Knowledge-aware NLP Techniques for Trustworthy AI Systems

Reporter： LIU, Ye

Research area： NLP, LLM, KG

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Basic Information

LIU, Ye

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Education

- **2024 – now** Hong Kong University of Science and Technology, Advisor: Prof. Xiaofang Zhou
  Visiting Ph.D. Student, in Computer Science and Engineering
- **2019 – now** University of Science and Technology of China, Advisor: Prof. Enhong Chen
  Ph.D. Candidate, in Data Science - Computer Science and Technology, GPA: 3.90/4.3
- **2015 – 2019** University of Science and Technology of China,
  B.E., in Electronic Information Engineering, GPA: 3.78/4.3

Research Interest

- **Natural Language Processing**
- **Knowledge Graph, Large Language Models**

Basic Information

Publications

- **Preprints:**
  - ✓ 4 papers, including 1 first author paper, 1 co-first author paper
- **Publications:**
  - ✓ 22 papers, including 4 first author papers
- **Representative Publications:**

1. ***Ye Liu***, Kai Zhang, Zhenya Huang, Kehang Wang, Yanghai Zhang, Qi Liu, Enhong Chen. Enhancing Hierarchical Text Classification through Knowledge Graph Integration. Findings of the 61st annual meeting of the Association for Computational Linguistics (ACL-Findings), 2023.
2. ***Ye Liu***, Han Wu, Zhenya Huang, Hao Wang, Yuting Ning, Jianhui Ma, Qi Liu, Enhong Chen*. TechPat: Technical Phrase Extraction for Patent Mining. ACM Transactions on Knowledge Discovery from Data (ACM TKDD), 2023.
3. ***Ye Liu***, Kai Zhang, Aoran Gan, Linan Yue, Feng Hu, Qi Liu, Enhong Chen. Empowering Few-Shot Relation Extraction with The Integration of Traditional RE Methods and Large Language Models. The 29th International Conference on Database Systems for Advanced Applications (DASFAA), 2024.
4. ***Ye Liu***, Han Wu, Zhenya Huang, Hao Wang, Jianhui Ma, Qi Liu, Enhong Chen*, Hanqing Tao and Ke Rui. Technical Phrase Extraction for Patent Mining: A Multi-level Approach. The 2020 IEEE International Conference on Data Mining (ICDM), 2020.

Basic Information

Publications

- **Representative Publications:**

5. Yanghai Zhang, ***Ye Liu***, Shiwei Wu, Kai Zhang, Xukai Liu, Qi Liu, Enhong Chen. Leveraging Entity Information for Cross-Modality Correlation Learning: The Entity-Guided Multimodal Summarization. The 62nd annual meeting of the Association for Computational Linguistics (ACL-Findings), 2024.
6. Xukai Liu, Kai Zhang, ***Ye Liu***, Enhong Chen, Zhenya Huang, , Linan Yue, Jiaxian Yan. RHGH: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs. Findings of the 61st annual meeting of the Association for Computational Linguistics (ACL-Findings), 2023.
7. ***Ye Liu***, Jiajun Zhu, Kai Zhang, Haoyu Tang, Yanghai Zhang, Xukai Liu, Qi Liu, Enhong Chen. Detect, Investigate, Judge and Determine: A Novel LLM-based Framework for Few-shot Fake News Detection. AAAI 2025 (Under Review).
8. Haoyu Tang (equal contribution), ***Ye Liu (equal contribution)***, Xukai Liu, Kai Zhang, Yanghai Zhang, Qi Liu, Enhong Chen. Learn while Unlearn: An Iterative Unlearning Framework for Generative Language Models. ICLR 2025 (Under Review).

Honors

- **2016**, National Scholarship
- **2023**, CICAI Finalist of Best Paper Award (Top-3)
- **2019, 2020, 2022, 2023**, Graduate Student First-class Academic Scholarship

OUTLINE

CONTENTS

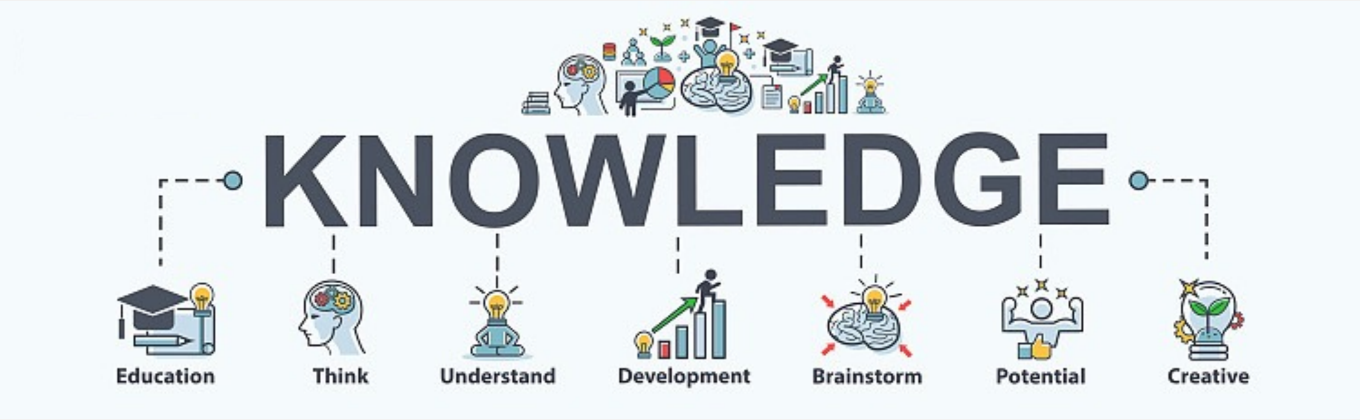
Background

- Rapid advancement of NLP technologies has significantly improved various real-world applications.
  - ChatGPT
  - Llama
  - ChatGLM
  - Bring the total change to human daily life
    - ✓ AI assistant Writing
    - ✓ AI assistant Coding
    - ✓ AI assistant Search
    - ✓ AI for Science
    - ✓ AI for Medicine …

Background

- Faced with severe trustworthiness challenges.
  - ***Hallucination***
  - ***Knowledge Limitation***
  - Especially for domain specific tasks, such as domain-specific text ***Classification*** and ***Generation***.
    - ✓ AI for Law
    - ✓ AI for Health
    - ✓ AI for Science
  - How to build a trustworthy AI system lies a severe problem in AI progress.

Background



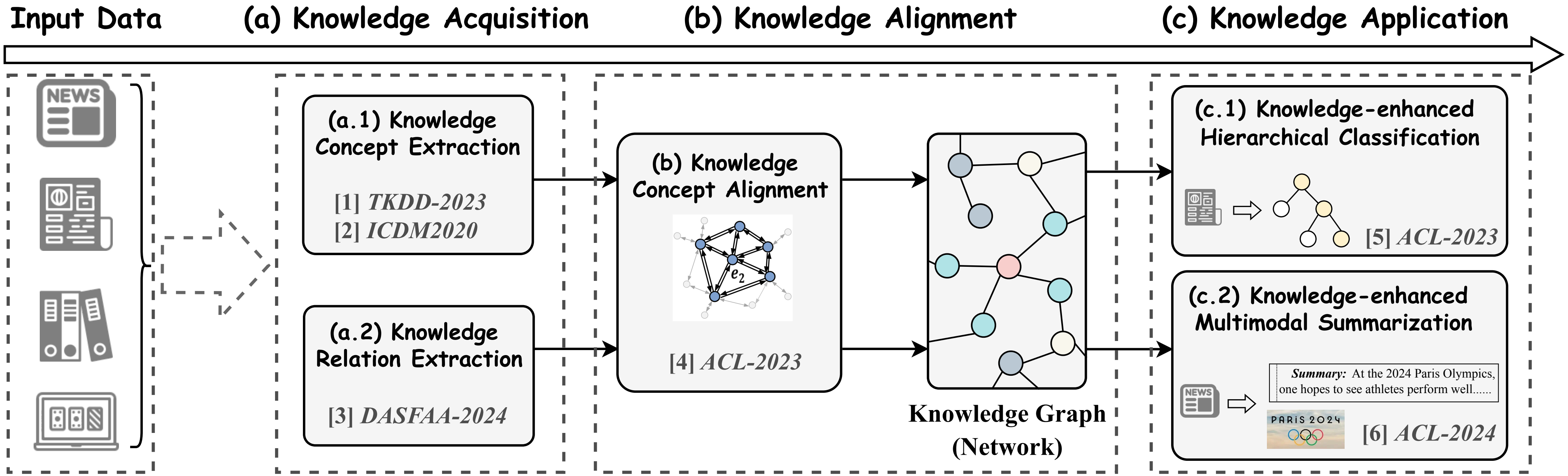
Under this circumstance,

knowledge-aware NLP technique becomes increasingly important

Background

Knowledge-aware NLP techniques

- Knowledge ***Acquisition***
- Knowledge ***Alignment***
- Knowledge ***Application***



OUTLINE

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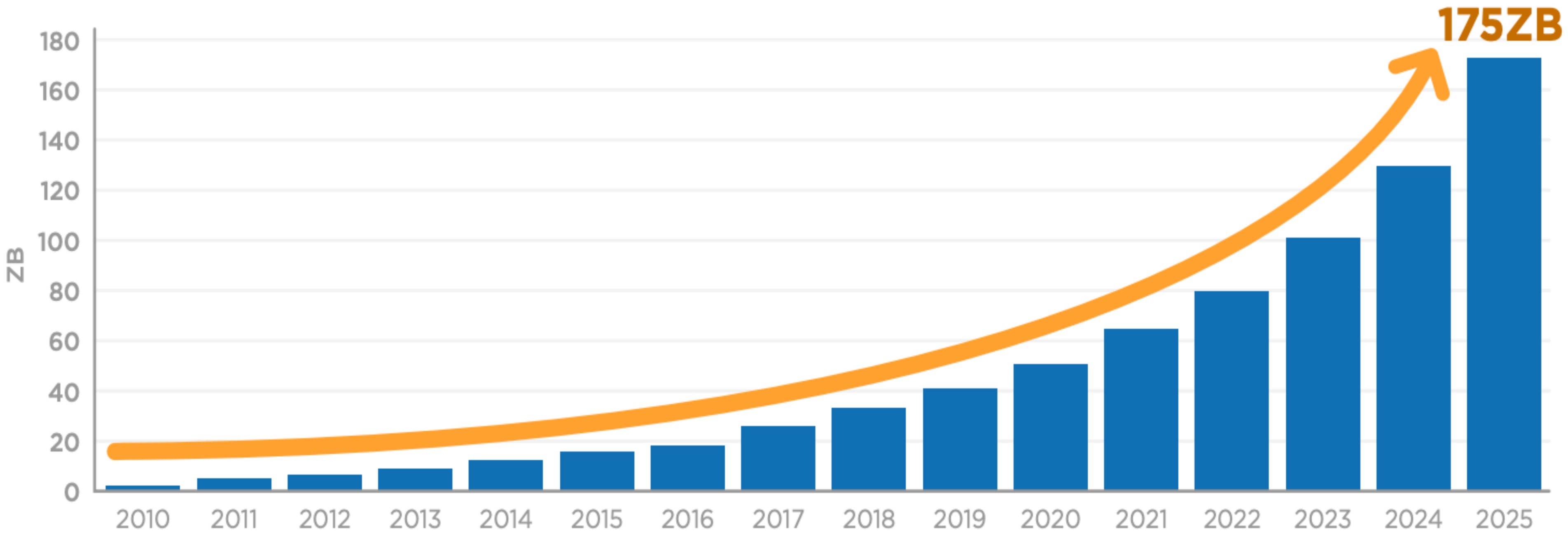
Knowledge Acquisition

- Age of Information Explosion
  - Massive amounts of data and knowledge in networks everyday
  - Seagate Technology Report
    - Global data volume will reach ***175 ZB*** by ***2025***



Knowledge Acquisition

☐ Age of Information Explosion

- Only a small fraction of daily data is effectively used
- How to extract effective knowledge from massive data is an increasingly serious challenge

<u>60-73%</u> of daily generated data is not effectively used for analysis due to various reasons.

—— Forrester Research, Inc.

Knowledge Acquisition

Knowledge Acquisition aims to extract <u>structured knowledge</u> from large-scale documents:

1. ***Knowledge Concept Extraction***
2. ***Knowledge Relation Extraction***

<u>60-73%</u> of daily generated data is not effectively used for analysis due to various reasons.

—— Forrester Research, Inc.

Knowledge Acquisition

Unsupervised Knowledge Concept Extraction

- A well-defined problem
- Identify **knowledge concepts** from various documents without the aid of data annotation.

- Example:

Title:
Support vector machine for remote sensing image …

Abstract:
… Among these machine learning algorithms, Random Forest (RF) and Support Vector Machines (SVM) have drawn attention to image…

1. Support Vector Machine
2. Machine Learning
3. Random Forest

……

TechPat: Technical Phrase Extraction for Patent Mining, TKDD2023, ICDM2020

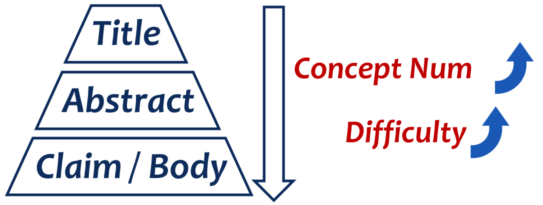
Knowledge Acquisition

Related Work

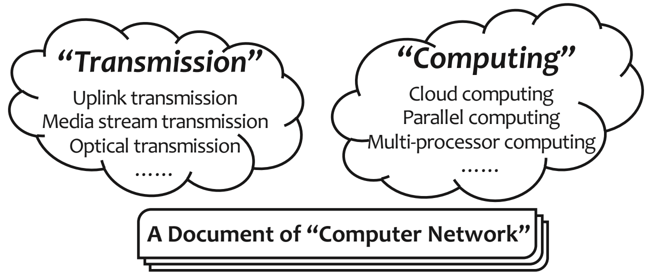
- **Feature Engineering Methods: Autophrase (TKDE'2018)**
  - ✓ Introduce remote quality supervision, trained with the help of cross-domain data
- **Pretrained Methods: JMLGC (EMNLP'2021)**
  - ✓ Mine deep semantic features within the text with pre-trained models (BERT)

Shortcomings

- Lacks consideration of ***multi-level structure***
  - ✓ Title, Abstract, etc.
  - ✓ Concept Num ⇧,   Extraction Difficulty ⇧



- Overlooks the complex ***semantic associations between concepts***, especially in long texts.

