

SDM 2025 Tutorial: Integrating Textual and Graph Data: Advancing Knowledge Discovery with Semantic and Structural Insights

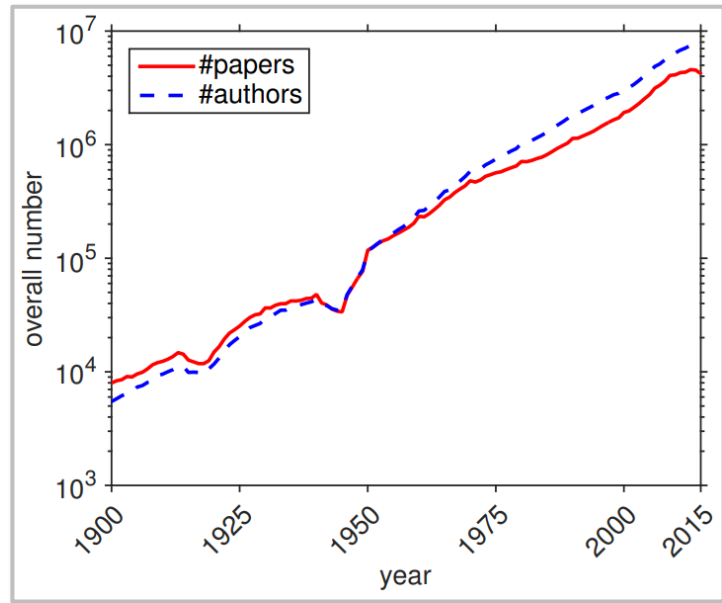
Part III: Domain-Specific Applications

Bowen Jin, Yu Zhang, Yunyi Zhang, Jiawei Han

Apr 30, 2025

Explosion of Scientific Text Data

- The volume of scientific publications is growing exponentially.
 - Doubling every **12** years [1]
 - Reaching **240,000,000** in 2019 [2]



- Papers on emerging topics can be released in a torrent.
 - About **4,000 peer-reviewed** papers on COVID-19 by the end of April 2020 [3]
 - DeepSeek-R1 was uploaded to arXiv on **January 22, 2025** and **cited 721 times** on **April 20, 2025**.

Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning

[PDF] arXiv

[D Guo, D Yang, H Zhang, J Song, R Zhang...](#) - arXiv preprint arXiv ..., 2025 - arxiv.org

... **reasoning capabilities** using pure **reinforcement learning** (RL). Our goal is to explore the potential of **LLMs** to develop **reasoning capabilities** ... on their self-evolution **through** a pure RL ...

☆ Cited by 721 Related articles

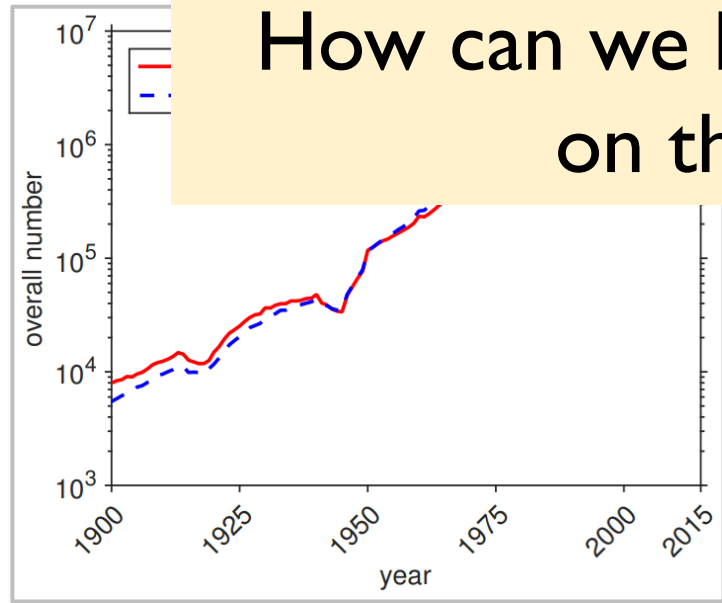
[1] A Century of Science: Globalization of Scientific Collaborations, Citations, and Innovations. KDD 2017.

[2] Microsoft Academic Graph: When Experts are Not Enough. Quantitative Science Studies 2020.

[3] <https://www.economist.com/science-and-technology/2020/05/07/scientific-research-on-the-coronavirus-is-being-released-in-a-torrent>

Explosion of Scientific Text Data

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How can we help researchers **stay updated** on their fields of interest?

capability in llms via reinforcement learning

[D Guo, D Yang, H Zhang, J Song, R Zhang...](#) - arXiv preprint arXiv ..., 2025 - arxiv.org

... **reasoning capabilities** using pure **reinforcement learning** (RL). Our goal is to explore the potential of **LLMs** to develop **reasoning capabilities** ... on their self-evolution **through** a pure RL ...

☆ Cited by 721 Related articles 🔗

[PDF] arXiv

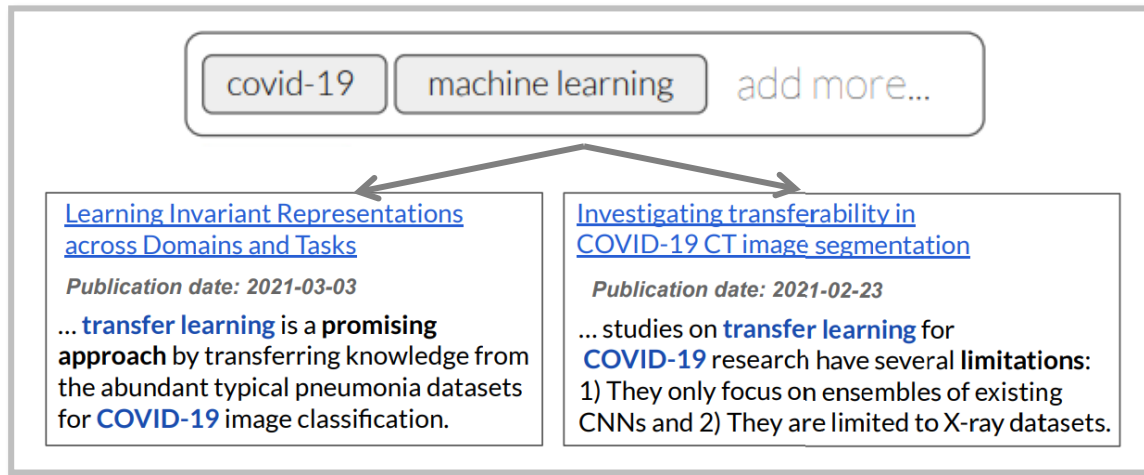
[1] A Century of Science: Globalization of Scientific Collaborations, Citations, and Innovations. KDD 2017.

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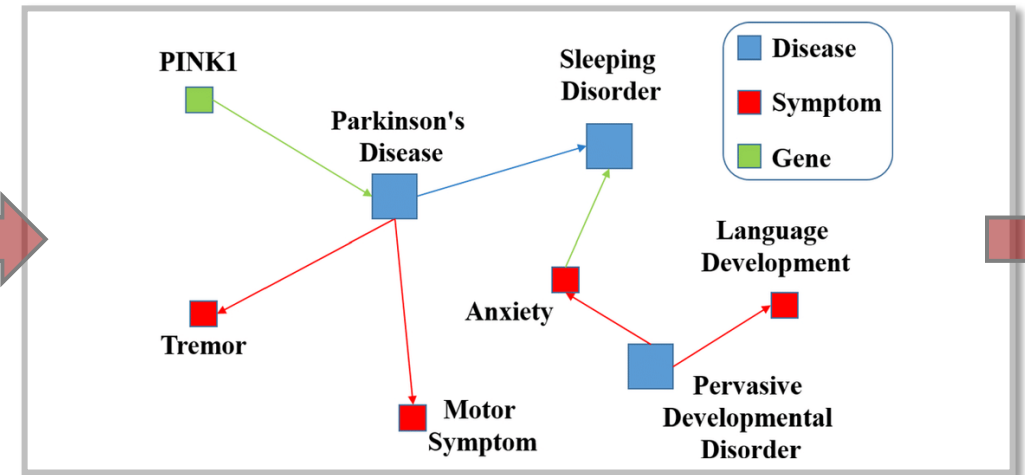
[3] <https://www.economist.com/science-and-technology/2020/05/07/scientific-research-on-the-coronavirus-is-being-released-in-a-torrent>

How can scientific text mining assist research?

Retrieving and Analyzing Relevant Literature



Uncovering Knowledge Structures/Graphs



• Example tasks:


- Predict the diseases, chemicals, and viruses relevant to each paper.
- Retrieve papers relevant to both “Betacoronavirus” and “Paxlovid”.
- Find papers refuting the claim “CX3CR1 impairs T cell survival”.


• Example tasks:


- Find protein entities relevant to “Parkinson's disease” from relevant literature.
- Predict the relationship between “Tremor” and “Sleeping Disorder”.

How can scientific text mining assist research?

Generating Hypotheses and Suggesting Directions



 **Hypothesis:** Graph convolutional networks (GCNs) can effectively model polypharmacy side effects by leveraging the intricate relationships among drugs, their targets, and biological pathways encoded in drug-target interaction networks, enabling the prediction of potential adverse drug interactions and facilitating personalized medication management.



- **Example tasks:**

- Generate a new hypothesis based on the 100 most recent papers on “*Polypharmacy Side Effects*”.
- Evaluate the novelty of an idea for modeling “*Polypharmacy Side Effects*” in comparison with previous studies.

Reviewing Research Outcomes

Reviewer Console

Bidding 1 - 4 of 4 ◀ ◻ ▶ 1 ▶▶ **Show:** 25 50 100 All Clear All Filters

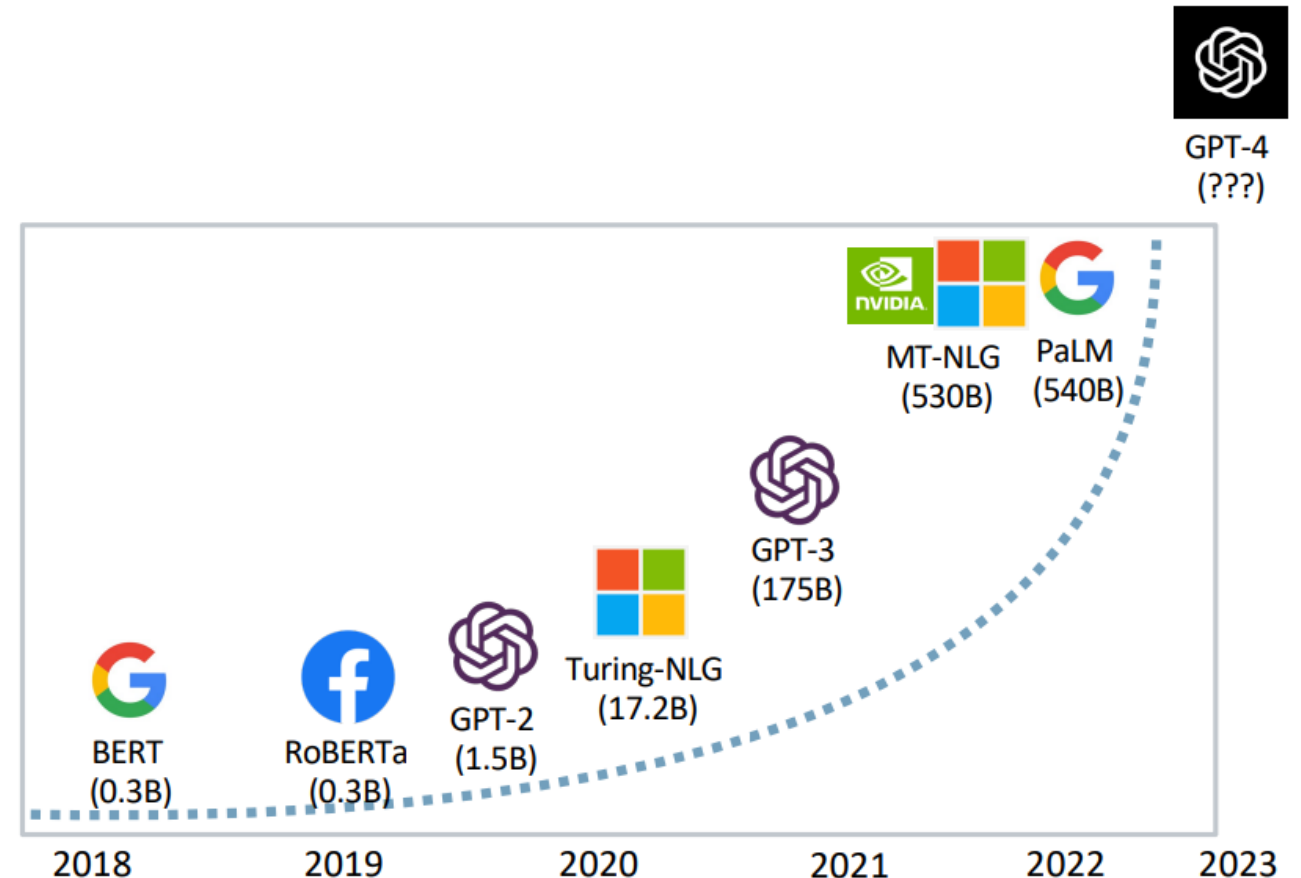
Paper ID↑	Title	Subject Areas		Review & Discussion	Relevance
		Primary	Secondary		
<input type="text" value="e.g. <3"/> Clear	<input type="text" value="filter..."/> Clear	<input type="text" value="filter..."/> Clear	<input type="text" value="filter..."/> Clear		<input type="text" value="e.g. <3"/> Clear
26	Research Paper Zero 1 Show Abstract	MARINE VESSELS -> Hull	AUTOMOBILES -> Engines		0.32
27	Scientific Paper Z Show Abstract	AUTOMOBILES -> Engines	MARINE VESSELS		0.80

- **Example tasks:**

- Find qualified reviewers to review a submission.
- Provide constructive feedback to a paper draft.

