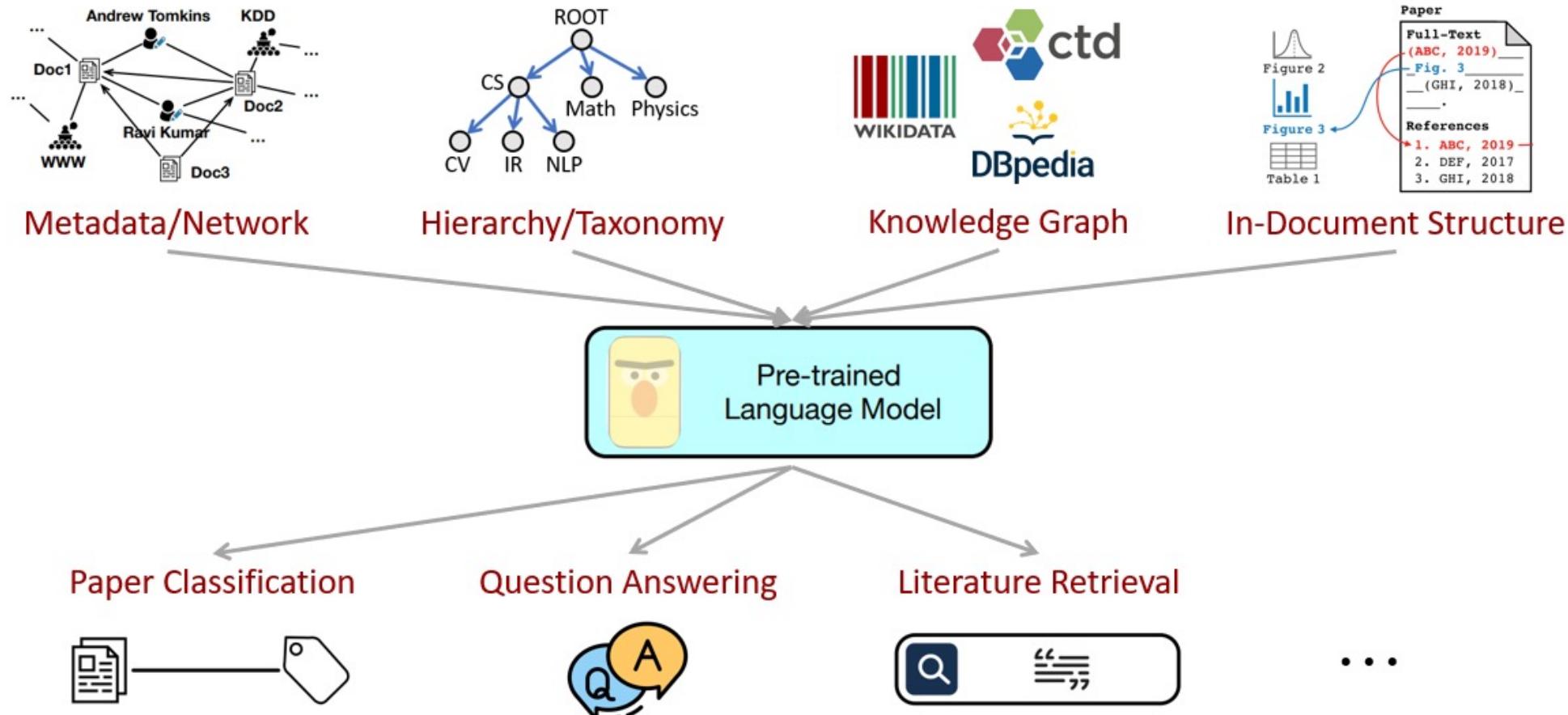
“Myoglobin holds oxygen in muscles.”

- Although LLMs have shown remarkable text reasoning ability, it is underexplored whether such ability can be generalized to graph scenarios.
- How can we adopt LLMs on graphs?

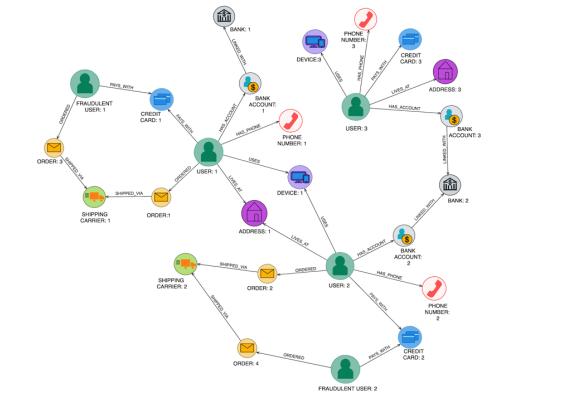
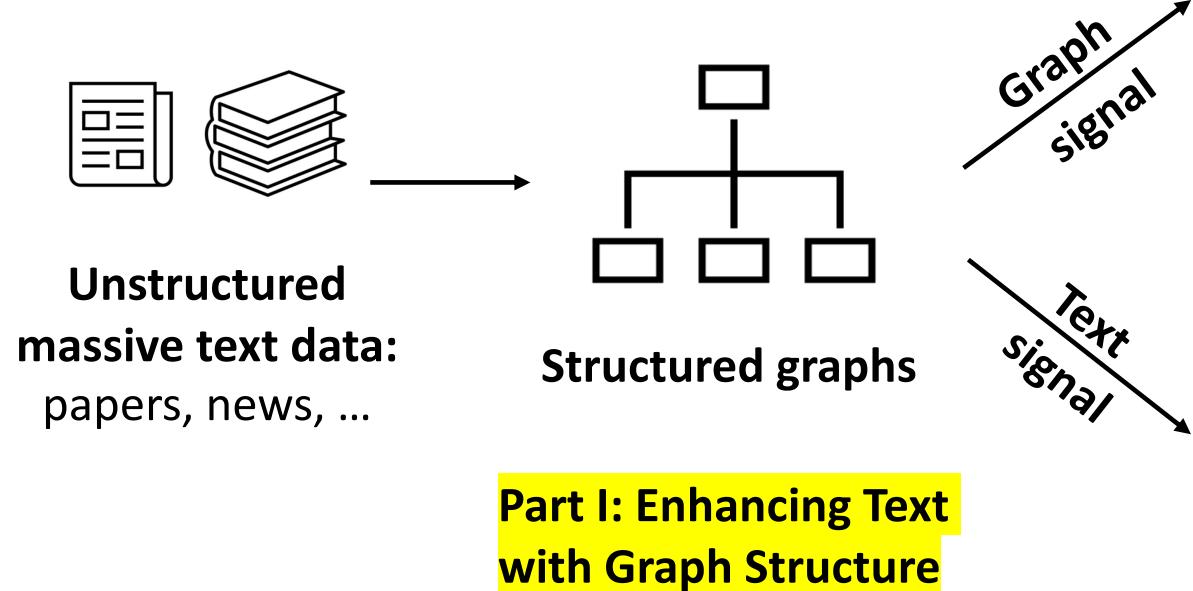


Overview of Text Mining with Structured Information

- Text data are often associated with or accompanied by structured information.
- How to inject structured information into pre-trained language models for various text mining tasks?



Our Roadmap of This Tutorial



Part II: Graph Mining with Large Language Model



Part III: Text Mining with Structure Information

Part IV: Summary & Looking Forward