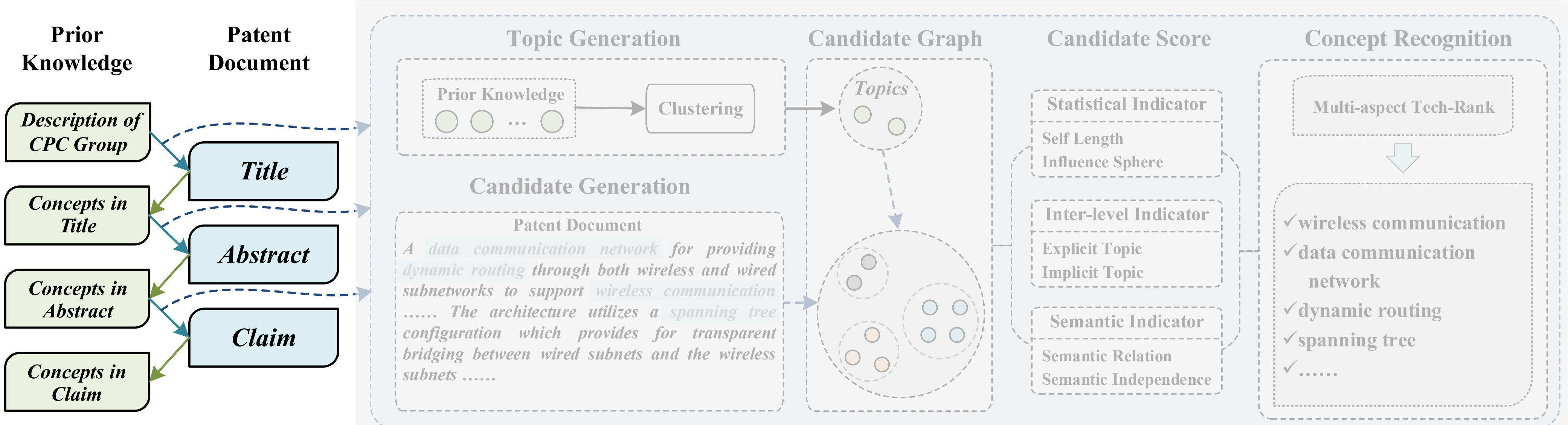


TechPat: Technical Phrase Extraction for Patent Mining, TKDD2023, ICDM2020

Knowledge Acquisition

☐ *Multi-level Extraction Architecture*

- Extract concepts from short sections (e.g., titles) to ***Guide*** extraction from long sections (e.g., abstracts, bodies/claims)
- Follow the principle of learning from ***simple*** to ***complex***



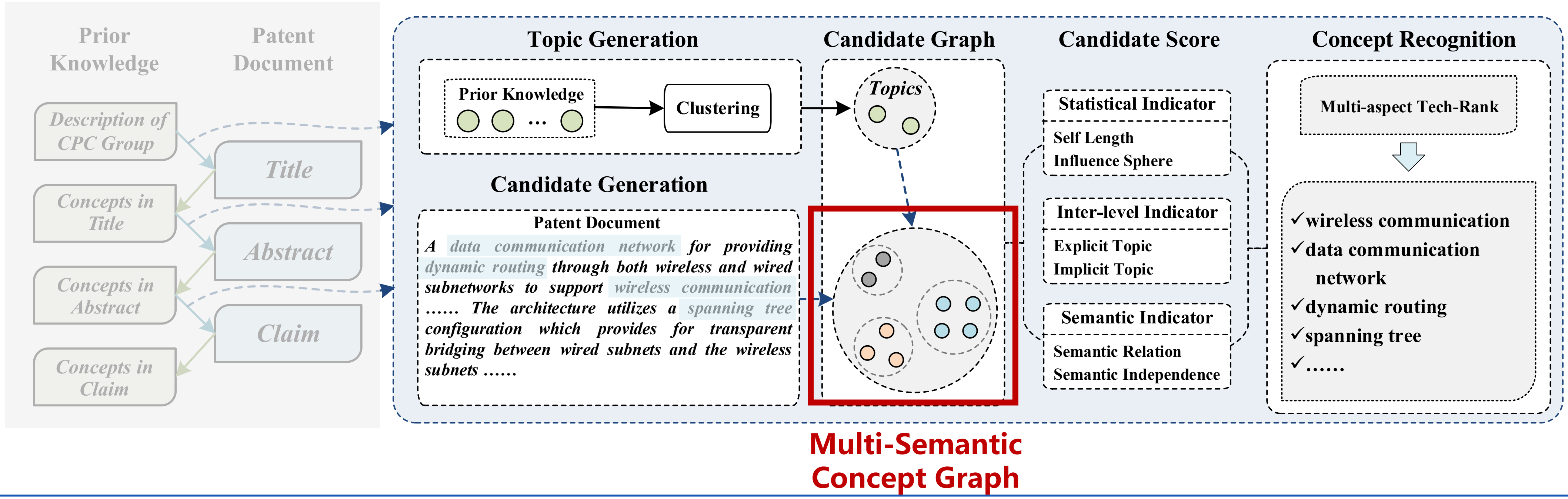
Multi-level Extraction Architecture

TechPat: Technical Phrase Extraction for Patent Mining, TKDD2023, ICDM2020

Knowledge Acquisition

Multi-Semantic Concept Graph

- Generation & Selection
  - ✓ **Node** → Candidate Concept
  - ✓ **Subgraph** → Topic



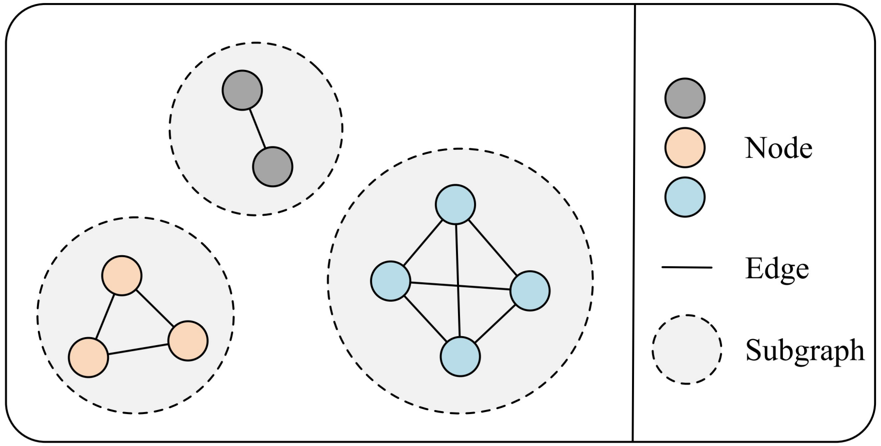
TechPat: Technical Phrase Extraction for Patent Mining, TKDD2023, ICDM2020

Knowledge Acquisition

☐ *Multi-Semantic Concept Graph*

- **Node** → Candidate Concept
- **Subgraph** → Topic

- Design the ***Multi-Semantic Graph based Propagation Algorithm*** to identify these important and salient concepts



ALGORITHM 1: Multi-aspect Tech-Rank

Input: Multi-aspect graph, $G = (V, S, E, W)$; The normalized score of nodes, I_{node}; Damping factor, d; Harmonic factor, β

Output: Ranked possible phrase list, P_{list}

Initialize the ranking value list uniformly, R_{list}
while not converge **do**
    Calculate the ranking value $R(s_i)$ for each subgraph $s_i \in S$.
    Update R_{list} from local and global perspectives.
end while
Rank all candidate phrases according to R_{list} to get ranked phrase list, P_{list}
return P_{list}

TechPat: Technical Phrase Extraction for Patent Mining, TKDD2023, ICDM2020

Knowledge Acquisition

Experiments

- **Datasets**
  - ✓ USTPO Patent
  - ✓ Scientific Paper

Dataset	Num. Doc	Avg. sentences of Title	Avg. sentences of Abstract
Engineering	11,186	1.00	3.85
Electricity	84,069	1.00	3.89
Paper	100,000	1.02	7.01

- **Compared Baselines**
  - ✓ Traditional Methods: Rake, Spacy, DBpedia …
  - ✓ DL Methods: ECON, JMLGC …

- **Evaluation Metrics**
  - ✓ Precision
  - ✓ Recall
  - ✓ F1-score

Method	Mechanical Engineering			Electricity		
	Precision	Recall	F1-score	Precision	Recall	F1-score
ECON	26.70	10.43	14.01	23.76	8.19	11.35
DBpedia	**43.13**	11.49	16.80	35.08	10.29	14.99
Autophrase	28.18	26.83	25.47	27.49	31.83	27.27
NE-rank	20.01	31.05	22.81	21.53	33.23	24.11
Rake	16.17	26.89	18.78	14.03	24.53	16.53
Spacy	32.42	48.83	36.41	32.37	49.27	36.20
MultipartiteRank	37.80	51.21	40.66	36.37	49.15	38.84
JMLGC	34.86	48.58	37.92	37.67	50.05	39.92
UMTPE	37.04	54.58	41.28	38.49	54.93	41.66
TechPat	39.83	**55.32**	**43.10**	**38.98**	**55.10**	**41.89**

TechPat: Technical Phrase Extraction for Patent Mining, TKDD2023, ICDM2020

Knowledge Acquisition

- Lead the ***multi-level extraction*** paradigm
  - Inspired many following extraction models *[1-5]*

[1] Zhou P, Jiang X, Zhao S. Unsupervised technical phrase extraction by incorporating structure and position information[J]. Expert Systems with Applications, 2024.
[2] Miao R, Chen X, Hu L, et al. PatSTEG: Modeling Formation Dynamics of Patent Citation Networks via The Semantic-Topological Evolutionary Graph[C]//2023 IEEE International Conference on Data Mining (ICDM). IEEE, 2023: 1229-1234.
[3] Mao R, He K, Zhang X, et al. A survey on semantic processing techniques[J]. Information Fusion, 2024, 101: 101988.
[4] Marques T D, Gonçalves A L. UMA REVISÃO INTEGRATIVA PARA SISTEMAS DE BUSCA POR PATENTES SIMILARES UTILIZANDO IA: AVANÇOS, DESAFIOS E APLICAÇÕES[C]//Anais do Congresso Internacional de Conhecimento e Inovação–ciki. 2023.
[5] Gao W, Wang H, Liu Q, et al. Leveraging transferable knowledge concept graph embedding for cold-start cognitive diagnosis[C]//Proceedings of the 46th international ACM SIGIR conference on research and development in information retrieval. 2023: 983-992.

① TechPat: Technical Phrase Extraction for Patent Mining

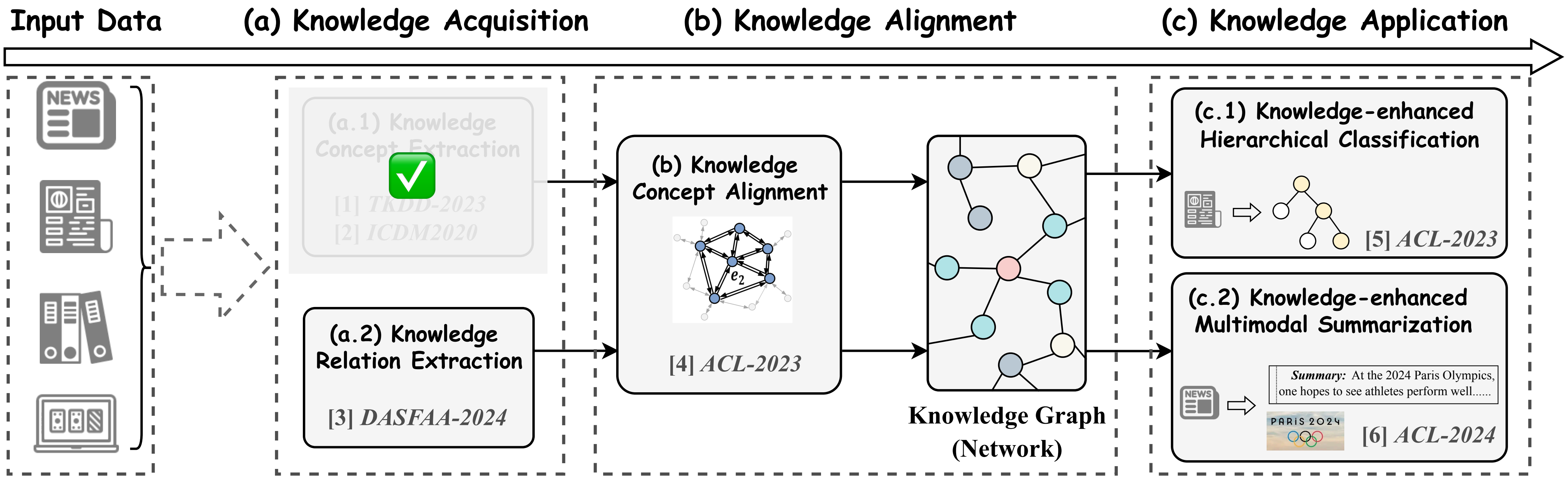
② Technical Phrase Extraction for Patent Mining: A Multi-level Approach

Published at TKDD2023, ICDM2020

TechPat: Technical Phrase Extraction for Patent Mining, TKDD2023, ICDM2020

Knowledge Acquisition

- Knowledge-aware NLP techniques
  - Knowledge ***Acquisition***
  - Knowledge Alignment
  - Knowledge Application



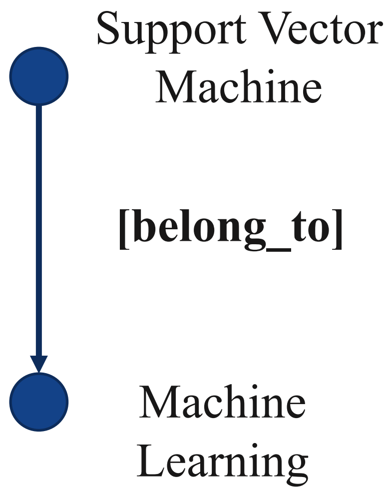
Knowledge Acquisition

Knowledge Relation Extraction

- A long-studied problem
- Given the ***concept pair (c_1, c_2)*** in text, determine the ***relationship*** between two concepts: $r \in R$, where R is the set of relationships defined in advance.