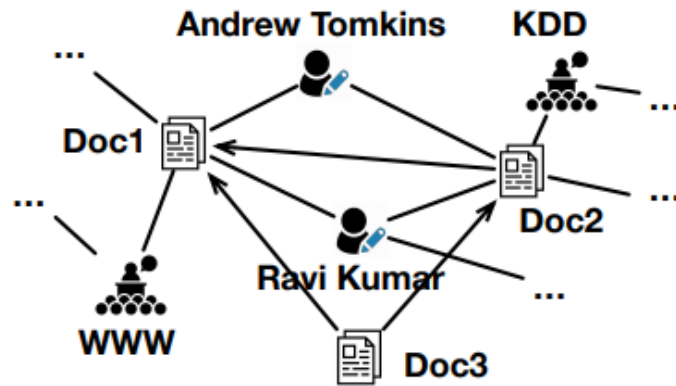
Large Language Models (LLMs) for Text Mining

- A **unified** model to perform different NLP tasks **with a few or zero examples**
 - I went to the zoo to see giraffes, lions, and {zebras, spoon}. (*Lexical semantics*)
 - I was engaged and on the edge of my seat the whole time. The movie was {good, bad}. (*Text classification*)
 - The word for “pretty” in Spanish is {bonita, hola}. (*Translation*)
 - $3 + 8 + 4 = \{\underline{15}, 11\}$ (*Math*)
 - ...

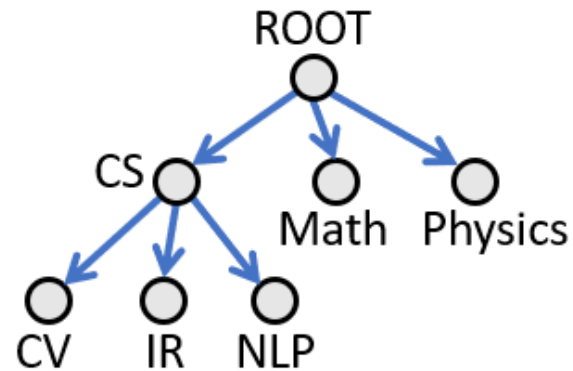


Are LLMs aware of **structured information**?

Structured Information Associated with Scientific Text



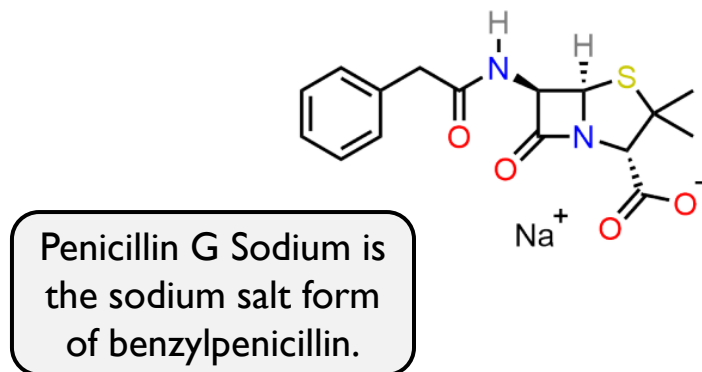
Metadata/Network



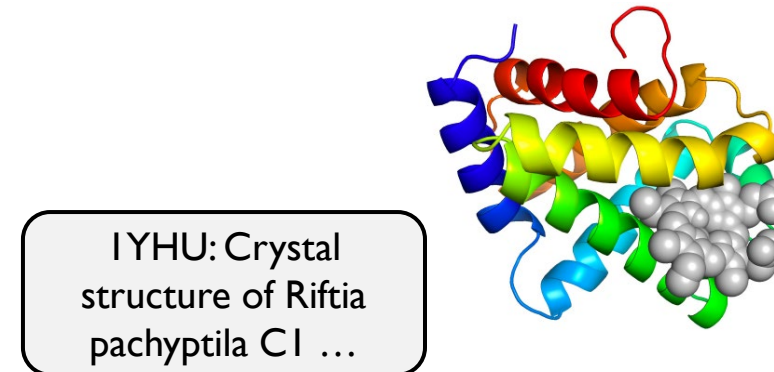
Hierarchy/Taxonomy



Knowledge Graph



Text-Paired Molecule



Text-Paired Protein

LLMs may not be structure-aware!



You

What is the most cited paper in WWW 2017? Please list its title and authors.



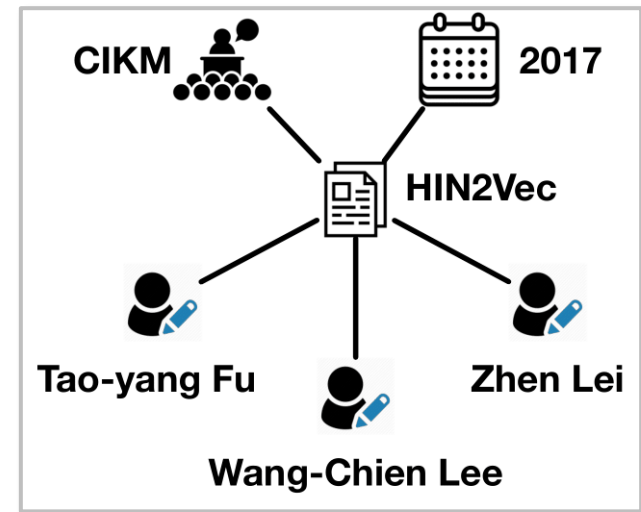
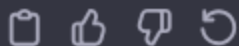
ChatGPT

As of my last update in January 2022, I don't have the real-time citation information, but one of the highly cited papers from WWW 2017 is:

Title: "HIN2Vec: Explore Meta-paths in Heterogeneous Information Networks for Representation Learning"

Authors: Cheng Yang, Zhiyuan Liu, Deli Zhao, Maosong Sun, Edward Y. Chang

Please verify the latest citation counts and updates from reliable sources or academic databases for the most current information.



HIN2Vec was published in **CIKM 2017**.

HIN2Vec was written by **Tao-yang Fu, Wang-Chien Lee, and Zhen Lei**.

LLMs may not be structure-aware!

What is the most cited paper in WWW 2017? Please list its title and authors.



Searched 5 sites ▾

The most cited paper from WWW 2017 is "Attention is All You Need," which introduced the Transformer model, a groundbreaking architecture in natural language processing that uses attention mechanisms without relying on recurrent or convolutional layers. The authors of the paper are Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin [ARXIV](#) [NEURIPS PROCEEDINGS](#).

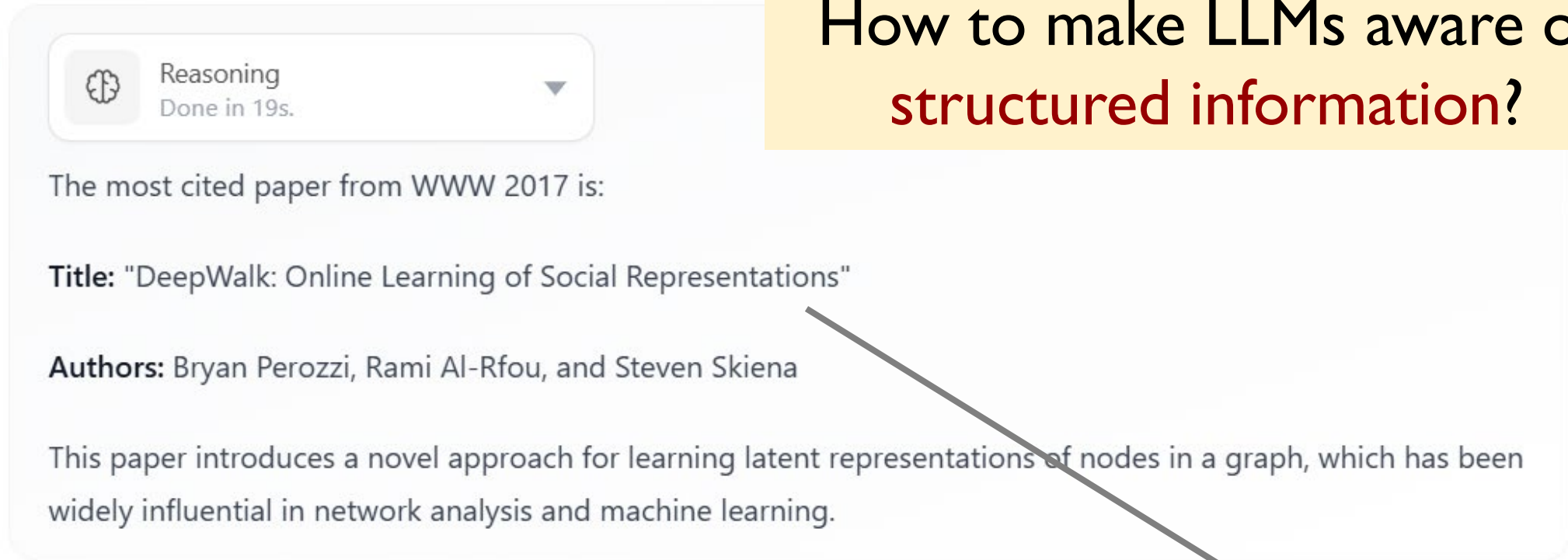


ChatGPT 4o, queried on October 12, 2024

Transformer was published
in **NeurIPS 2017**.

LLMs may not be structure-aware!

What is the most cited paper in WWW 2017? Please list its title and authors.



The screenshot shows a reasoning interface with a dropdown menu labeled 'Reasoning' and 'Done in 19s.'. Below the menu, the text reads: 'The most cited paper from WWW 2017 is:'. The response is structured as follows: 'Title: "DeepWalk: Online Learning of Social Representations"', 'Authors: Bryan Perozzi, Rami Al-Rfou, and Steven Skiena', and a paragraph: 'This paper introduces a novel approach for learning latent representations of nodes in a graph, which has been widely influential in network analysis and machine learning.' An arrow points from the title to a box at the bottom right.

Reasoning
Done in 19s.

The most cited paper from WWW 2017 is:

Title: "DeepWalk: Online Learning of Social Representations"

Authors: Bryan Perozzi, Rami Al-Rfou, and Steven Skiena

This paper introduces a novel approach for learning latent representations of nodes in a graph, which has been widely influential in network analysis and machine learning.