- Example:

…Support vector machines (SVMs) are supervised learning models in machine learning, which is usually adopted to……



Knowledge Acquisition

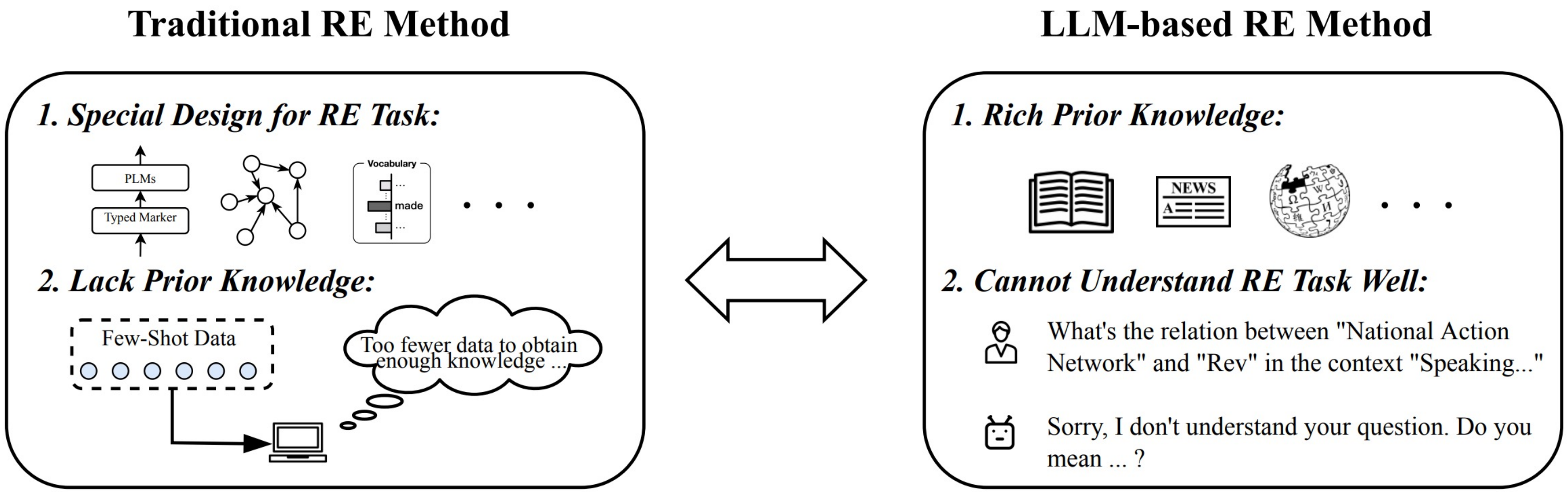
Knowledge Relation Extraction

- A long-studied problem
- Given the ***concept pair (c_1, c_2)*** in text, determine the ***relationship*** between two concepts: $r \in R$, where R is the set of relationships defined in advance.

- ***Low resource setting:***
  - ✓ Data resources are limited: there are only K samples for each relationship in the training and validation stages.
  - ✓ K=8 → 8-shot
  - ✓ K=16 → 16-shot

Knowledge Acquisition

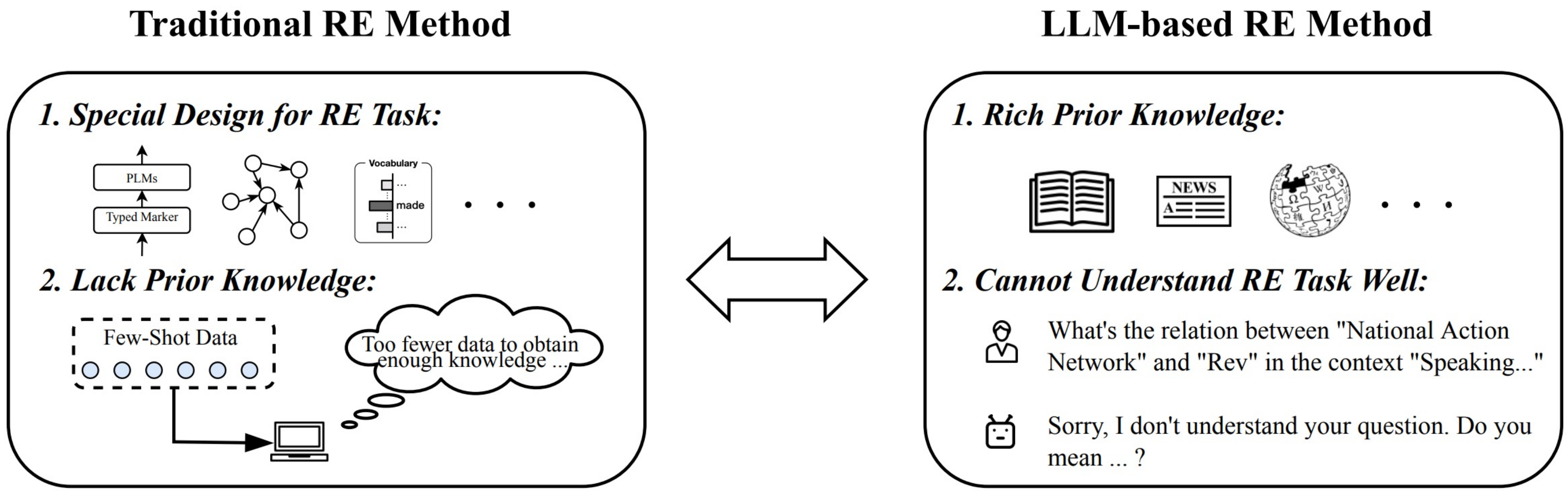
- Related Work:
  - Traditional Methods: KnowPrompt (WWW'2022)
    - ✓ ***Lacks prior knowledge*** in low resource settings
  - LLM Methods: Unleash (ACL'2023 Workshop)
    - ✓ Has sufficient prior knowledge but ***struggles with specific tasks*** due to training on the general corpus



Knowledge Acquisition

- Related Work:
  - Traditional Methods: KnowPrompt (WWW'2022)
    - Lacks prior knowledge in low resource settings
  - LLM
    - Has sufficient prior knowledge but *struggles with specific tasks* due to training on the general corpus

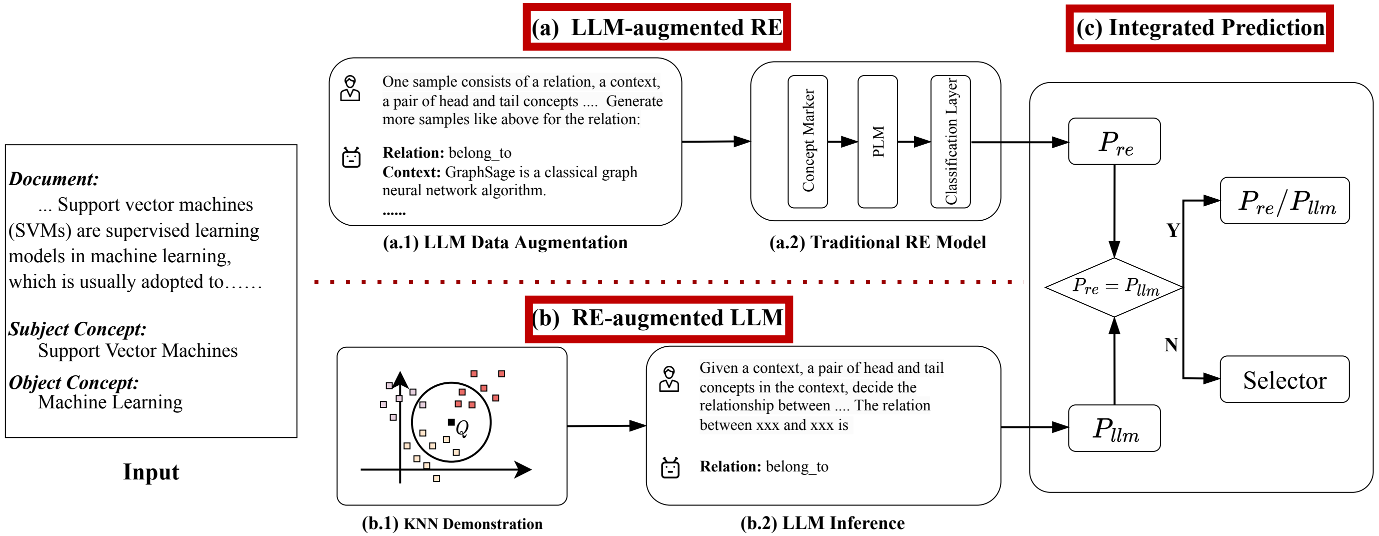
Can we integrate the strengths of the two kinds of methods to complement each other?



Knowledge Acquisition

Dual-System Augmented Relation Extractor (DSARE)

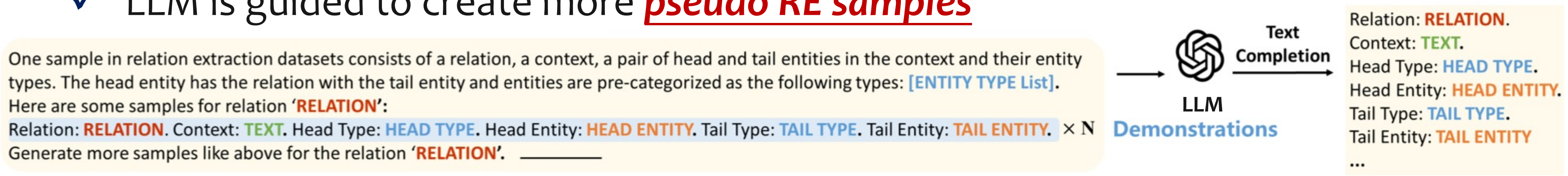
- ***LLM-augmented RE:***
  - ✓ Impart the prior knowledge inherent in LLMs to the traditional RE models
- ***RE-augmented LLM:***
  - ✓ Transfer traditional RE model's understanding of the RE to LLMs
- ***Integrated Prediction module***
  - ✓ Jointly consider these two respective predictions and obtain final results



Knowledge Acquisition

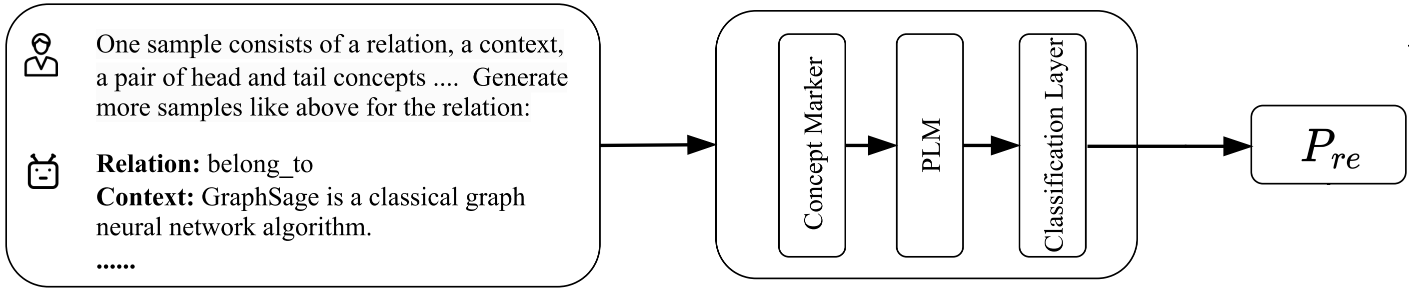
LLM-augmented RE:

- Impart the prior knowledge inherent in LLMs to traditional RE models
- **(a.1) LLM Data Augmentation**
  - ✓ LLM is guided to create more ***pseudo RE samples***



- **(a.2) Traditional RE Model → P_{re}**

(a) LLM-augmented RE

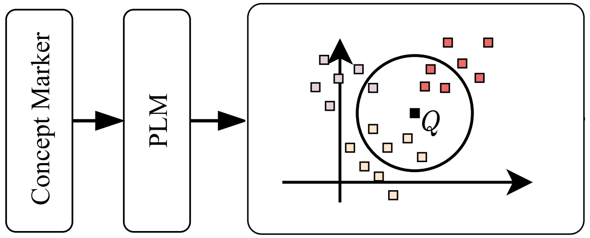


(a.1) LLM Data Augmentation **(a.2) Traditional RE Model**

Knowledge Acquisition

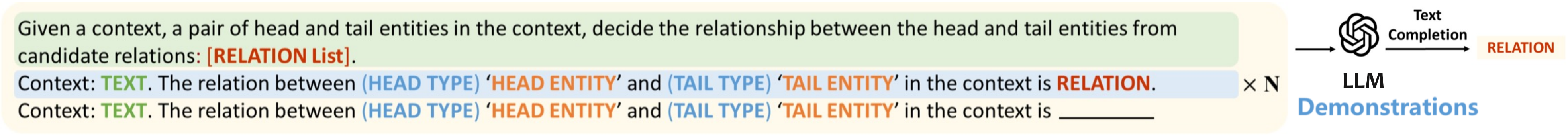
RE-augmented LLM:

- Transfer traditional RE model's understanding of the RE to LLMs.
- **(b.1) KNN Demonstration**
  - ✓ Utilize k-nearest neighbors (KNN) search method to retrieve more valuable samples from the training set



- **(b.2) LLM Inference → P_{llm}**

$$P(y_{test} \mid Instructions \uplus \mathcal{N} \uplus x_{test})$$



Empowering Few-Shot Relation Extraction with The Integration of Traditional RE Methods and Large Language Models, DASFAA2024

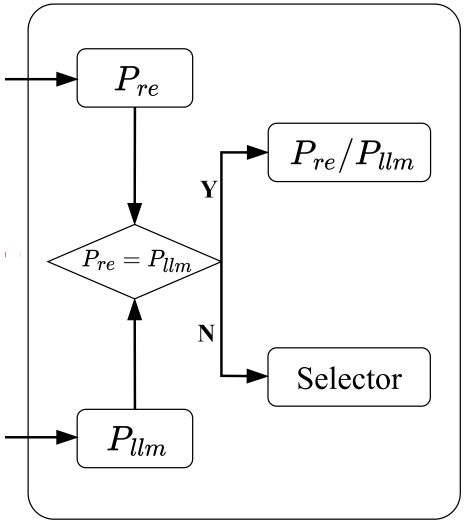
Knowledge Acquisition

Integrated Prediction

- Two results are equivalent $P_{re} = P_{llm}$
  - ✓ Directly yields the predicted relation
- Two results diverge $P_{re} \,!= \; P_{llm}$
  - ✓ Implies a conflict between the traditional RE model and the Large Language Model
  - ✓ Retrieve m samples labeled with these two relations from the training dataset
  - ✓ Ask the LLM to obtain the final result P_f

$$P(y_{test} \mid Instructions \uplus \mathcal{N} \uplus x_{test})$$

(c) Integrated Prediction



Given a context, a pair of head and tail entities in the context, decide the relationship between the head and tail entities from candidate relations: [RELATION List].
Context: TEXT. The relation between (HEAD TYPE) 'HEAD ENTITY' and (TAIL TYPE) 'TAIL ENTITY' in the context is RELATION. ×2m
Context: TEXT. The relation between (HEAD TYPE) 'HEAD ENTITY' and (TAIL TYPE) 'TAIL ENTITY' in the context is ________

Text Completion
RELATION
LLM
Demonstrations

Knowledge Acquisition

Experiments

- **Datasets**
  - ✓ TACRED
  - ✓ TACREV…

Dataset	#Train	#Dev	#Test	#Rel
TACRED	8/16/32	8/16/32	15,509	42
TACREV	8/16/32	8/16/32	15,509	42
Re-TACRED	8/16/32	8/16/32	13,418	40

- **Compared Baselines**
  - ✓ Traditional methods: TYP Marker, PTR, Knowprompt …
  - ✓ LLM Methods: GPT-3.5, Llama2 ..
- **Few-shot Setting**
  - ✓ K = 8, 16, 32
- **Evaluation Metrics**
  - ✓ Micro F1-score

Methods	TACRED			TACREV			Re-TACRED		
	K=8	K=16	K=32	K=8	K=16	K=32	K=8	K=16	K=32
① TYP Marker	29.02	31.35	31.86	26.28	29.24	31.55	51.32	55.60	57.82
② PTR	28.34	29.39	30.45	28.63	29.75	30.79	47.80	53.83	60.99
③ KnowPrompt	30.30	33.53	34.42	30.47	33.54	33.86	56.74	61.90	65.92
④ GenPT	35.45	35.58	35.61	33.81	33.93	36.72	57.03	57.66	65.25
⑤ GPT-3.5	29.72			29.98			39.06		
⑥ LLama-2	22.68			21.96			34.31		
⑦ Zephyr	37.10			38.83			35.81		
⑧ Unleash	32.24	33.81	34.76	32.70	34.53	35.28	58.29	64.37	66.03
DSARE (ours)	**43.84**	**45.40**	**45.94**	**44.69**	**46.61**	**46.94**	**60.04**	**66.83**	**67.13**

Knowledge Acquisition

Experiments

- **Datasets**
  - ✓ TACRED
  - ✓ TACREV…

Dataset	#Train	#Dev	#Test	#Rel
TACRED	8/16/32	8/16/32	15,509	42
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- **Compared Baselines**
  - ✓ Traditional methods: TYP Marker, PTR, Knowprompt …
  - ✓ LLM Methods: GPT-3.5, Llama2 ..
- **Few-shot Setting**
  - ✓ K = 8, 16, 32
- **Evaluation Metrics**
  - ✓ Micro F1-score

Noisy Data (TACRED, TACREV) — *Clean Data* (Re-TACRED)

Methods	TACRED K=8	TACRED K=16	TACRED K=32	TACREV K=8	TACREV K=16	TACREV K=32	Re-TACRED K=8	Re-TACRED K=16	Re-TACRED K=32
① TYP Marker	29.02	31.35	31.86	26.28	29.24	31.55	51.32	55.60	57.82
② PTR	28.34	29.39	30.45	28.63	29.75	30.79	47.80	53.83	60.99
③ KnowPrompt	30.30	33.53	34.42	30.47	33.54	33.86	56.74	61.90	65.92
④ GenPT	35.45	35.58	35.61	33.81	33.93	36.72	57.03	57.66	65.25
⑤ GPT-3.5		29.72			29.98			39.06	
⑥ LLama-2		22.68			21.96			34.31	
⑦ Zephyr		37.10			38.83			35.81	
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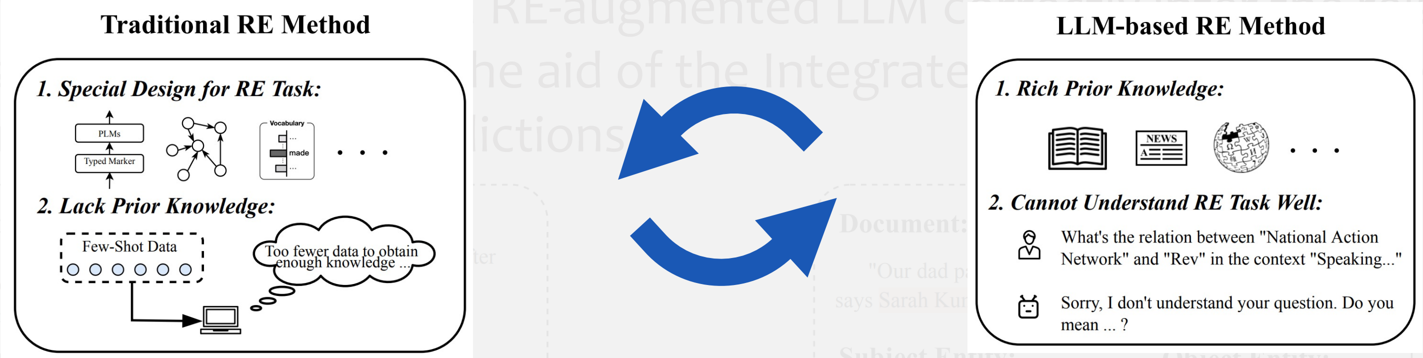
Empowering Few-Shot Relation Extraction with The Integration of Traditional RE Methods and Large Language Models, DASFAA2024

Knowledge Acquisition

First attempt to combine traditional RE models with LLMs



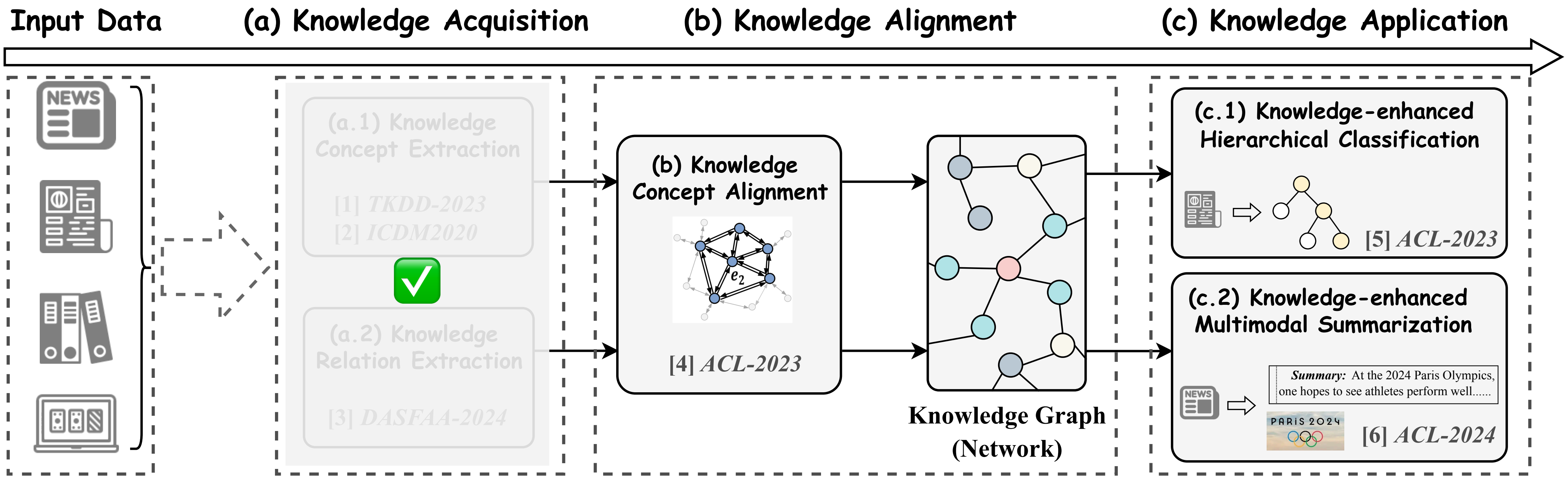
Empowering Few-Shot Relation Extraction with The Integration of Traditional RE Methods and Large Language Models

Published at DASFAA2024

Empowering Few-Shot Relation Extraction with The Integration of Traditional RE Methods and Large Language Models, DASFAA2024

Knowledge Acquisition

- Knowledge-aware NLP techniques
  - Knowledge Acquisition
  - Knowledge ***Alignment***
  - Knowledge Application



OUTLINE
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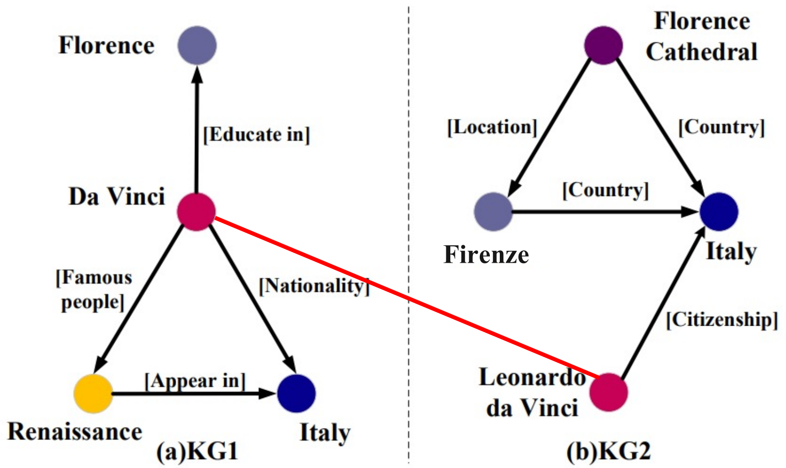
Knowledge Alignment

Knowledge Concept Alignment

- Given two knowledge graphs, knowledge concept alignment aims to find equivalent concepts across two KGs.
  - ✓ ***Da Vinci*** ~ ***Leonardo da Vinci***



- A single KG is usually incomplete
- Concept alignment is a crucial task for knowledge graph fusion

RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs, ACL2023

Knowledge Alignment

Related Work

- Existing methods
  - ✓ ***Translational Principle***: TransE, MtransE, IPTransE, AlignE
  - ✓ ***Neighbor-based Models***: GCNAlign, AliNet, HyperKA

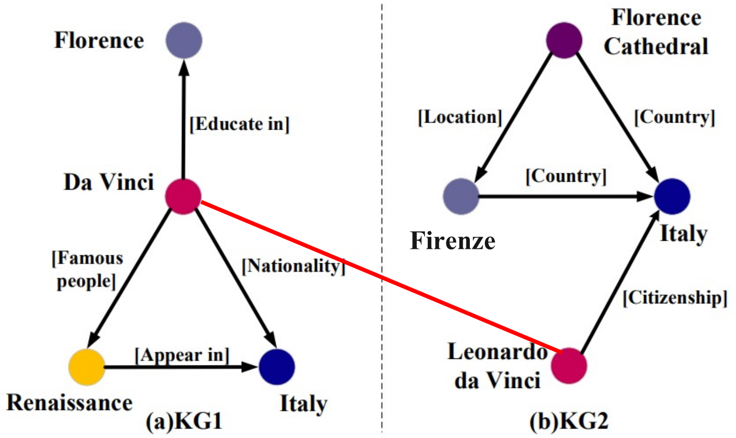
    ➡ ***Fail to separate relation from concept representation***

  - ✓ ***Relation-based Models***: RSN4EA, KE-GCN, IMEA

    ➡ ***Simple functions as message functions, barely distinguishing relations from concepts***

Challenge 1:

Distinction between KG concept and relation



RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs, ACL2023

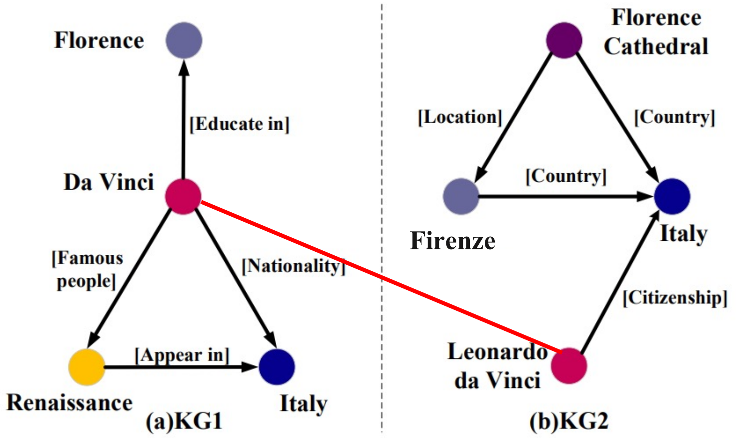
Knowledge Alignment

Related Work

Challenge 2:

Heterogeneity between different knowledge graphs

- ***(1) Neighbor Heterogeneity***
  - ✓ Same concept, different neighbors.
  - ✓ ***Da Vinci***: 3 neighbors in KG1; ***Leonardo da Vinci***: 1 neighbor in KG2
- ***(2) Relation heterogeneity***
  - ✓ Same relation, various expressions.
  - ✓ (***Italy, Nationality, Da Vinci***) in KG1
  - ✓ (***Italy***, ***Citizenship***, ***Leonardo da Vinci***) in KG2