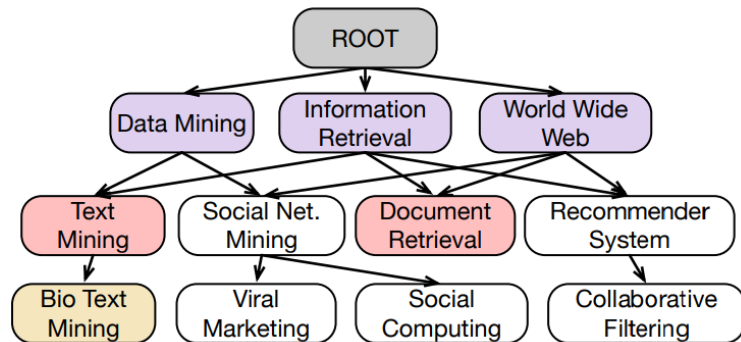
How to make LLMs aware of
structured information?

DeepSeek-R1-Distill-Llama-70B, queried on March 21, 2025

DeepWalk was published in
KDD 2014.

Overview of Part III

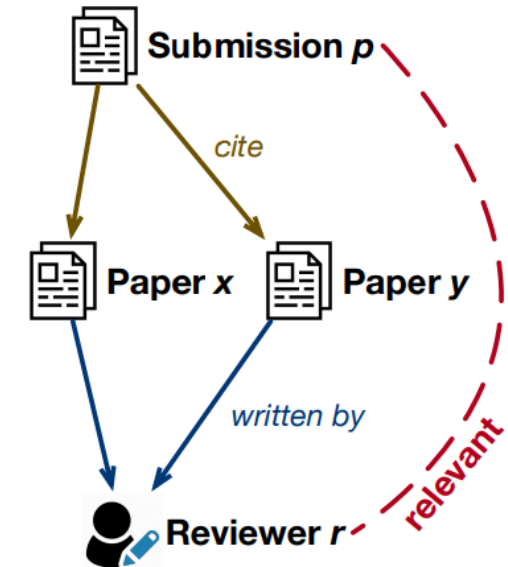
Structure-Aware LLMs for Scientific Paper Classification



Structure-Aware LLMs for Scientific Literature Search

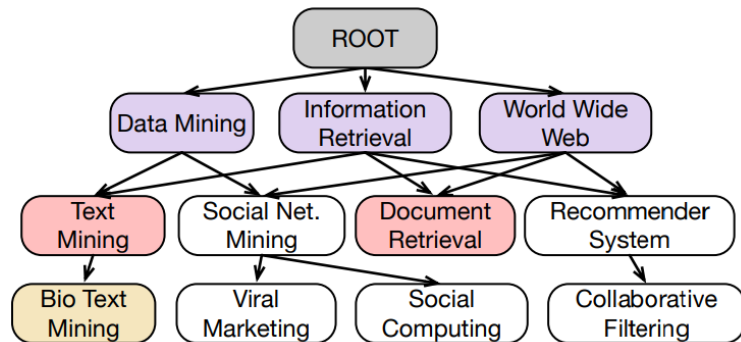


Structure-Aware LLMs for Paper-Reviewer Matching

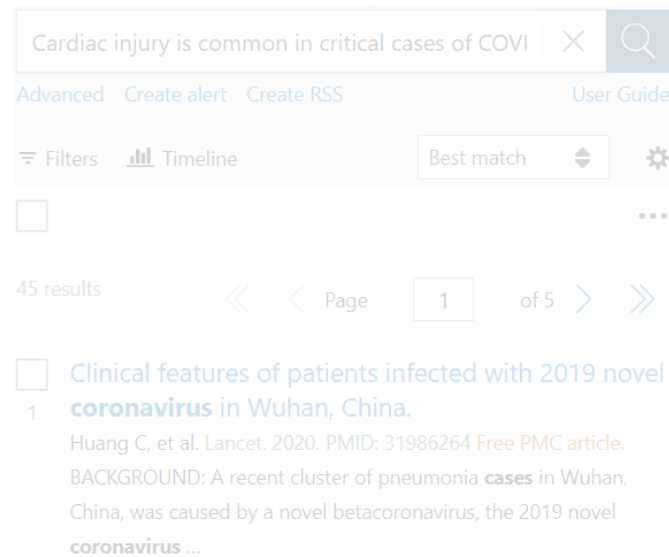


Overview of Part III

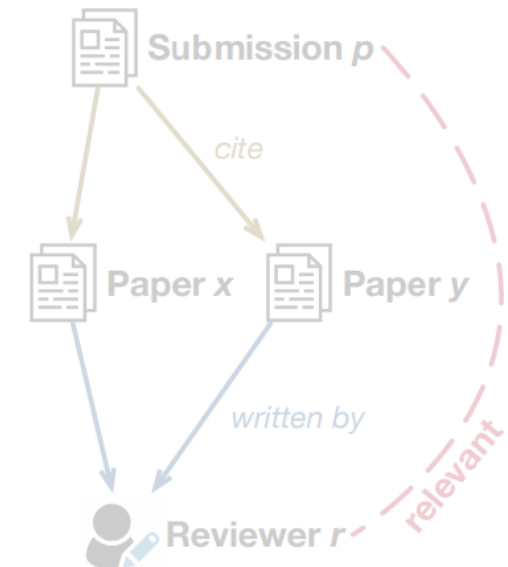
Structure-Aware LLMs for Scientific Paper Classification



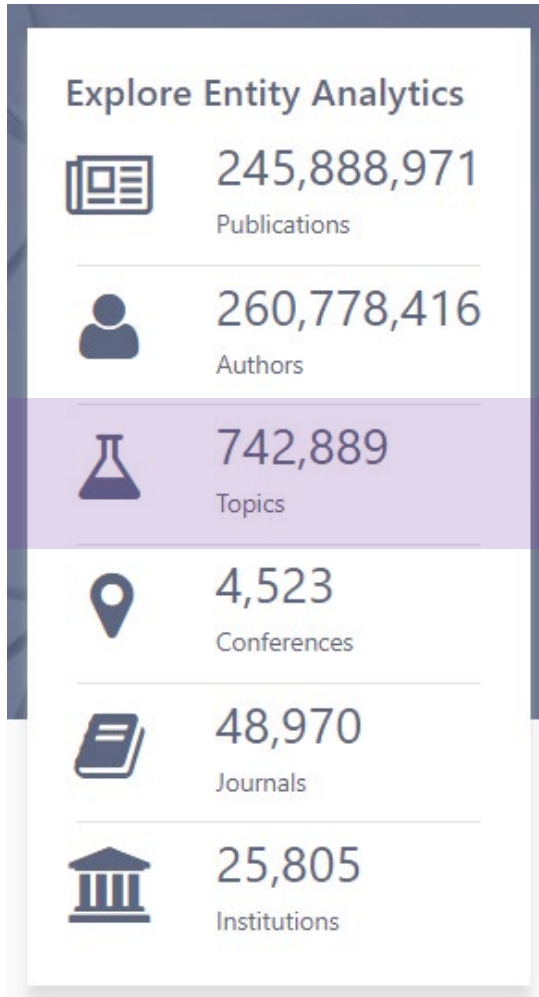
Structure-Aware LLMs for Scientific Literature Search




Structure-Aware LLMs for Paper-Reviewer Matching



Extremely Fine-Grained Scientific Paper Classification



- The Microsoft Academic Graph has **740K+** categories.
- The Medical Subject Headings (MeSH) for indexing PubMed papers contain **30K+** categories.
- Each paper can be relevant to **more than one** category (5-15 categories for most papers).

 Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study.

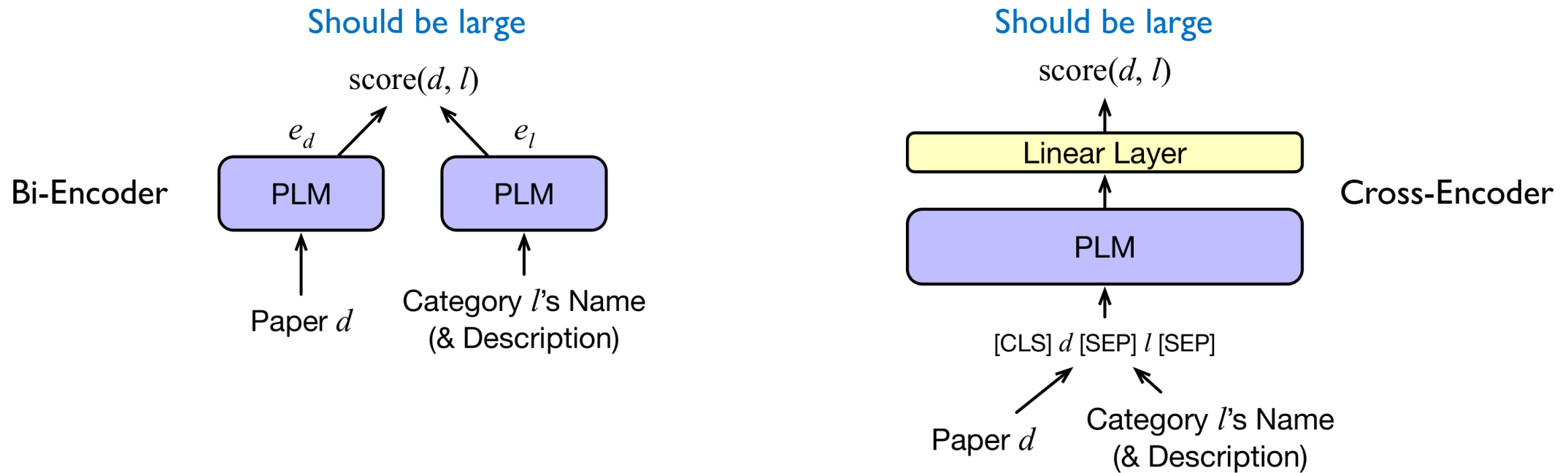
- **Relevant categories:** Betacoronavirus, Cardiovascular Diseases, Comorbidity, Coronavirus Infections, Fibrin Fibrinogen Degradation Products, Mortality, Pandemics, Patient Isolation, Pneumonia, ...

Fine-grained classification can be viewed as a retrieval task.

Query: Paper; **Candidates:** Category Names

If we could have some training data ...

- We could use relevant (paper, category) pairs to fine-tune a pre-trained language model.
- Both **Bi-Encoder** and **Cross-Encoder** are applicable.



- However, human-annotated training samples are **NOT available** in many cases!
 - We are asking annotators to find ~ 10 relevant categories from $\sim 100,000$ candidates!

Using Structured Information to Replace Annotations

- If relevant (paper, category) pairs are not available, can we automatically create **relevant (paper, paper)** pairs?
 - Two papers sharing **the same author(s)** are assumed to be similar.
 - Two papers sharing **the same reference(s)** are assumed to be similar.
 - ...
- The notion of meta-paths and meta-graphs



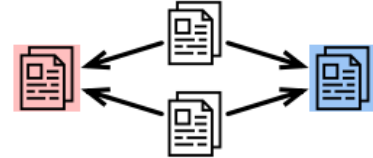
(a) meta-path: PAP



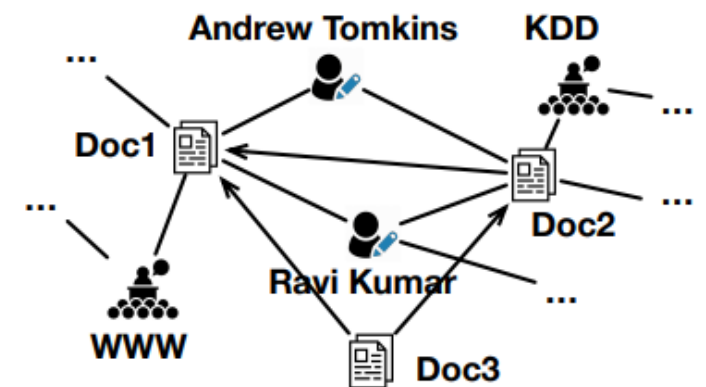
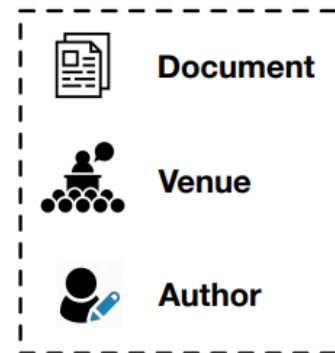
(b) meta-path: P->P<-P



(c) meta-graph: P(AV)P



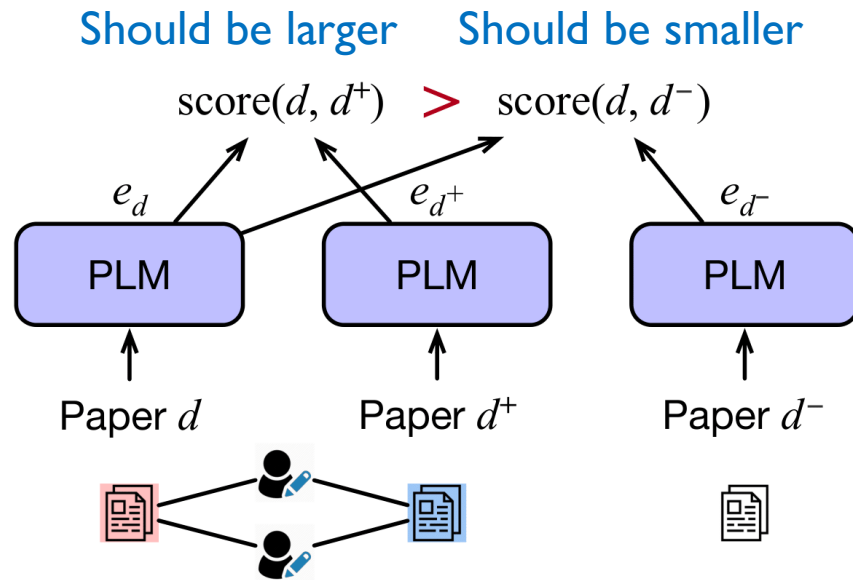
(d) meta-graph: P<-(PP)->P



Structure-Induced Contrastive Learning

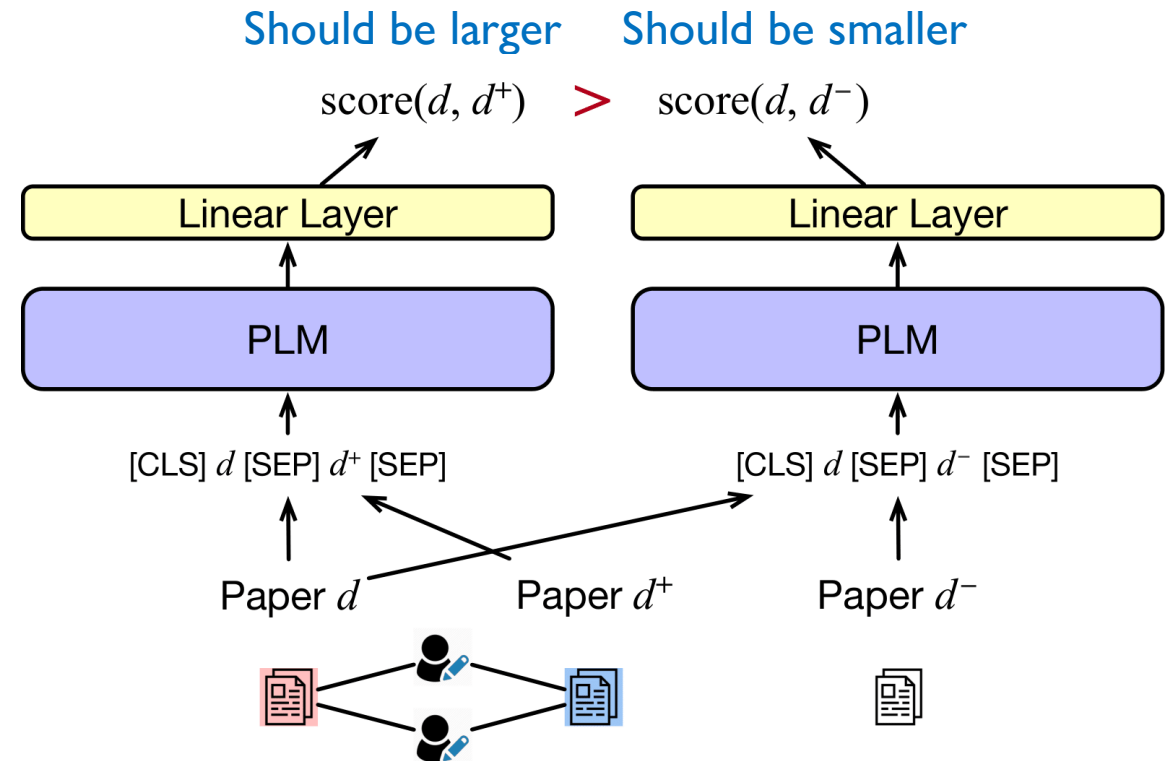
- Two papers connected via a certain meta-path/meta-graph should be more similar than two randomly selected papers.

Bi-Encoder



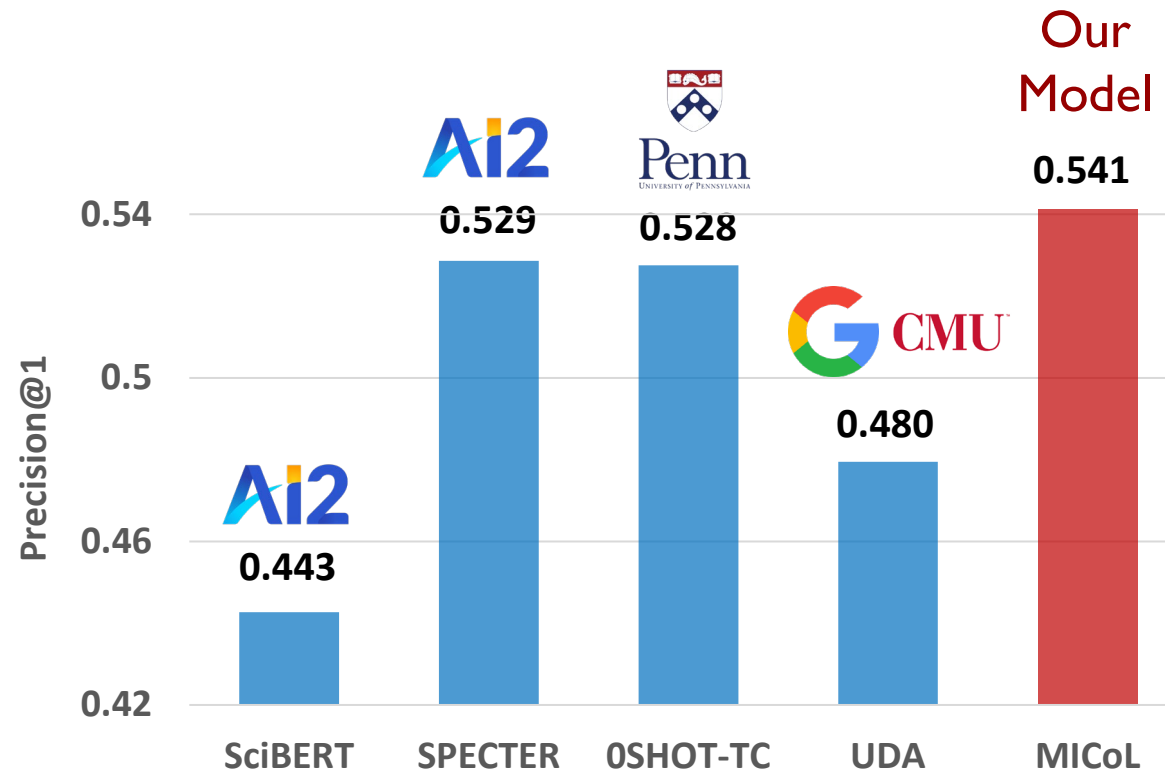
$$-\log \frac{\exp(\cos(\mathbf{e}_d, \mathbf{e}_{d^+})/\tau)}{\exp(\cos(\mathbf{e}_d, \mathbf{e}_{d^+})/\tau) + \sum_{i=1}^N \exp(\cos(\mathbf{e}_d, \mathbf{e}_{d_i^-})/\tau)}$$

Cross-Encoder



Comparison with Previous Approaches

- Dataset: Microsoft Academic Graph and PubMed
- Metric: Precision@1, 3, and 5



Case Study

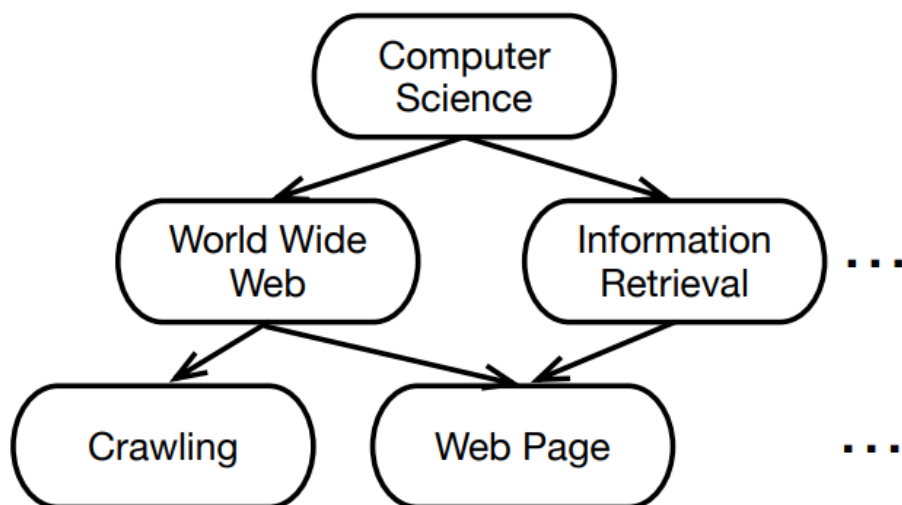
- Title: Improving Text Categorization Methods for Event Tracking
- Venue: SIGIR (2000)
- Authors: Yiming Yang, Tom Ault, Thomas Pierce, Charles W. Lattimer
- Abstract: : Automated tracking of events from chronologically ordered document streams is a new challenge for statistical text classification. Existing learning techniques must be adapted or improved in order to effectively handle difficult situations where the number of positive training instances per event ...

- Top-5 Predictions of a Text-Only Baseline: K Nearest Neighbors Algorithm (✓), Data Mining (✓), Pattern Recognition (✓), Machine Learning (✓), Nearest Neighbor Search (X)

- Top-5 Predictions of our Metadata-Aware Method: K Nearest Neighbors Algorithm (✓), Data Mining (✓), Information Retrieval (✓), Pattern Recognition (✓), Machine Learning (✓)

How about other types of structured information?

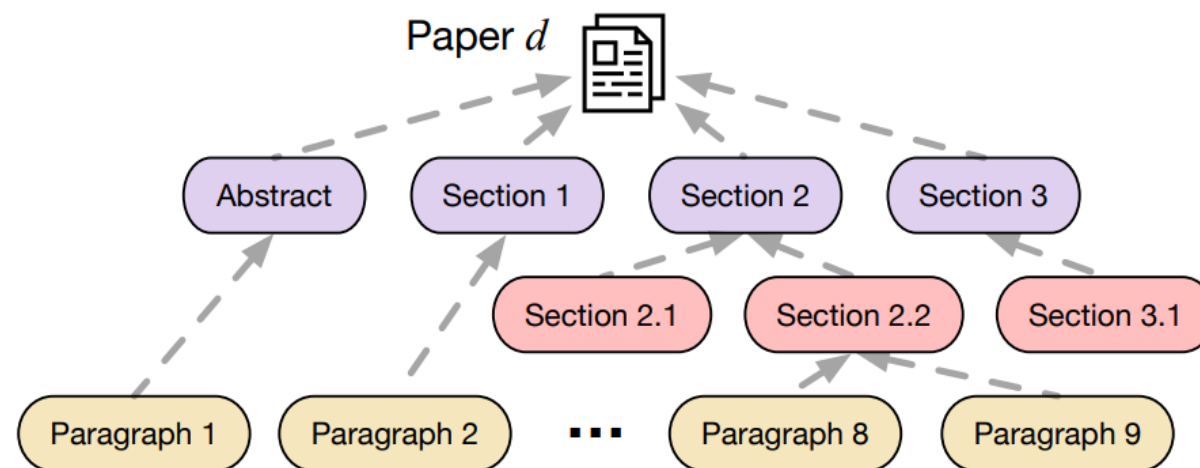
Label Hierarchy



Top-Down Pruning:

Irrelevant to **WWW** \Rightarrow Irrelevant to **Crawling**

In-Document Structure



Bottom-Up Aggregation:

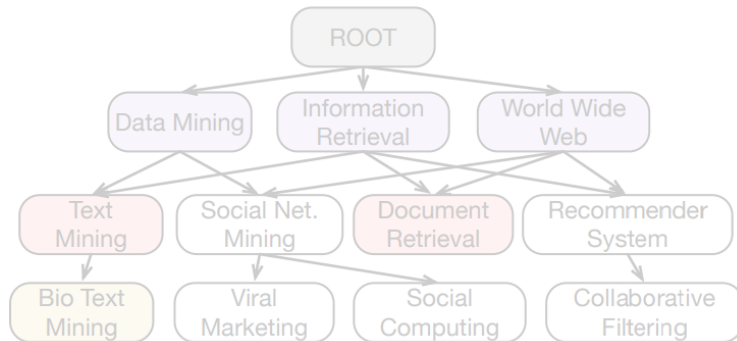
Paragraphs \rightarrow **Subsections** \rightarrow **Sections** \rightarrow Paper

Overview of Part III

Structure-Aware LLMs
for Scientific Paper
Classification

Structure-Aware LLMs
for Scientific Literature
Search

Structure-Aware LLMs
for Paper-Reviewer
Matching



Cardiac injury is common in critical cases of COVI

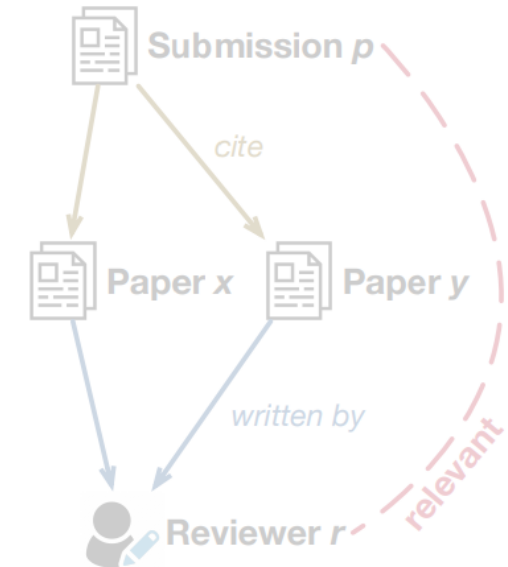
Advanced Create alert Create RSS User Guide

Filters Timeline Best match

45 results

Page 1 of 5

1 Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China.
Huang C, et al. Lancet. 2020. PMID: 31986264 Free PMC article.
BACKGROUND: A recent cluster of pneumonia cases in Wuhan, China, was caused by a novel betacoronavirus, the 2019 novel coronavirus ...



Link Prediction

DOI: 10.48550/arXiv.2406.10833 • Corpus ID: 270560416

A Comprehensive Survey of Scientific Large Language Models and Their Applications in Scientific Discovery

Yu Zhang, Xiusi Chen, +4 authors Jiawei Han • Published in [Conference on Empirical...](#) 16 June 2024 • Computer Science, Biology

TLDR This paper comprehensively survey over 260 scientific LLMs, discusses their commonalities and differences, as well as summarize pre-training datasets and evaluation tasks for each field and modality, and investigates how LLMs have been deployed to benefit scientific discovery. [Expand](#)

What papers should this survey cite?

BioBERT

Med-PaLM

DeepSeekMath

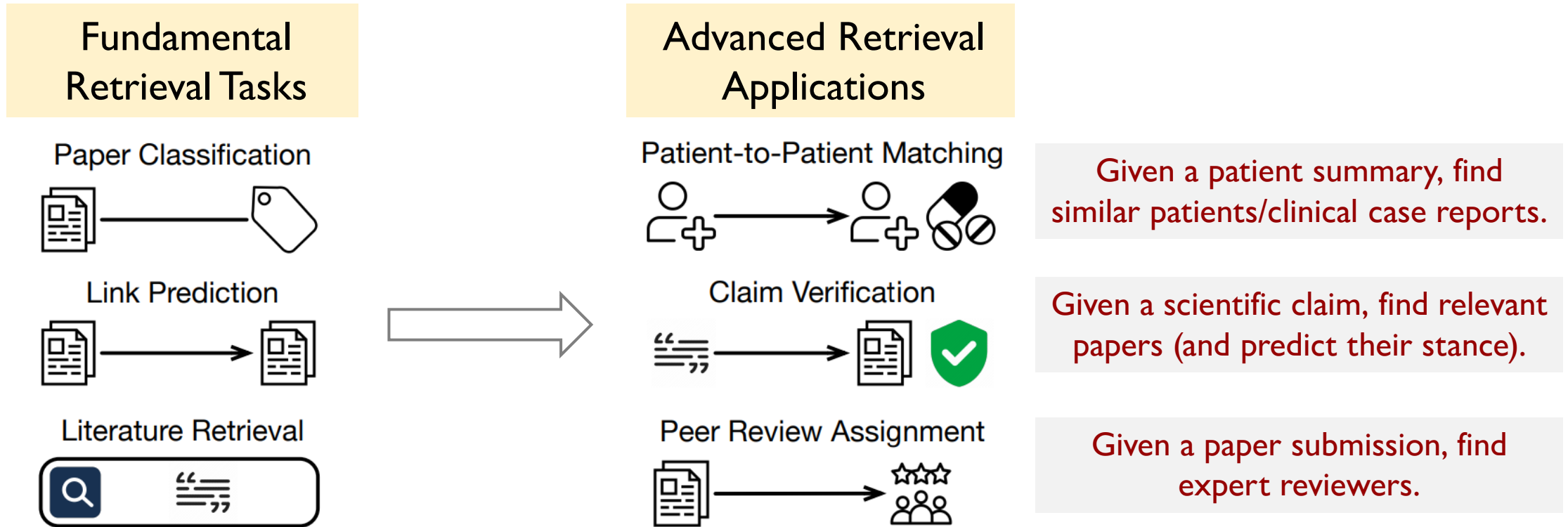
What other papers have these authors written?

What other papers have published in this venue?

Link prediction can be viewed as a retrieval task.

Query: Paper; **Candidates:** Papers

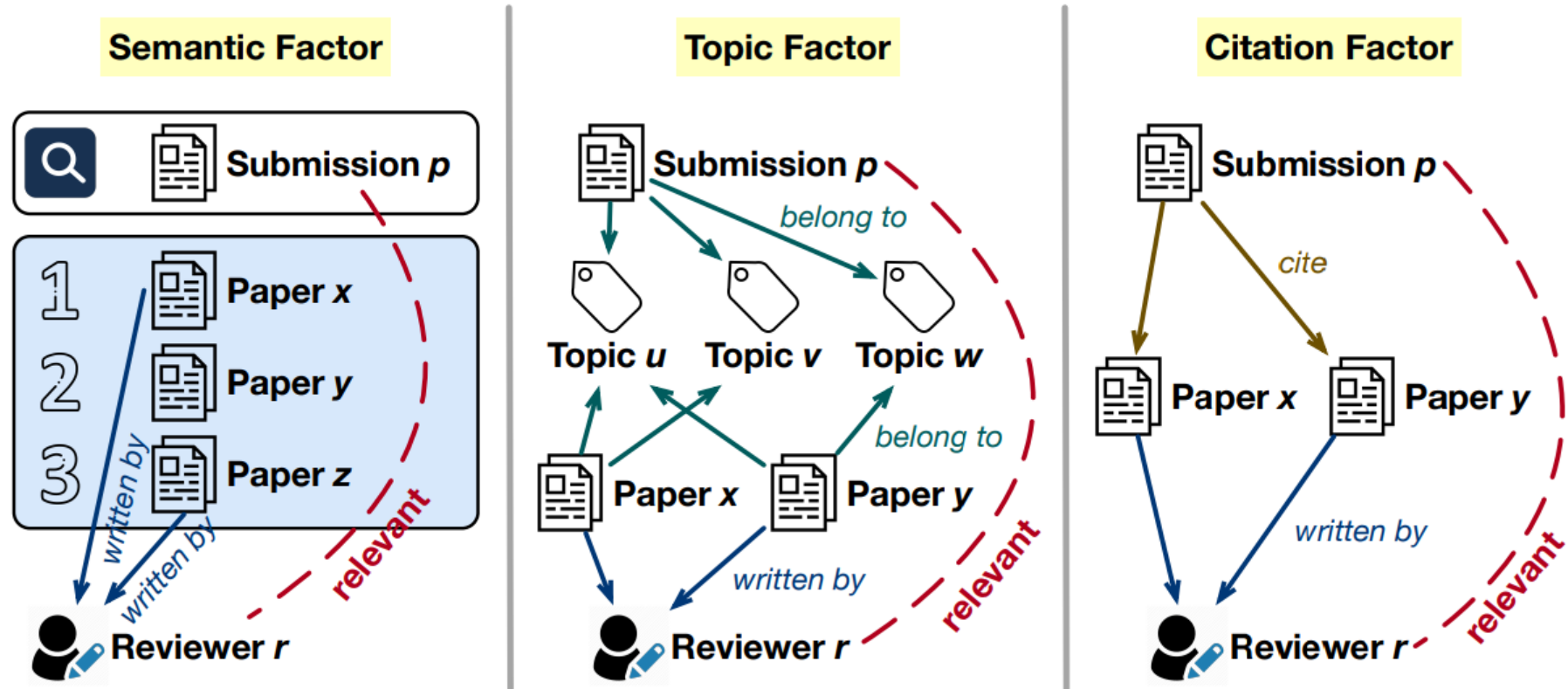
Fundamental Retrieval Tasks vs. Advanced Retrieval Applications



- Why are some tasks more complex?
 - **Multiple** factors should be considered when judging the **relevance**.

Multiple Factors for Judging Relevance

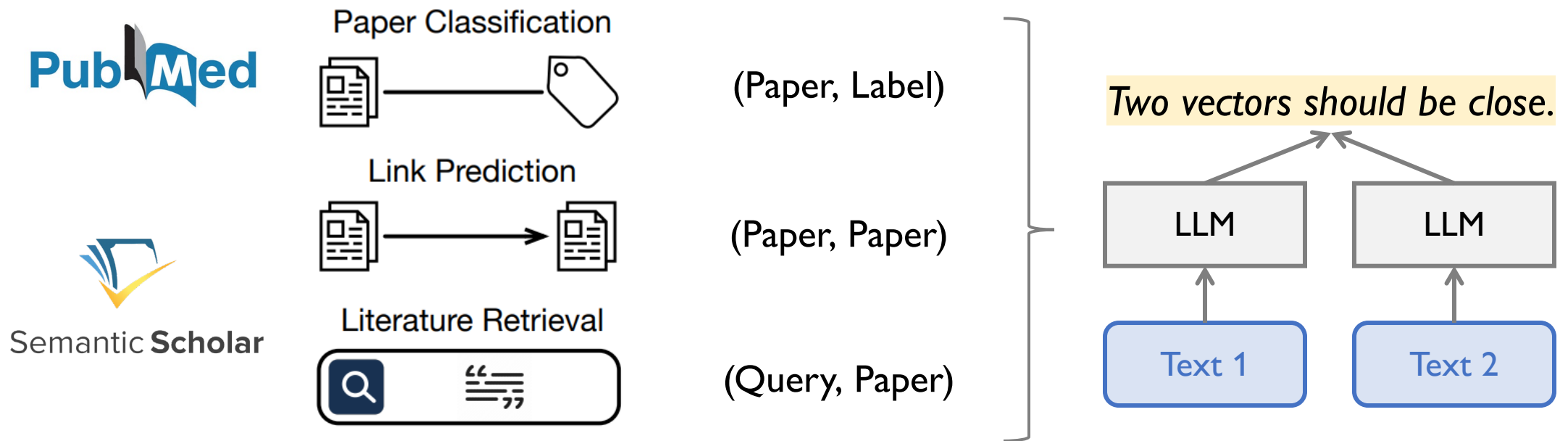
- Example: Paper-Reviewer Matching
 - Why is a pair of (Paper, Reviewer) **relevant**?



- Multiple factors exist in other tasks (e.g., Patient-to-Article Matching) as well.