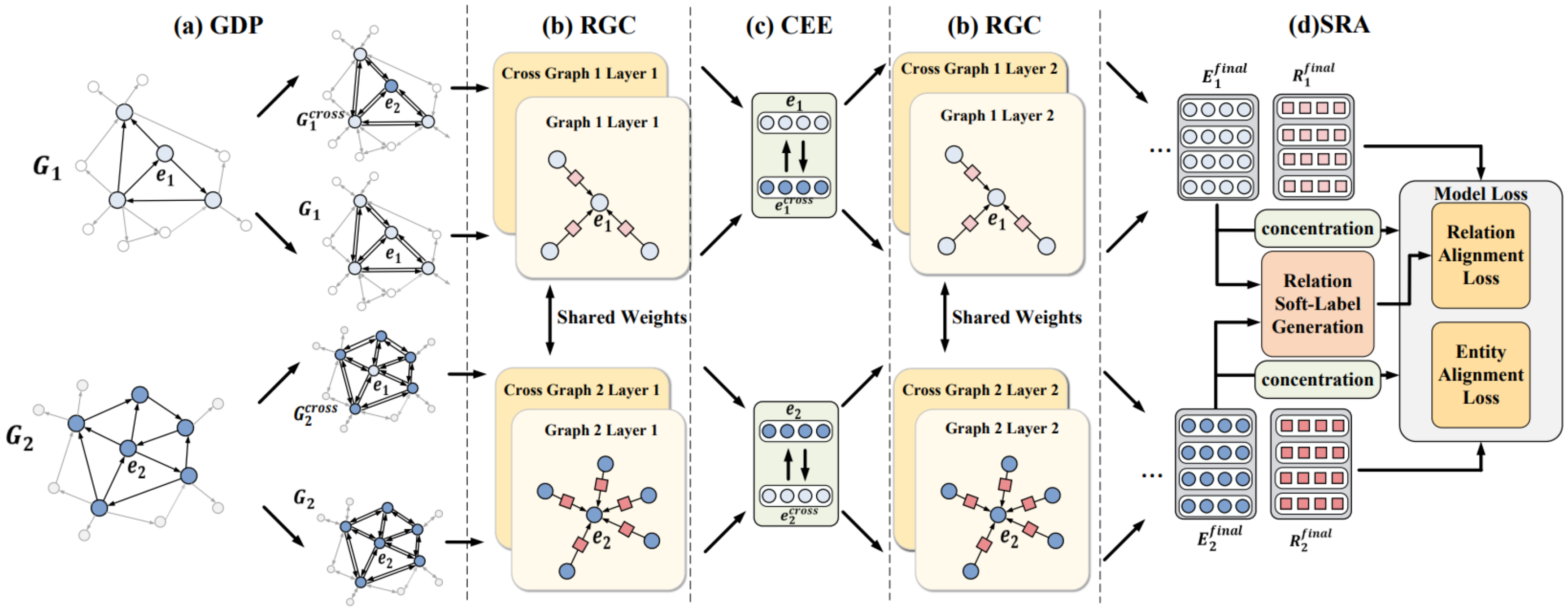


RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs, ACL2023

Knowledge Alignment

Relation-gated Heterogeneous Graph Network (RHGH)

- **(a) Graph Data Preprocessing (GDP):** Preprocesses graphs
- **(b) Relation Gated Convolution (RGC):** Aggregate information of concept and rels.
- **(c) Cross-graph Embedding Exchange(CEE):** Exchanges embeddings of cross graphs
- **(d) Soft Relation Alignment (SRA):** Produce soft labels for relation alignment



RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs, ACL2023

Knowledge Alignment

Graph Data Preprocessing (GDP)

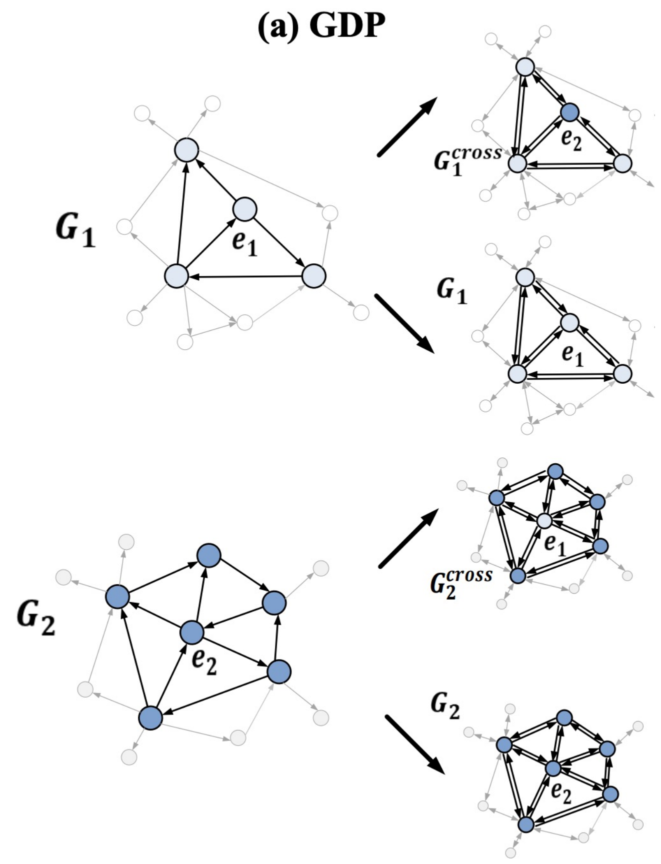
- ***Inverse Relation Embedding***
  - ✓ Complete unidirectional relation.
  - ✓ Inverse relation: $r_{inv_i} = W_{inv} r_i$
  - ✓ New graph:

$$T' = T \cup \{(t, r_{inv}, h) | (h, r, t) \in T\}$$

- ***Cross Graph Construction***
  - ✓ Address neighbor heterogeneity
  - ✓ Cross Graph:

$$e_1^{cross} = \begin{cases} e_2 & \text{if} \quad e_1 \in S'_{KG_1,KG_2} \; and \; e_1 \sim e_2 \\ e_1 & \text{else.} \end{cases}$$

$$e_2^{cross} = \begin{cases} e_1 & \text{if} \quad e_2 \in S'_{KG_1,KG_2} \; and \; e_2 \sim e_1 \\ e_2 & \text{else.} \end{cases}$$



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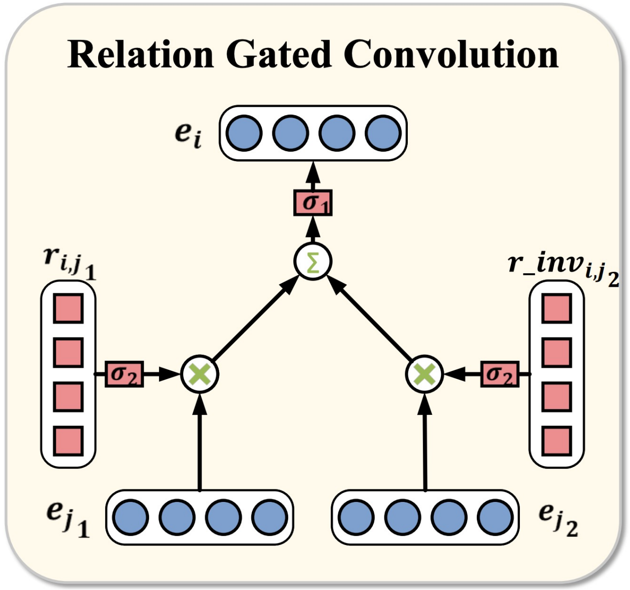
Knowledge Alignment

□ Relation Gated Convolution (RCG)

- Separate the semantic space of relations and concepts.
- Utilize the relation as the ***Signal*** to control the information from its neighbors
- ***Gate mechanism*** through a non-linear activation function (σ2)

$$e_i^{k+1} = \sigma_1 (\sum_{j \in N(i)} W_e^k (e_j^k \otimes \sigma_2 (r_{i,j}^k)))$$



- Relation updating:

$$r_{i,j}^{k+1} = W_r^k r_{i,j}^k$$

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Knowledge Alignment

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Addressed Challenge 1:

Concept Relation Distinction

RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs, ACL2023

Knowledge Alignment

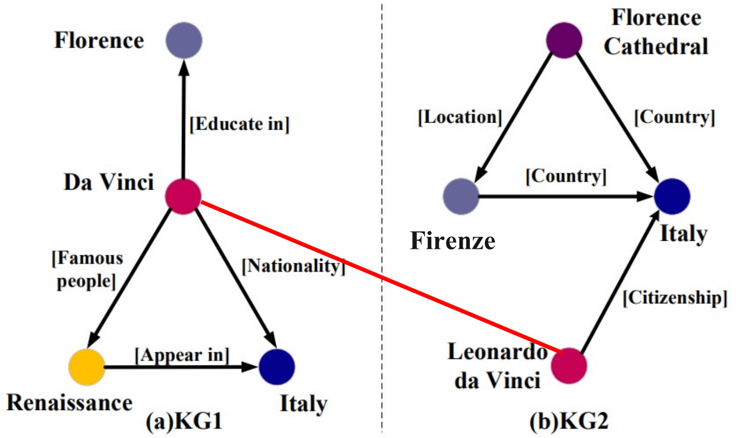
Cross-graph Embedding Exchange (CEE)

- Cross-graph embedding exchange embedding on both original and cross graphs
- Reduce the concept ***semantic distance*** between KGs.
- Formula:

$$E^{k+1} = RGC(E^k_{cross}, R^k, G^k, W^k)$$

$$E^{k+1}_{cross} = RGC(E^k, R^k_{cross}, G^k_{cross}, W^k)$$

- Distance of Florence in tow KGs
- Traditional method:
  - ✓ 4 edges and 3 nodes
- Our CEE:
  - ✓ 3 edges and 2 nodes



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Addressed Challenge 2.1:

Concept Heterogeneity

Knowledge Alignment

Soft Relation Alignment (SRA)

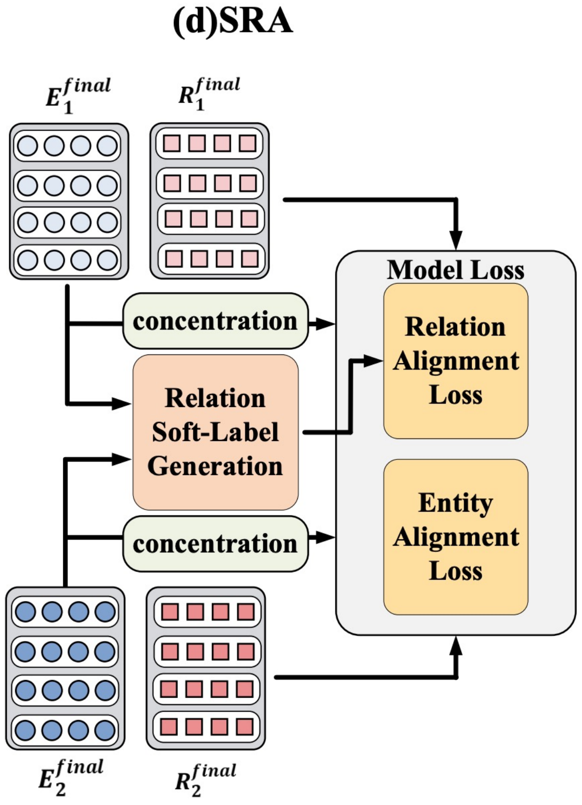
- Address relation heterogeneity
- Soft Relation Alignment Labels
  - ✓ Relation label embedding

$$r' = concat[\frac{1}{H_r}\sum_{e_i \in H_r} e_i,\ \frac{1}{T_r}\sum_{e_j \in T_r} e_j]$$

  - ✓ Relation alignment label

$$y_{ij} = \mathbb{I}(cos(r'_i, r'_j) > \gamma)$$

  - ✓ Reducing the semantic distance of similar relations



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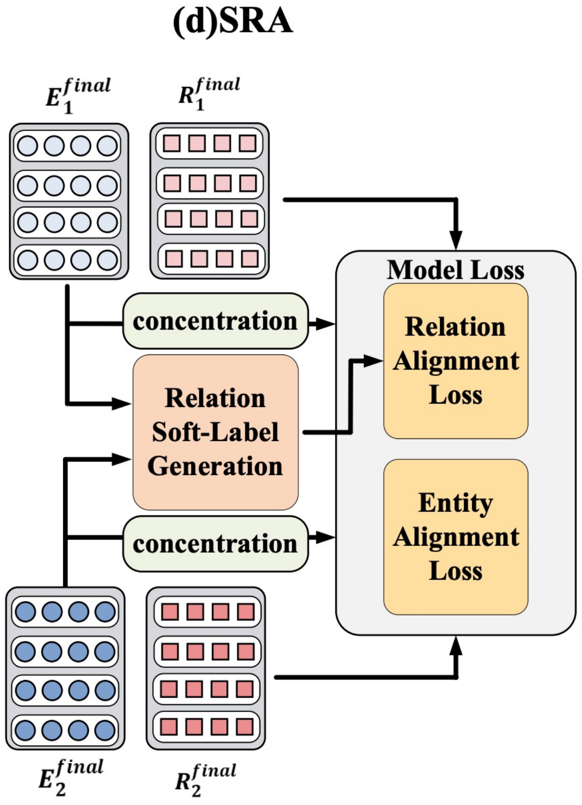
Addressed Challenge 2.2:
Relation Heterogeneity