Contrastive Learning for an Advanced Task – A Naïve Way

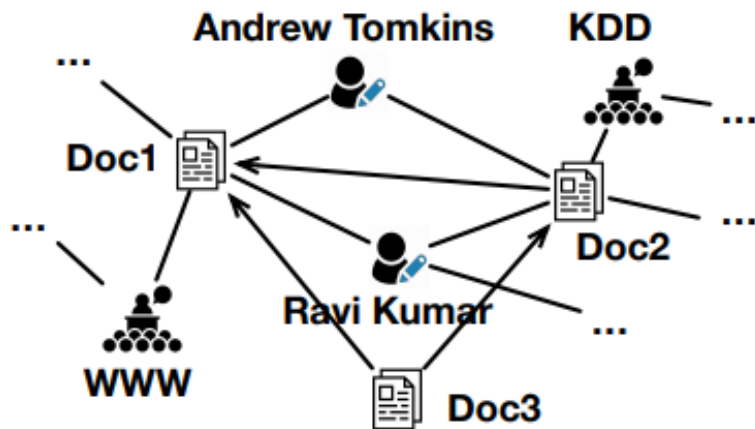
- Each factor (topic, citation, and semantic) relies on one **fundamental** retrieval task.
- Directly combining pre-training data from different tasks to train a model?



- **Task Interference**: The model is confused by different types of “relevance”.

A Toy Example of Task Interference

- Imagine you have two “tasks”.
 - **Task 1:** Given Paper1 and Paper2, predict if **Paper1 should cite Paper2**.
 - **Task 2:** Given Paper1 and Paper2, predict if **Paper1 and Paper2 share the same venue**.
- What if we directly merge the collected relevant (paper, paper) pairs for these two tasks?
 - Is (Doc2, Doc1) relevant?
 - The model does not know **which task you are referring to**, so it will get confused!



Should Doc2 cite Doc1?

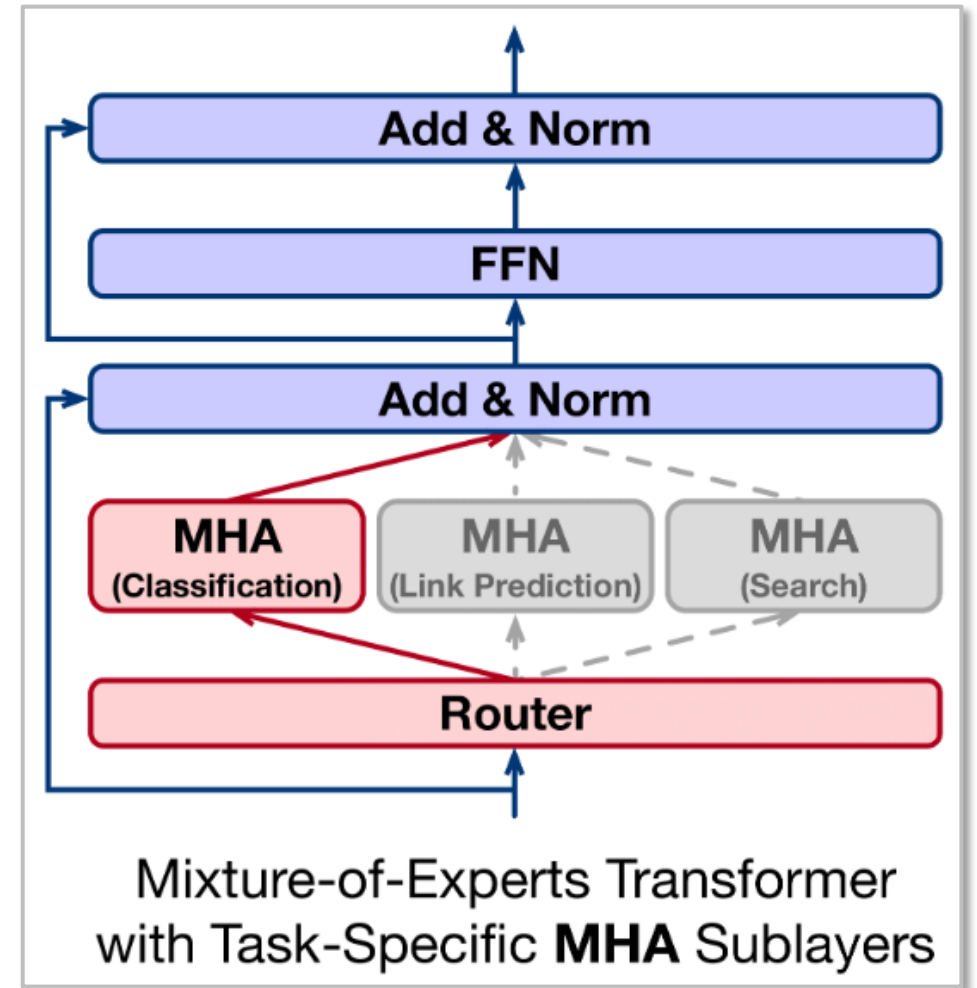


Do Doc2 and Doc1 share the same venue?

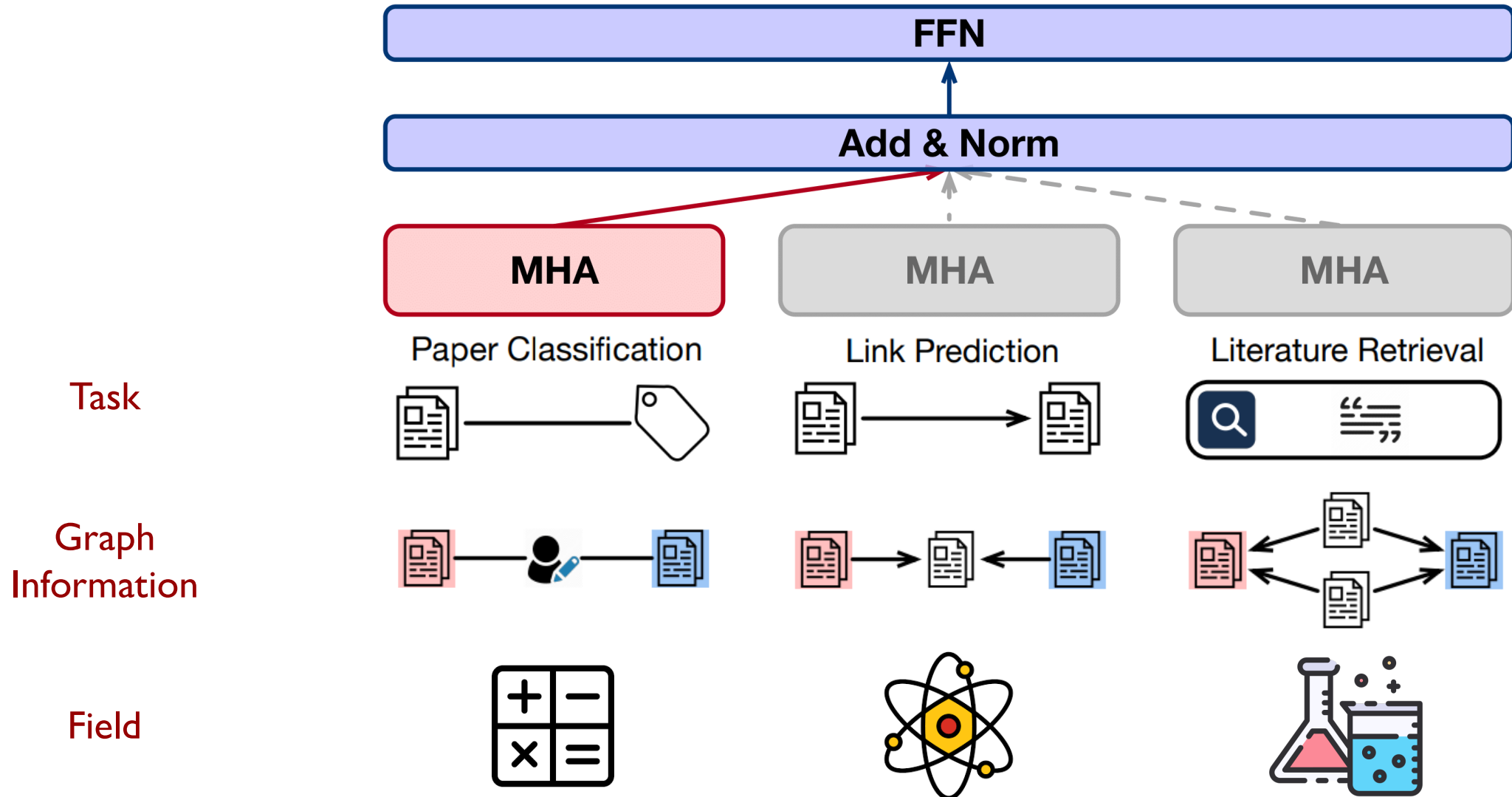


Tackling Task Interference: Mixture-of-Experts Transformer

- A typical Transformer layer
 - **1** Multi-Head Attention (MHA) sublayer
 - **1** Feed Forward Network (FFN) sublayer
- A Mixture-of-Experts (MoE) Transformer layer
 - **Multiple** MHA sublayers
 - **1** FFN sublayer
 - (Or 1 MHA & Multiple FFN)
- Specializing some parts of the architecture to be an “expert” of one task
- The model can learn both **commonalities** and **characteristics** of different tasks.



Tackling Task Interference: Mixture-of-Experts Transformer

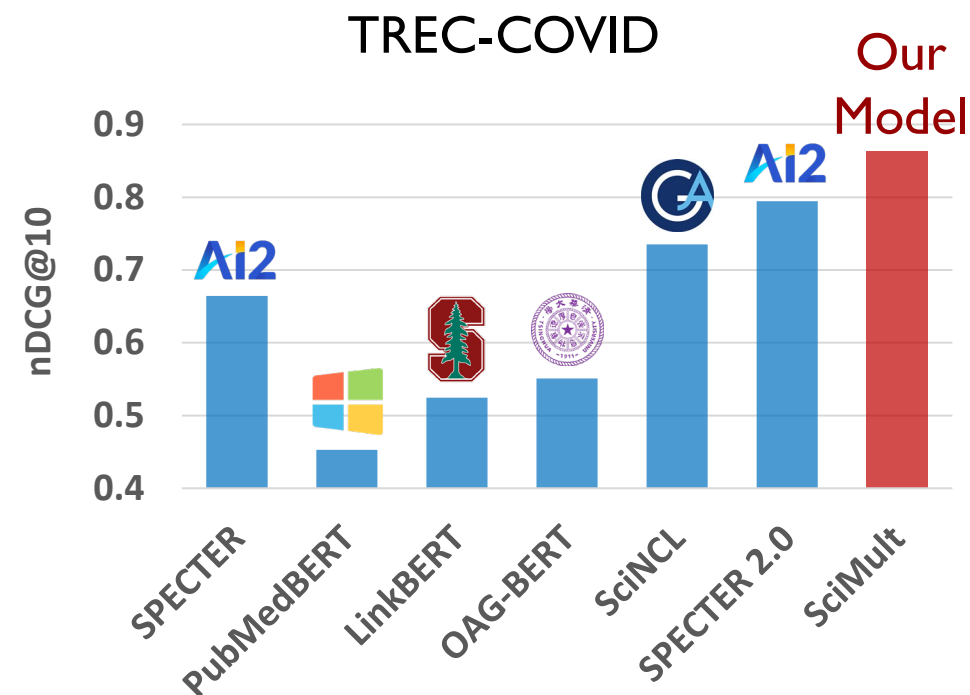


Comparison with Previous Approaches

- New **SOTA** on the PMC-Patients benchmark (**patient-to-article retrieval**)
- Outperforming previous scientific pre-trained language models in classification, link prediction, literature retrieval (**TREC-COVID**), paper recommendation, and claim verification (**SciFact**)

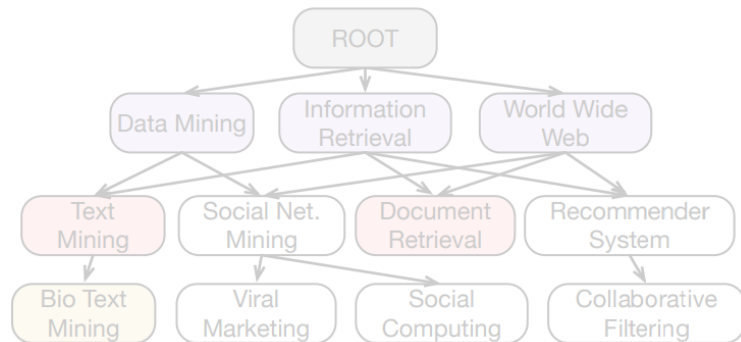
Patient-to-Article Retrieval (PAR) Leaderboard					
	Model	MRR (%)	P@10 (%)	nDCG@10 (%)	R@1k (%)
Our Model 1 June 25, 2023	DPR (SciMult-MHAExpert) UIUC/Microsoft (Zhang et al. 2023)	29.89	9.35	13.79	53.71
2 Apr 5, 2023	RRF Tsinghua University (Zhao et al. 2023)	29.86	8.86	13.36	49.45

<https://pmc-patients.github.io/>

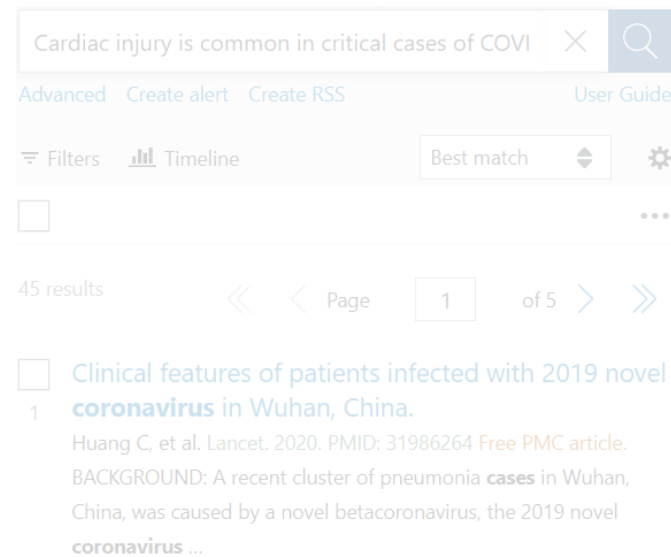


Overview of Part III

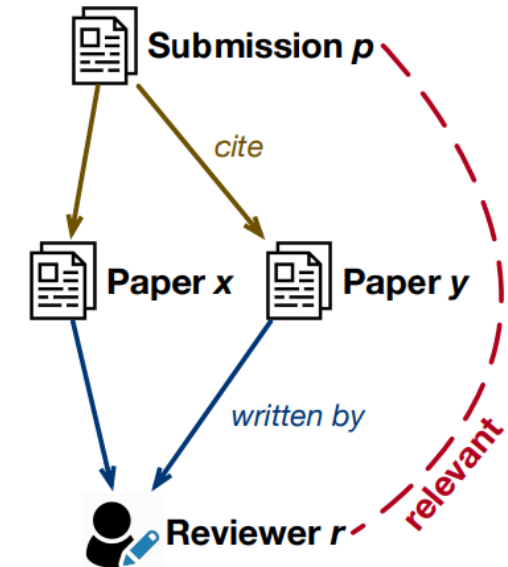
Structure-Aware LLMs for Scientific Paper Classification



Structure-Aware LLMs for Scientific Literature Search

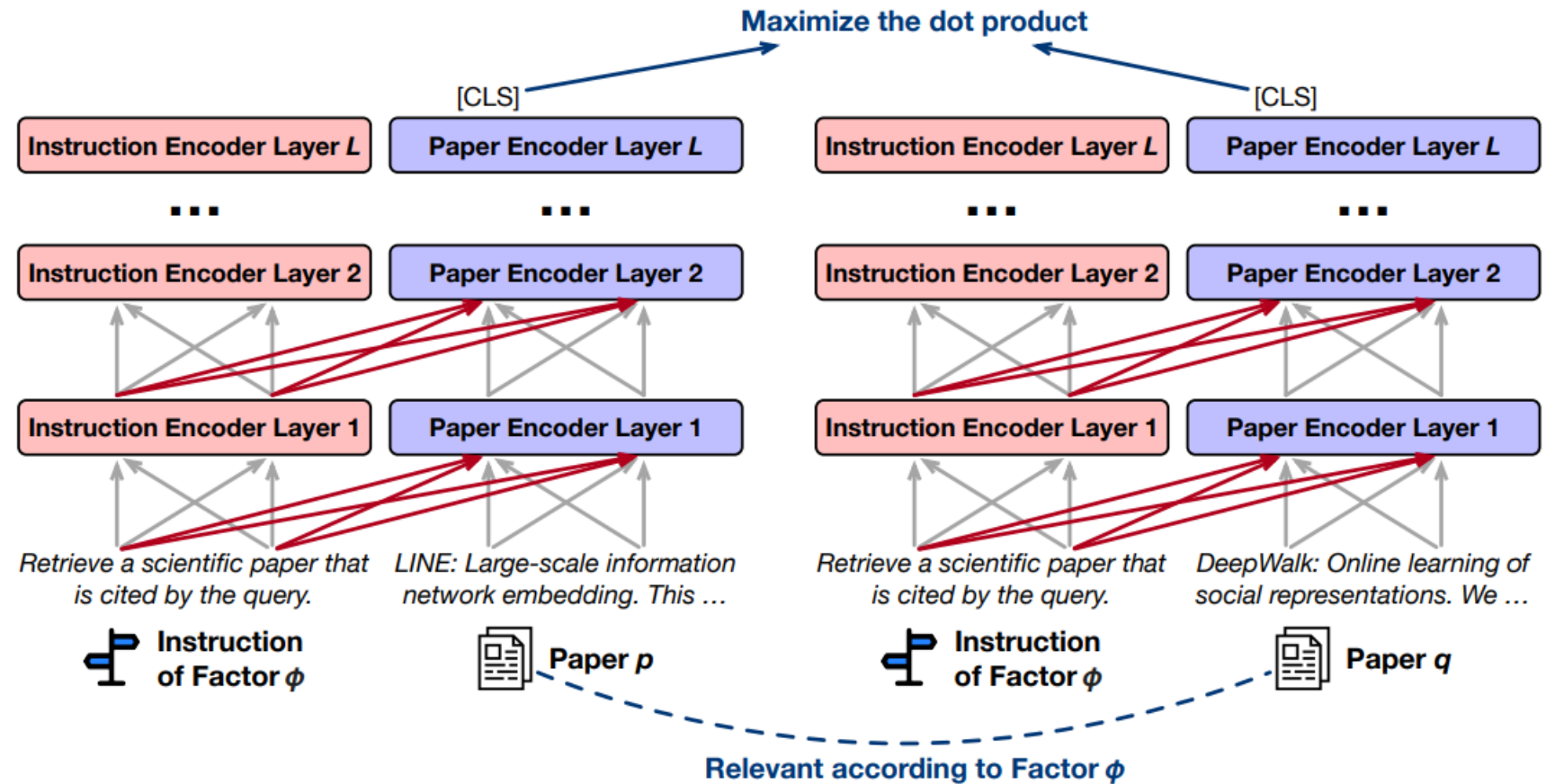


Structure-Aware LLMs for Paper-Reviewer Matching



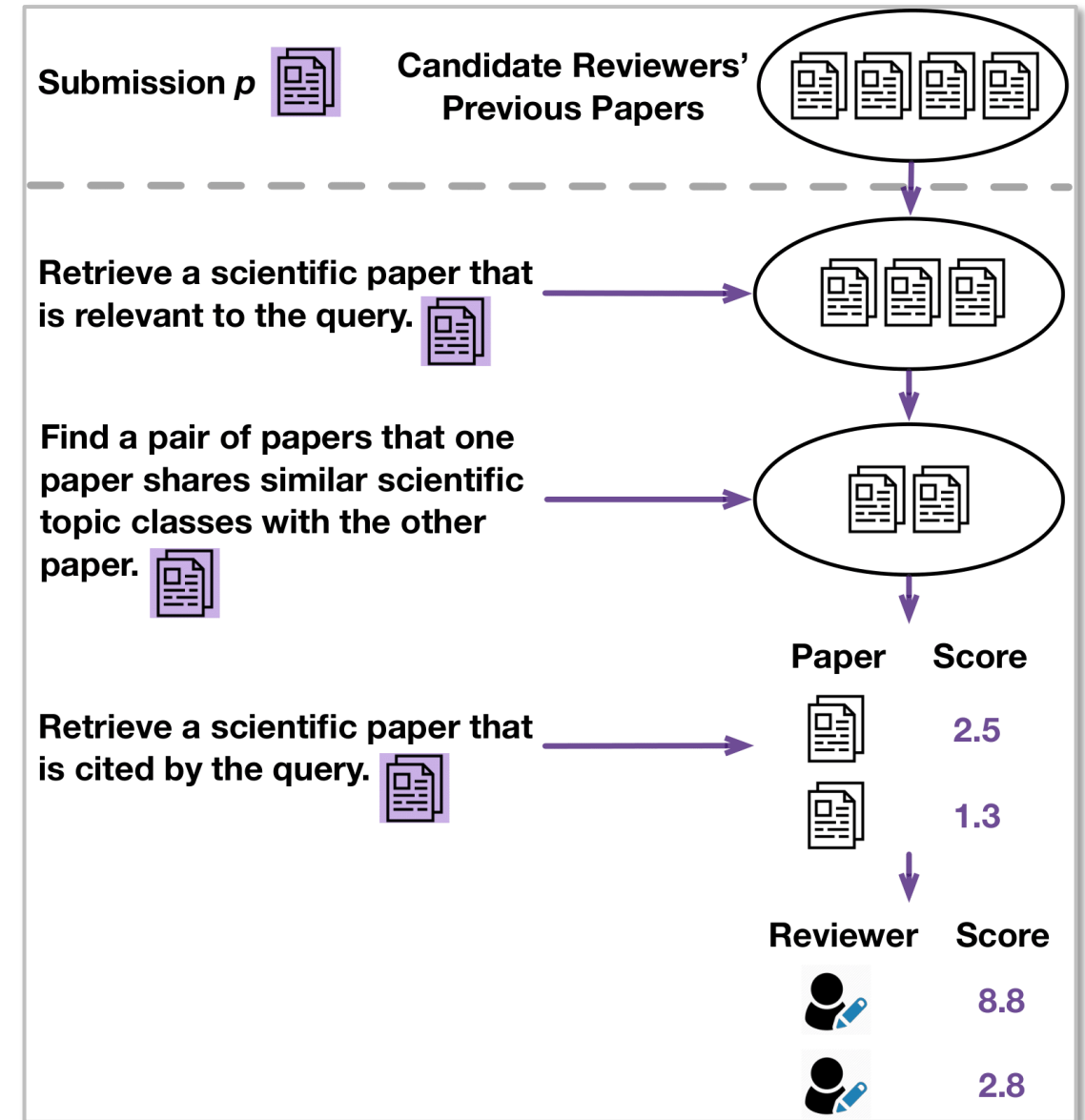
Tackling Task Interference: Instruction Tuning

- Using a **factor-specific instruction** to guide the paper encoding process
- The instruction serves as the context of the paper.
- The paper does NOT serve as the context of the instruction.









Chain-of-Factors Reasoning

- Consider semantic, topic, and citation factors in a **step-by-step, coarse-to-fine** manner.
- Step 1:** **Semantic** relevance serves as the coarsest signal to filter totally irrelevant papers.
- Step 2:** Then, we can classify each submission and each relevant paper to a fine-grained **topic** space and check if they share common topics.
- Step 3:** After confirming that a submission and a reviewer's previous paper have common topics, the **citation** link between them will become an even stronger signal, indicating that the two papers may focus on the same task or datasets.