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Knowledge Alignment

Training

Concept Alignment Loss

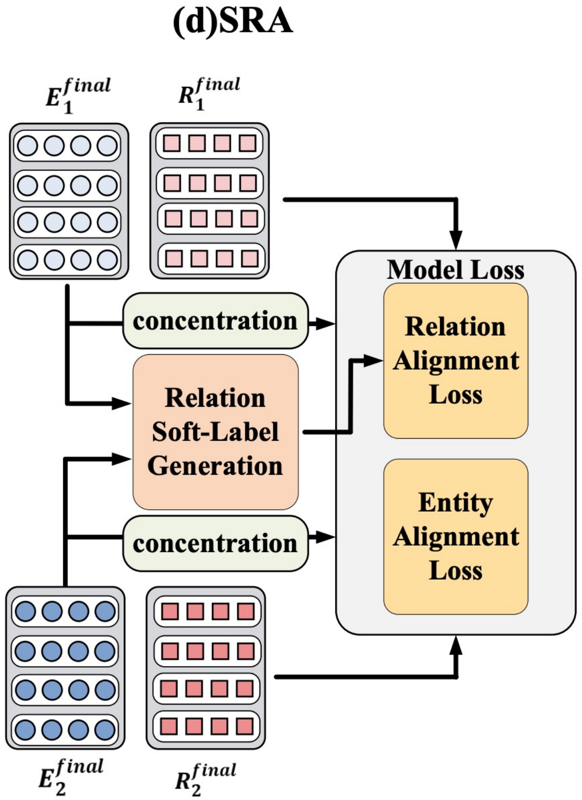
- ✓ Minimize the contrastive alignment
- ✓ Shorten distance of aligned concepts
- ✓ Pull away non-aligned concepts

$$\mathcal{L}_1 = \sum_{(i,j)\in A^+} ||e_i - e_j|| + \sum_{(i',j')\in A^-} \alpha_1[\lambda - ||e_{i'} - e_{j'}||]_+$$

Relation Alignment Loss

- ✓ Multi-label classification task
- ✓ Cosine similarity of relations: $x_{ij} = cos(r_i, r_j)$
- ✓ Multi-label soft margin loss:

$$\mathcal{L}_2 = -\frac{1}{|R|}\sum_i (y_i \cdot log(\frac{1}{1+exp(-x_i)}) + (1-y_i)\cdot log\frac{exp(-x_i)}{1+exp(-x_i)}).$$



$$\boxed{\mathcal{L} = \mathcal{L}_1 + \alpha_2\mathcal{L}_2}$$

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Knowledge Alignment

Experiments

- **Datasets**
  - ✓ DBpedia: English-French and English-German
  - ✓ DBpedia-Wikidata and DBpedia-YAGO
- **Compared Baselines**
  - ✓ Triple-based Models: MtransE, IPTransE, AlignE, SEA
  - ✓ Neighbor-based Models: GCNAlign, AliNet, HyperKA
  - ✓ Relation-enhanced Models: RSN4EA, KE-GCN, IMEA
- **Evaluation Metrics**
  - ✓ Hits@1, Hits@5
  - ✓ MRR

Dataset	KG	#Ent.	#Rel.	#Rel tr.
EN-FR	EN	15,000	267	47,334
	FR	15,000	210	40,864
EN-DE	EN	15,000	215	47,676
	DE	15,000	131	50,419
D-W	DB	15,000	248	38,265
	WD	15,000	169	42,746
D-Y	DB	15,000	165	30,291
	YG	15,000	28	26,638

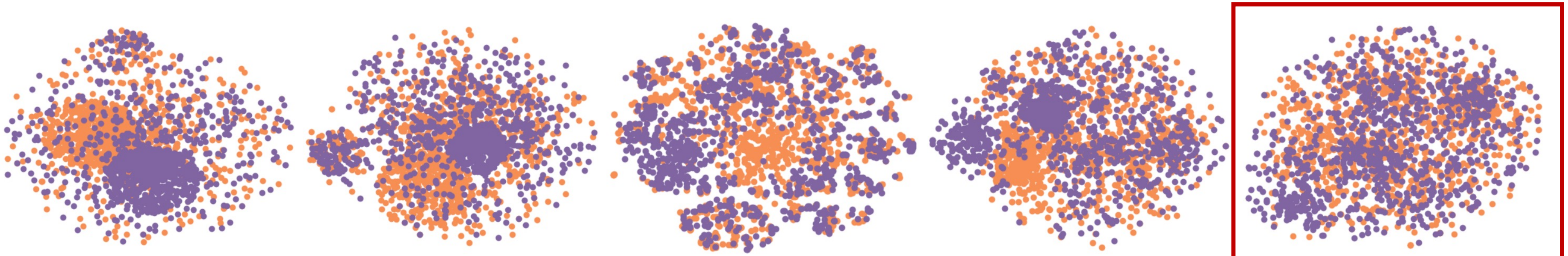
Dateset		EN_FR_V1			EN_DE_V1			D_W_V1			D_Y_V1		
Category	Method	H@1	H@5	MRR	H@1	H@5	MRR	H@1	H@5	MRR	H@1	H@5	MRR
Triple-based	MTransE	0.247	0.467	0.351	0.307	0.518	0.407	0.259	0.461	0.354	0.463	0.675	0.559
	IPTransE	0.169	0.320	0.243	0.350	0.515	0.430	0.232	0.380	0.303	0.313	0.456	0.378
	AlignE	0.357	0.611	0.473	0.552	0.741	0.638	0.406	0.627	0.506	0.551	0.743	0.636
	SEA	0.280	0.530	0.397	0.530	0.718	0.617	0.360	0.572	0.458	0.500	0.706	0.591
Neighbor-based	GCN-Align	0.338	0.589	0.451	0.481	0.679	0.571	0.364	0.580	0.461	0.465	0.626	0.536
	AliNet	0.364	0.597	0.467	0.604	0.759	0.673	0.440	0.628	0.522	0.559	0.690	0.617
	HyperKA	0.353	0.630	0.477	0.560	0.780	0.656	0.440	0.686	0.548	0.568	0.777	0.659
Relation-enhanced	RSN4EA	0.393	0.595	0.487	0.587	0.752	0.662	0.441	0.615	0.521	0.514	0.655	0.580
	KE-GCN	0.408	0.670	0.524	0.658	0.822	0.730	0.519	0.727	0.608	0.560	0.750	0.644
	IMEA	0.458	0.720	0.574	0.639	0.827	0.724	0.527	**0.753**	0.626	0.639	0.804	0.712
Ours	RHGN	**0.500**	**0.739**	**0.603**	**0.704**	**0.859**	**0.771**	**0.560**	**0.753**	**0.644**	**0.708**	**0.831**	**0.762**

RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs, ACL2023

Knowledge Alignment

Visualization of Concept Embedding

- Ideal Visualization:
- Concept distributions of two graphs overlap as much as possible
- Concept embeddings are sparsely distributed.



(a) GCN (b) GAT (c) R-GCN (d) CompGCN (e) RHGN

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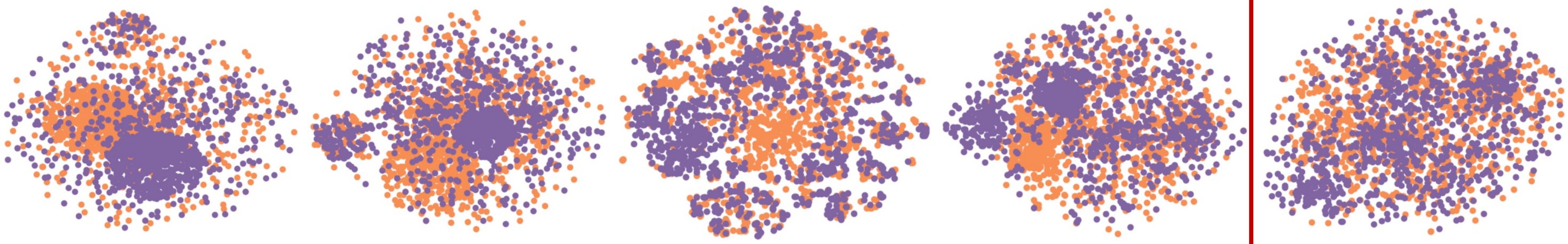
➡ ***Mitigating the over-smoothing limitation of traditional GCN.***



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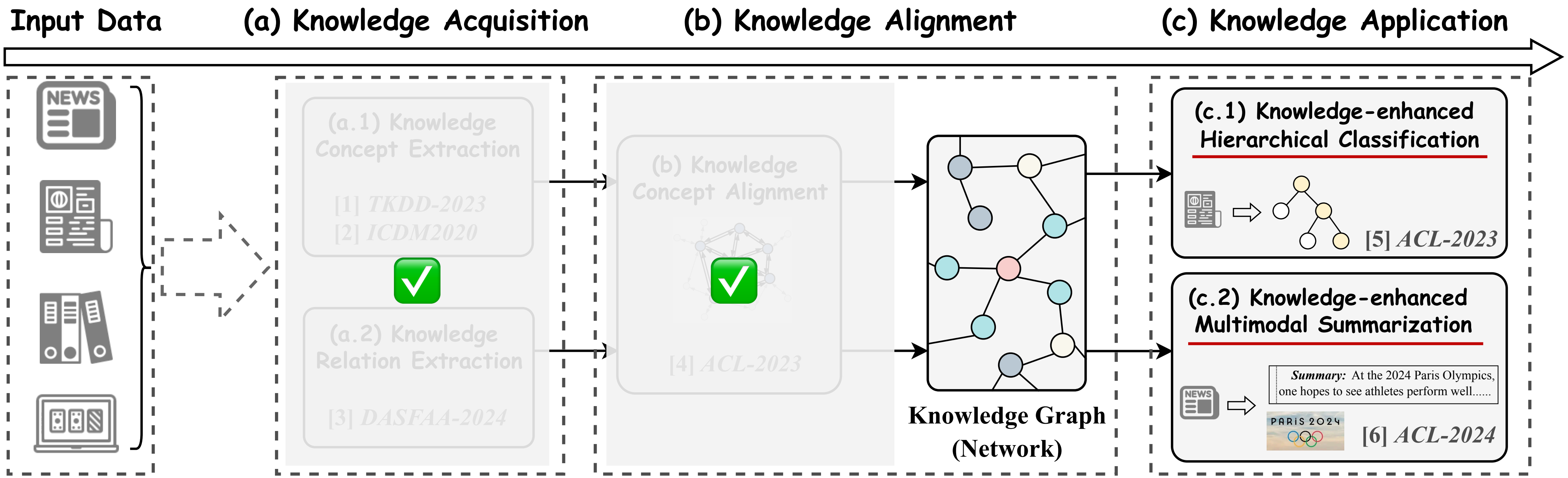
RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs

Published at ACL2023 (Finding)

RHGN: Relation-gated Heterogeneous Graph Network for Entity Alignment in Knowledge Graphs, ACL2023

Knowledge Alignment

- Knowledge-aware NLP techniques
  - Knowledge Acquisition
  - Knowledge Alignment
  - Knowledge ***Application***



OUTLINE

CONTENTS

Knowledge Application

Crucial in demonstrating the significance of Knowledge-aware NLP,
The final step toward trustworthy AI systems:

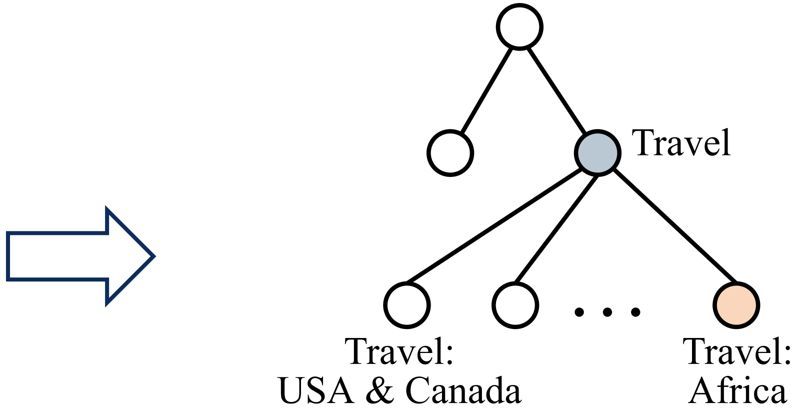
1. *Knowledge-enhanced Hierarchical Text Classification*
2. *Knowledge-enhanced Multimodal Summary Generation*

Knowledge Application

Knowledge-enhanced Hierarchical Text Classification

- Given an input document and a pre-defined ***hierarchical classification structure***, classify the document into one or more paths in the hierarchy.
- Example:

It is as vast as the USA and so arid that most bacteria cannot survive there. The author came to the Sahara to see it as its inhabitants do, riding its public transport, from Algiers to Dakar



Taxonomic Hierarchy

Enhancing Hierarchical Text Classification through Knowledge Graph Integration, ACL2023

Knowledge Application

Existing approaches for HTC mainly focus on the **representation learning** from the input text and hierarchical label structure.

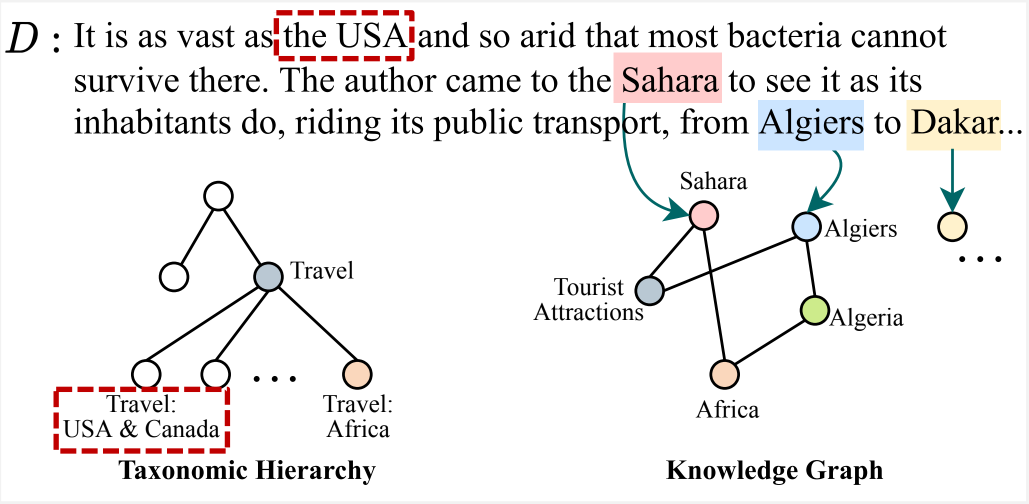
HTC Methods	HTC Methods
• **Local Methods** [1,2] • **Training multiple classifiers, each responsible for the corresponding local region (e.g., each label or level).**	• **Global Methods** [3,4,5] • **Building a single classifier for all classes, which will take the class hierarchy as a whole into account.**

[1] Siddhartha Banerjee, Cem Akkaya, Francisco PerezSorrosal, and Kostas Tsioutsiouliklis. 2019. Hierarchical transfer learning for multi-label text classification. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6295–6300.
[2] Kazuya Shimura, Jiyi Li, and Fumiyo Fukumoto. 2018. Hft-cnn: Learning hierarchical category structure for multi-label short text categorization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 811–816.
[3] Jie Zhou, Chunping Ma, Dingkun Long, Guangwei Xu, Ning Ding, Haoyu Zhang, Pengjun Xie, and Gongshen Liu. 2020. Hierarchy-aware global model for hierarchical text classification. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1106–1117.
[4] Haibin Chen, Qianli Ma, Zhenxi Lin, and Jiangyue Yan. 2021. Hierarchy-aware label semantics matching network for hierarchical text classification. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 4370–4379.
[5] Zihan Wang, Peiyi Wang, Lianzhe Huang, Xin Sun, and Houfeng Wang. 2022b. Incorporating hierarchy into text encoder: a contrastive learning approach for hierarchical text classification. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 7109–7119.

Knowledge Application

Shortcomings

- These approaches without ***domain knowledge*** have significant limitations and may lead to mistakes in many domain-specific cases.
- In this toy example, these methods may classify a document as belonging to the category ***Travel: USA & Canada*** simply based on the presence of the phrase ***The USA*** in the document.

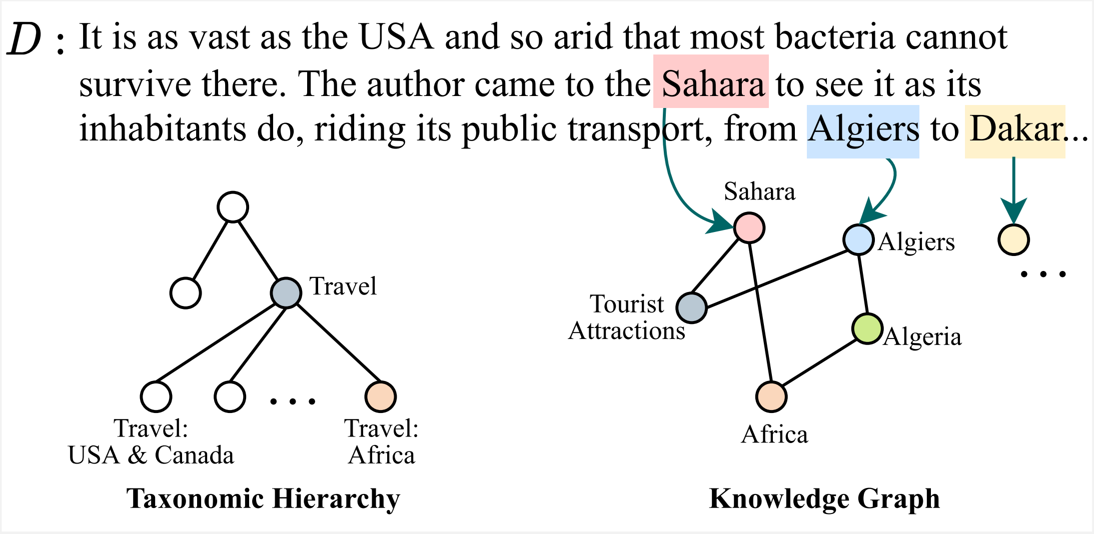


Knowledge Application

Shortcomings

- If machines are equipped with a relevant knowledge graph, they can mine more information from other concepts, such as ***Sahara*** and ***Algiers***.

- With the above relevant knowledge, machines will be more facilitated to make the correct inference, i.e., ***Travel*** and ***Travel: Africa*** in the taxonomic hierarchy.



Knowledge Application

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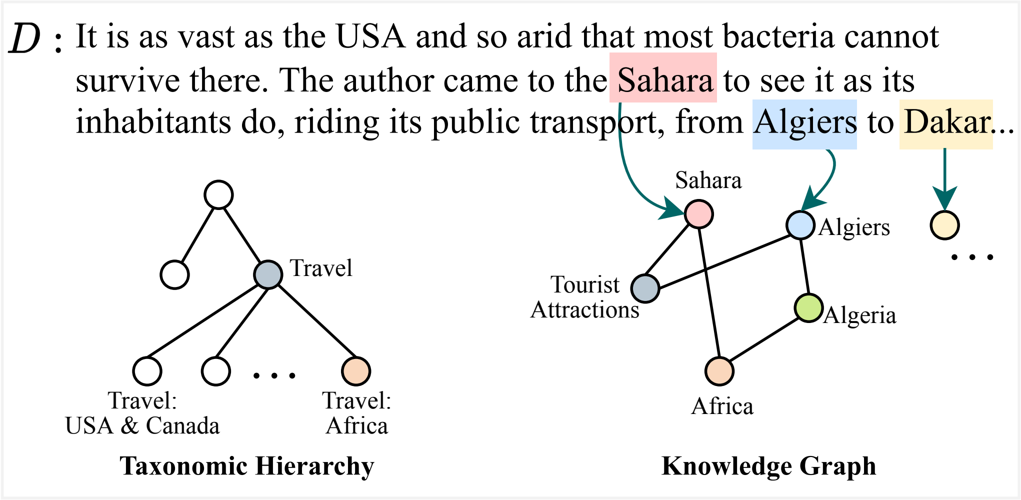
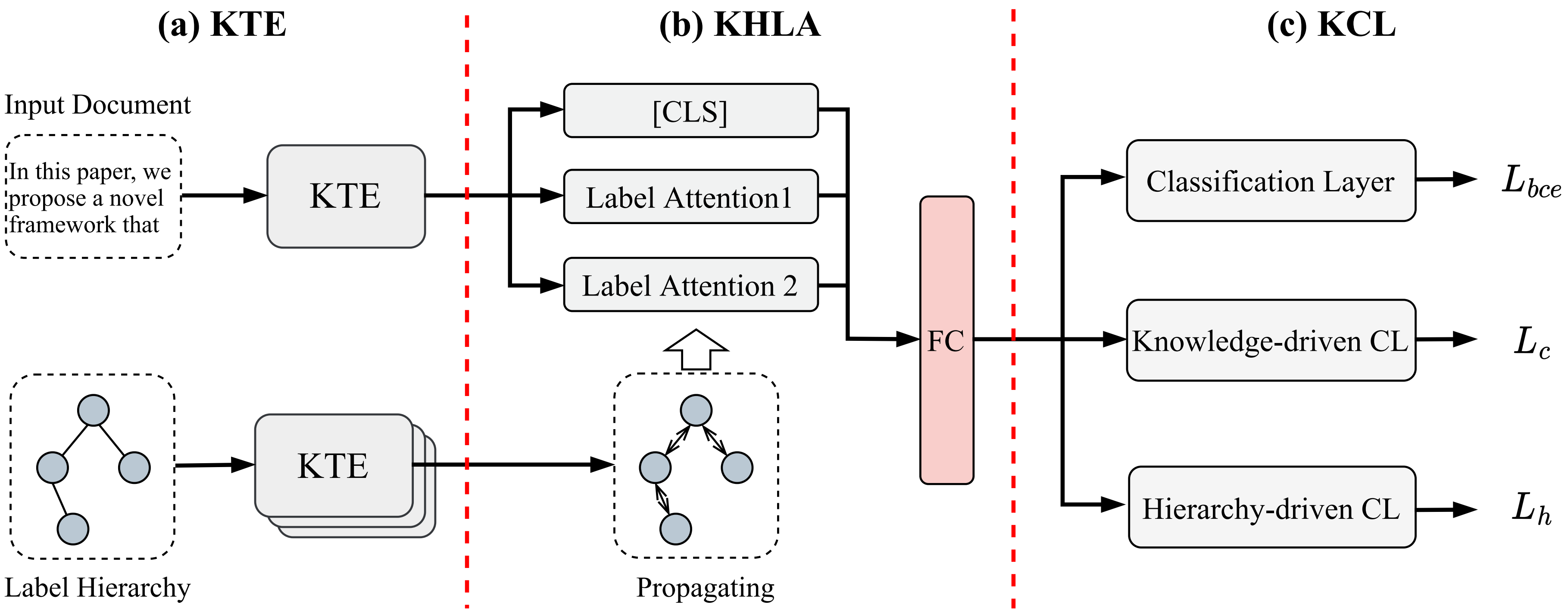


How to incorporate the <u>knowledge from KGs</u> into HTC process to mitigate the knowledge limitation problem?

Knowledge Application

Knowledge-enhanced Hierarchical Text Classification

- Knowledge-aware ***Text Encoder*** (KTE)
- Knowledge-aware ***Hierarchical Label Attention*** (KHLA)
- Knowledge-aware ***Contrastive Learning*** (KCL)



Enhancing Hierarchical Text Classification through Knowledge Graph Integration, ACL2023

Knowledge Application

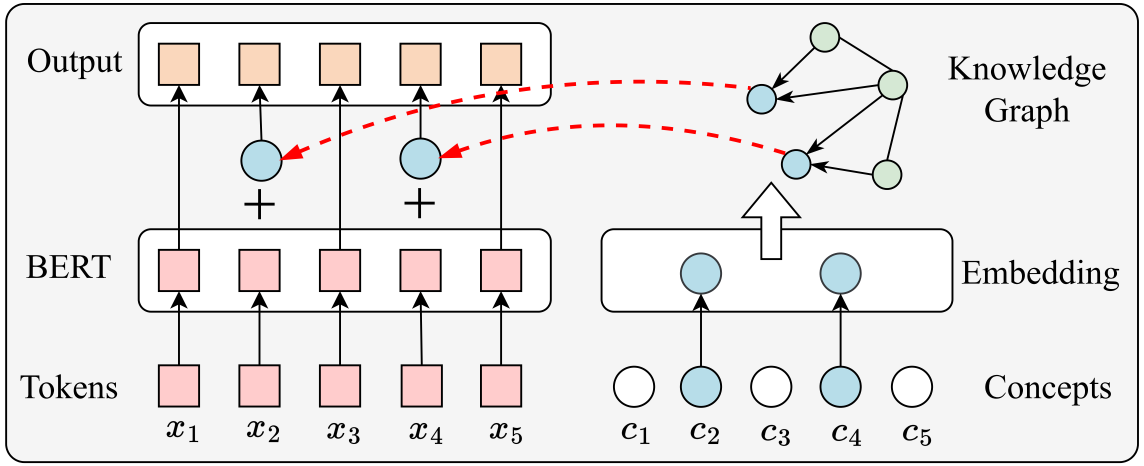
Knowledge-aware Text Encoder

- Fuse the ***text representation*** and its corresponding ***concept representation*** learned from KGs at the word granularity

$$\{w_1, ..., w_N\} = BERT(\{x_1, ..., x_N\})$$

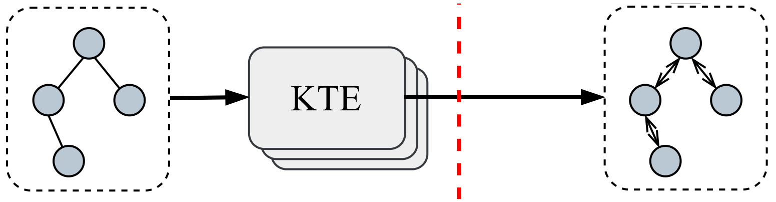
$$\{u_1, ..., u_N\} = U(\{c_1, ..., c_N\})$$

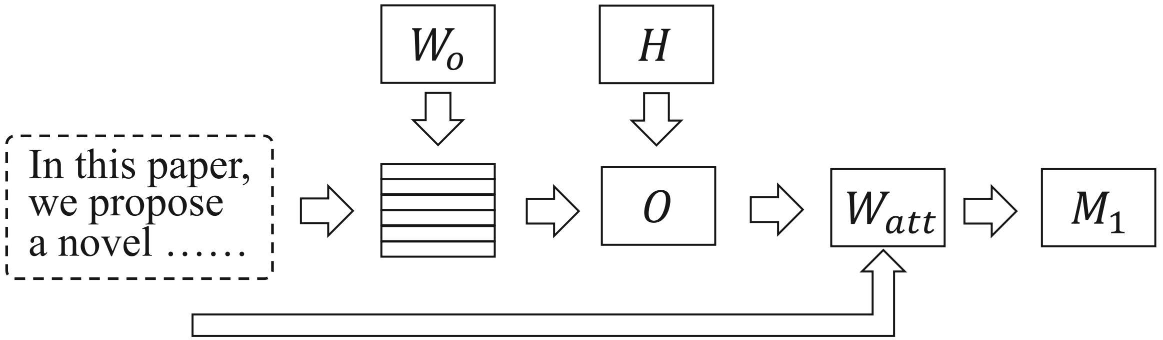
$$\{m_1, ..., m_N\} = \{w_1 + u'_1, ..., w_N + u'_N\}$$



Knowledge-aware Hierarchical Label Attention

- Employs external knowledge from KGs for ***label representation*** and optimizes it based on the hierarchical structure, which further enhances the document representation via a ***label attention mechanism***.





$$R_l^i = mean(KTE(L_i)), i = 1, ..., K,$$

$$R_l = [R_l^1, R_l^2, ..., R_l^K],$$

$$H^{(l+1)} = \sigma(\widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}),$$

$$R_d = KTE(D),$$

$$O = tanh(W_o \cdot R_d^T),$$

$$W_{att} = softmax(H \cdot O),$$

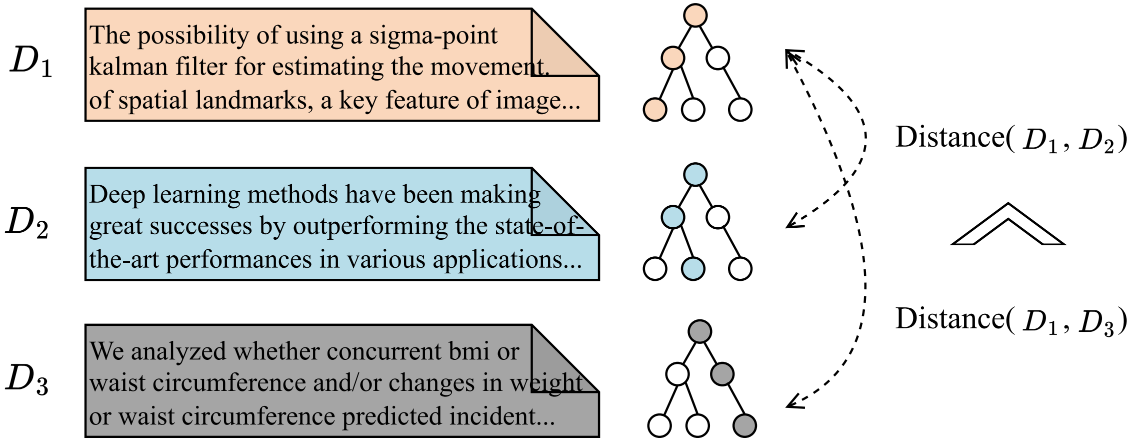
$$M_1 = mean(W_{att} \cdot R_d),$$

Enhancing Hierarchical Text Classification through Knowledge Graph Integration, ACL2023

Knowledge Application

Knowledge-aware Contrastive Learning

- The ***hierarchical structure / knowledge sharing*** may give another perspective (***progressive distance relationship***) on how to further improve the classification performance.