Comparison with Previous Approaches

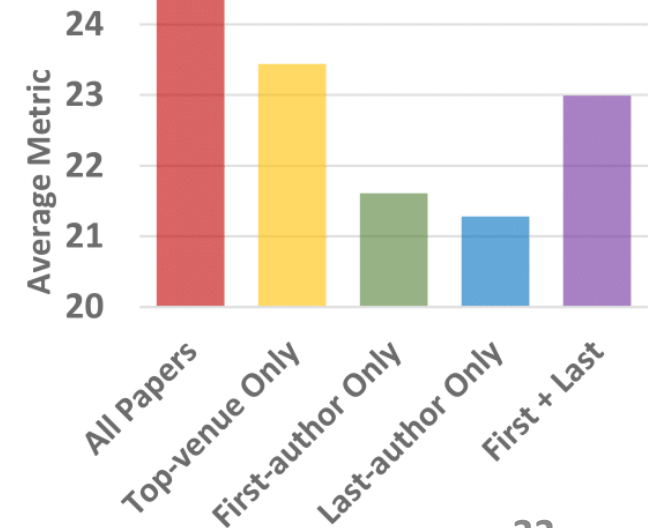
- Public benchmark datasets
 - Expert C judges whether Reviewer A is qualified to review Paper B.
- Outperforming the **Toronto Paper Matching System** (TPMS, used by Microsoft CMT)

		SciRepEval [44]					SIGIR [19]					KDD				
		Soft P@5	Soft P@10	Hard P@5	Hard P@10	Average	Soft P@5	Soft P@10	Hard P@5	Hard P@10	Average	Soft P@5	Soft P@10	Hard P@5	Hard P@10	Average
	TPMS [7]	62.06**	53.74**	31.40**	24.86**	43.02**	39.73**	38.36**	17.81**	17.12**	28.26**	17.01**	16.78**	6.78**	7.24**	11.95**
	SciBERT [6]	59.63**	54.39**	28.04**	24.49**	41.64**	34.79**	34.79**	14.79**	15.34**	24.93**	28.51**	27.36**	12.64**	12.70**	20.30**
	SPECTER [9]	65.23**	56.07	32.34**	25.42	44.77**	39.73**	40.00**	16.44**	16.71**	28.22**	34.94**	30.52**	15.17**	13.28	23.48**
	SciNCL [34]	66.92**	55.42**	34.02*	25.33	45.42**	40.55**	39.45**	17.81**	17.40*	28.80**	36.21**	30.86**	15.06**	12.70**	23.71**
	COCO-DR [56]	65.05**	55.14**	31.78**	24.67**	44.16**	40.00**	40.55*	16.71**	17.53	28.70**	35.06**	29.89**	13.68**	12.13**	22.69**
	SPECTER 2.0 CLF [44]	64.49**	55.23**	31.59**	24.49**	43.95**	39.45**	38.63**	16.16**	16.30**	27.64**	34.37**	30.63**	14.48**	12.64**	23.03**
	SPECTER 2.0 PRX [44]	66.36**	55.61**	34.21	25.61	45.45**	40.00**	38.90**	19.18**	16.85**	28.73**	37.13	31.03	15.86**	13.05*	24.27*
Our Model	CoF	68.47	55.89	34.52	25.33	46.05	45.57	41.69	22.47	17.76	31.87	37.63	31.09	16.13	13.08	24.48

 : semantic-based method  : topic-based method  : citation-based method

Impact of Reviewer's Profile on the Matching Performance

- Shall we include all papers written by a reviewer or set up some criteria?
- **Timespan**: What if we include papers published in the most recent Y years only (because earlier papers may have diverged from reviewers' current interests)?
 - Earlier papers still help, but the contribution becomes subtle when $Y \geq 10$.
- **Venue**: What if we include papers published in top venues only?
 - Harmful!
- **Rank in the author list**: What if we include each reviewer's first-author and/or last-author papers only?
 - Harmful!
- When the indication from reviewers is not available, putting the **entire** set of their papers into their publication profile is almost always helpful.



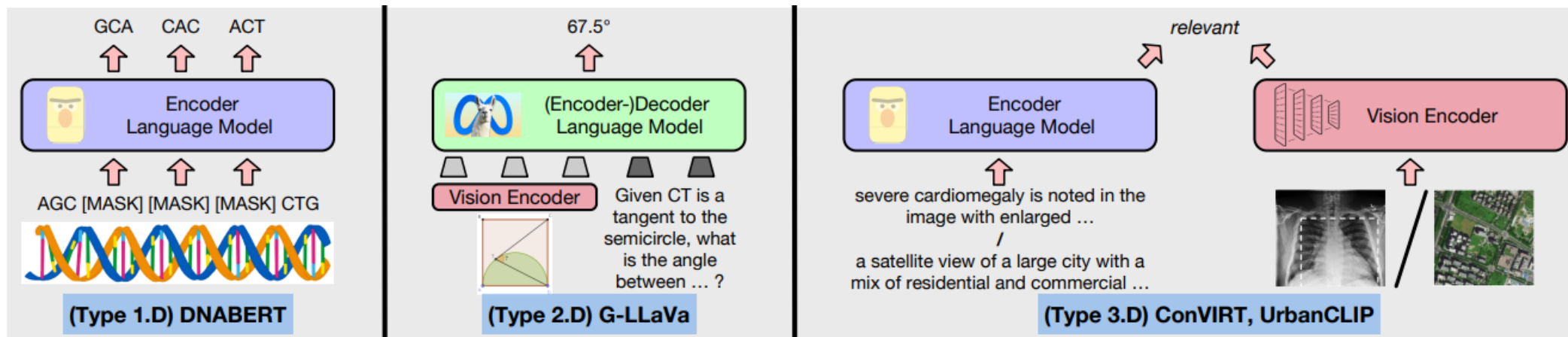
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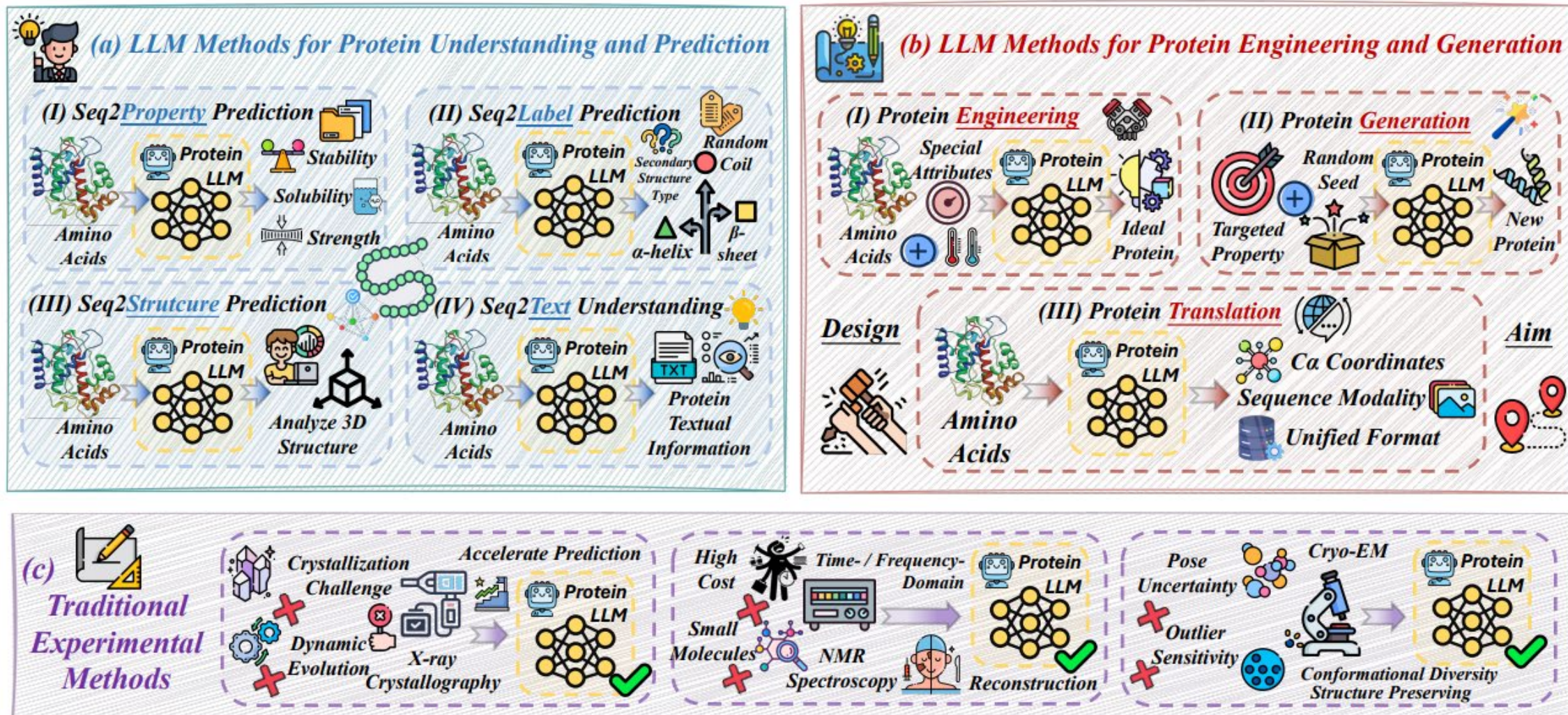
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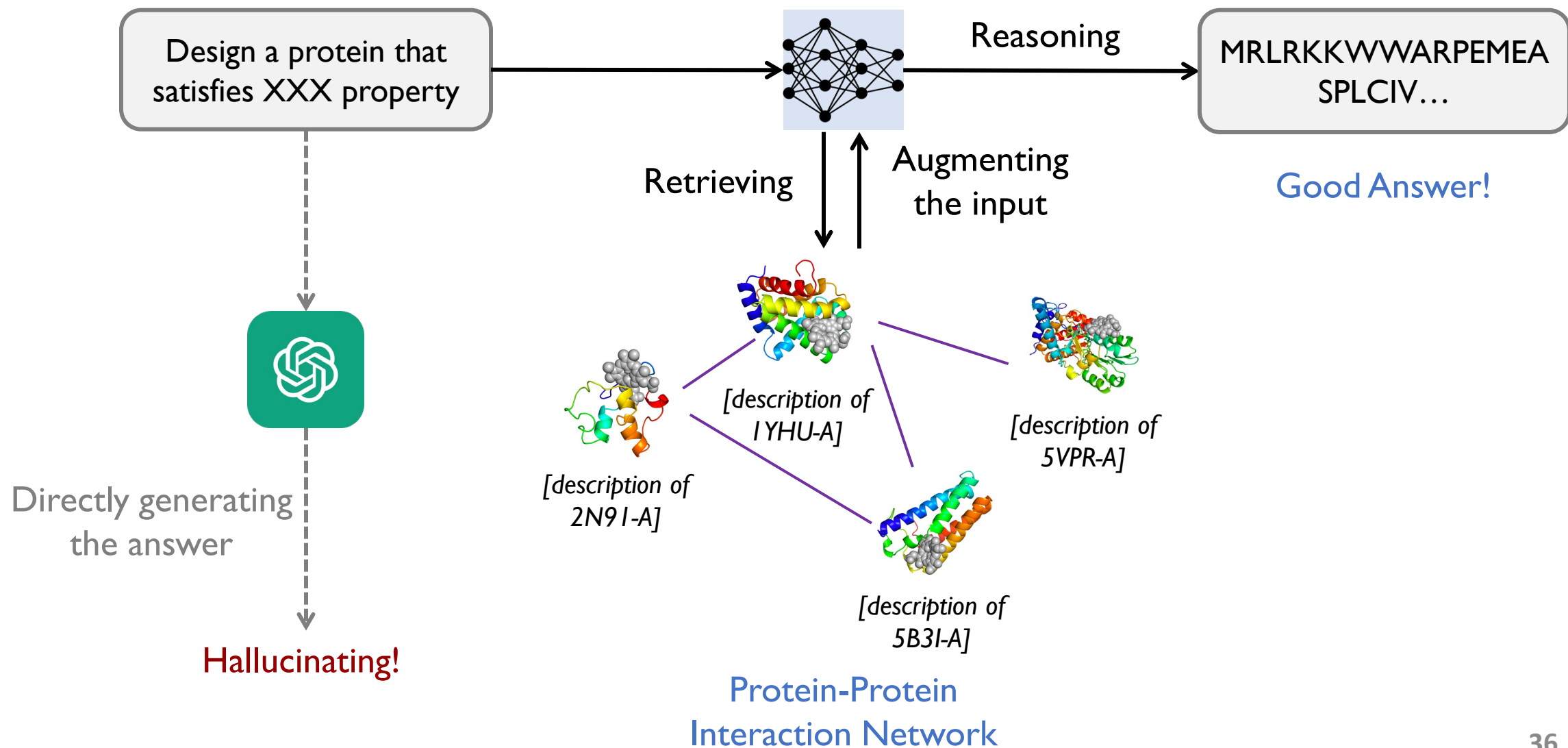
A curated list of pre-trained language models in scientific domains (e.g., mathematics, physics, chemistry, materials science, biology, medicine, geoscience), covering different model sizes (from 100M to 100B parameters) and modalities (e.g., language, graph, vision, table, molecule, protein, genome, climate time series).



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Thank you! Questions?