Share Label Illustration

Hierarchical Level	BGC	WOS
L-1	4.29	5.82
L-2	4.93	8.00
L-3	5.96	–
L-4	5.94	–
Total	3.12	4.87

Share Knowledge Concept Illustration

Knowledge Application

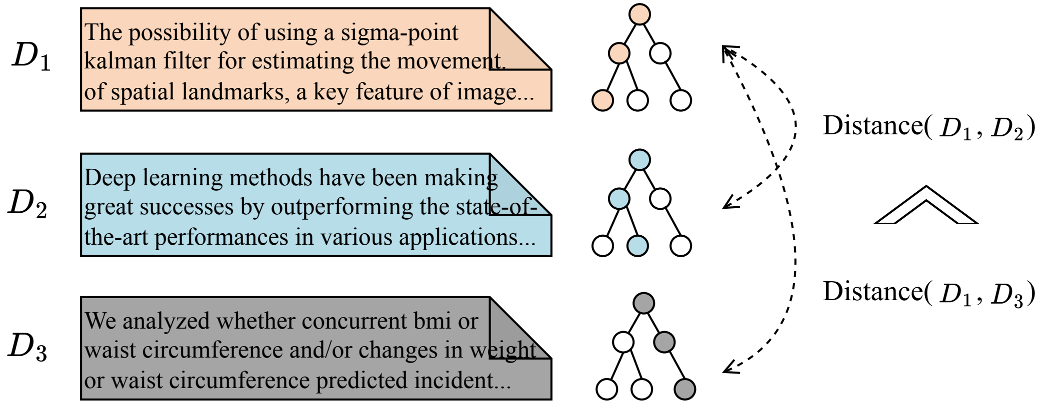
Knowledge-aware Contrastive Learning

- The ***hierarchical structure / knowledge sharing*** may give another perspective (***progressive distance relationship***) on how to further improve the classification performance.

- ***Progressive Distance Loss***：

$$L_c^{ij} = -\beta_{ij} \log \frac{e^{-d(z_i, z_j)/\tau}}{\sum_{k \in g(i)} e^{-d(z_i, z_k)/\tau}},$$

$$c_{ij} = |C_i \cap C_j|, \quad \beta_{ij} = \frac{c_{ij}}{\sum_{k \in g(i)} c_{ik}},$$



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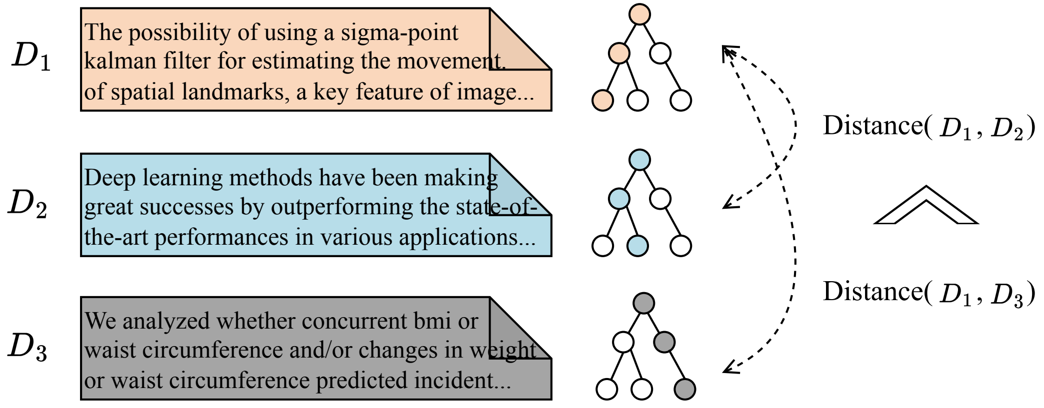


Knowledge Application

Experiments

- **Datasets**
  - ✓ BlurbGenreCollection-EN (BGC)
  - ✓ Web-of-Science (WOS)

Statistics	BGC	WOS
# total categories	146	141
# hierarchical levels	4	2
# avg categories per instance	3.01	2.0
# train instance	58,715	30,070
# dev instance	14,785	7,518
# test instance	18,394	9,397

- **Compared Baselines**
  - ✓ Hierarchy-Aware Methods: HiAGM, HTCInfoMax, HiMatch
  - ✓ Pre-trained Language Methods: KW-BERT, HGCLR, HPT …

- **Evaluation Metrics**
  - ✓ Precision, Recall,
  - ✓ Macro-F1, Micro-F1

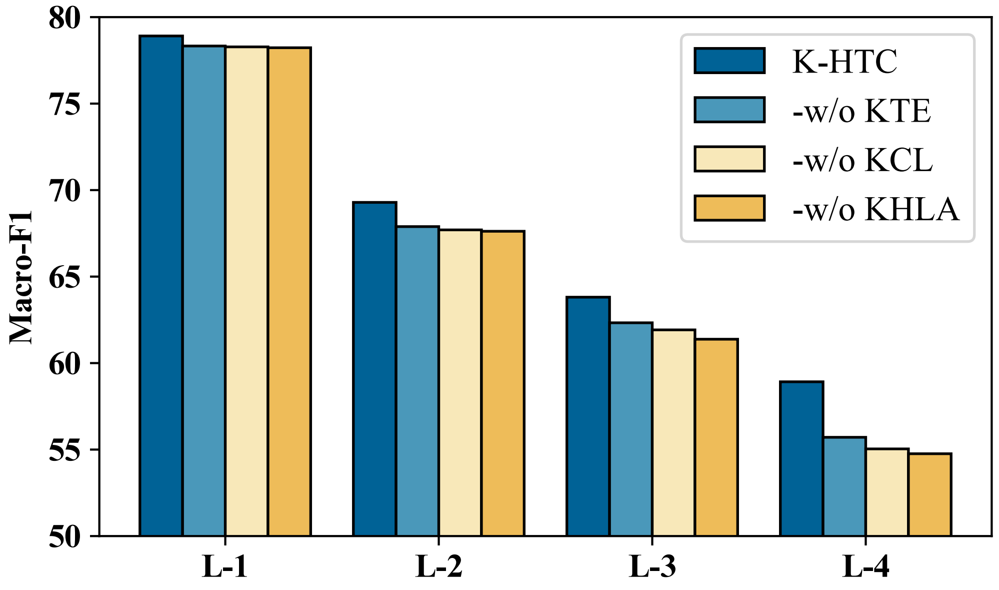
Methods	BGC				WOS			
	Precision	Recall	Macro-F1	Micro-F1	Precision	Recall	Macro-F1	Micro-F1
Hierarchy-Aware Methods								
HiAGM	57.41	53.45	54.71	74.49	82.77	78.12	80.05	85.95
HTCInfoMax	61.58	52.38	55.18	73.52	80.90	77.27	78.64	84.65
HiMatch	59.50	52.88	55.08	74.98	83.26	77.94	80.09	86.04
Pre-trained Language Methods								
HiAGM+BERT	65.61	61.79	62.98	78.62	81.81	78.86	80.09	85.83
HTCInfoMax+BERT	65.47	62.15	62.87	78.47	79.95	79.59	79.33	85.18
HiMatch+BERT	64.67	62.05	62.62	79.23	82.29	80.00	80.92	86.46
KW-BERT	66.39	62.68	63.72	79.24	82.88	78.75	80.30	86.19
HGCLR	67.65	61.28	63.64	79.36	83.67	79.30	81.02	87.01
HPT	70.27	62.70	65.33	**80.72**	83.71	79.74	81.10	86.82
K-HTC (ours)	**71.26**	**63.31**	**65.99**	80.52	**84.15**	**80.01**	**81.69**	**87.29**

Enhancing Hierarchical Text Classification through Knowledge Graph Integration, ACL2023

Knowledge Application

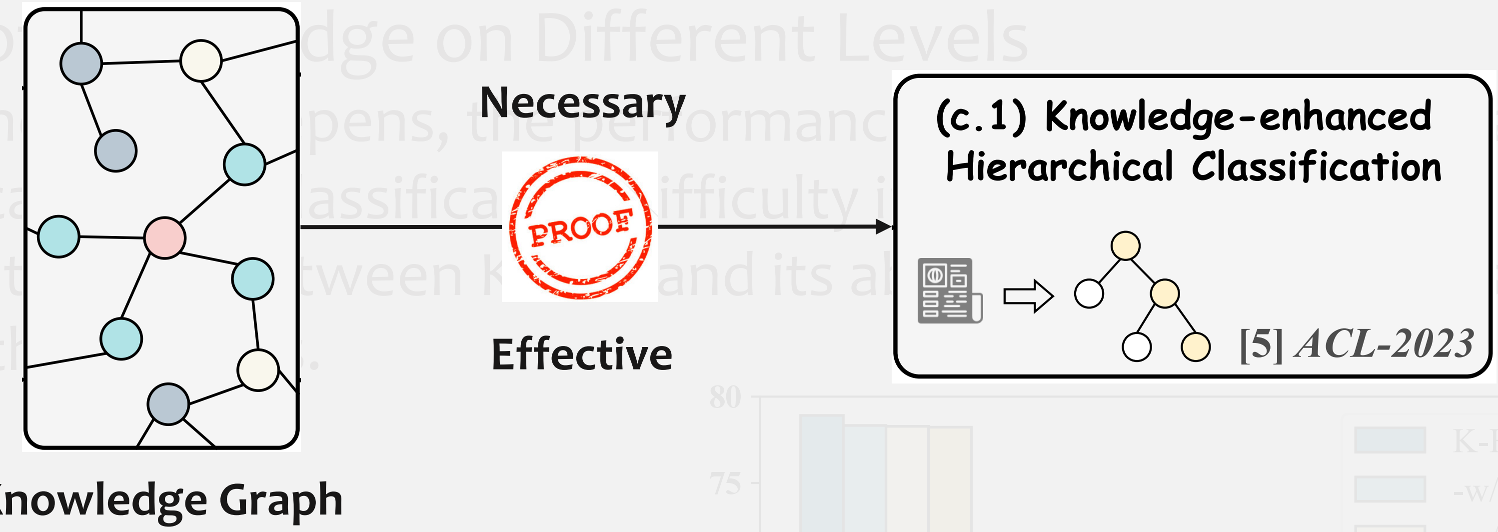
Effect of Knowledge on Different Levels

- As the level deepens, the performance of all methods decreases, indicating the classification difficulty increases significantly.
- And the gap between K-HTC and its ablation variants widens as the depth increases.



Performance on Different Levels of BGC

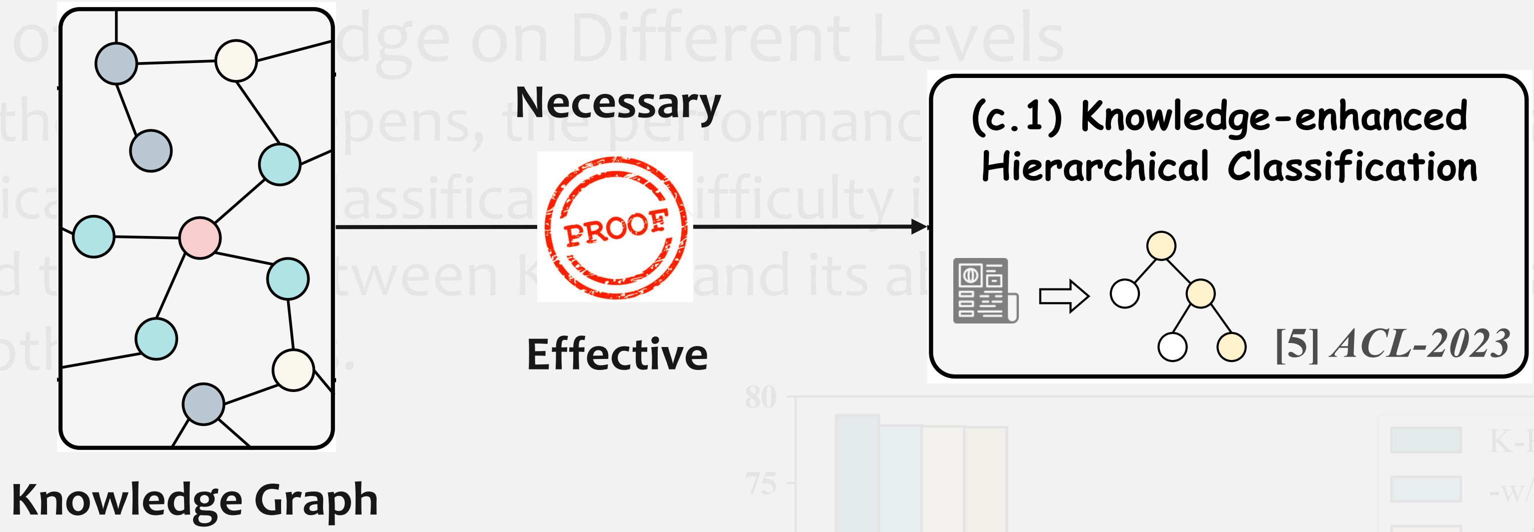
Knowledge Application



Demonstrates the effectiveness and necessity of knowledge application, especially for these difficult and complex tasks

Enhancing Hierarchical Text Classification through Knowledge Graph Integration, ACL2023

Knowledge Application



Enhancing Hierarchical Text Classification through Knowledge Graph Integration

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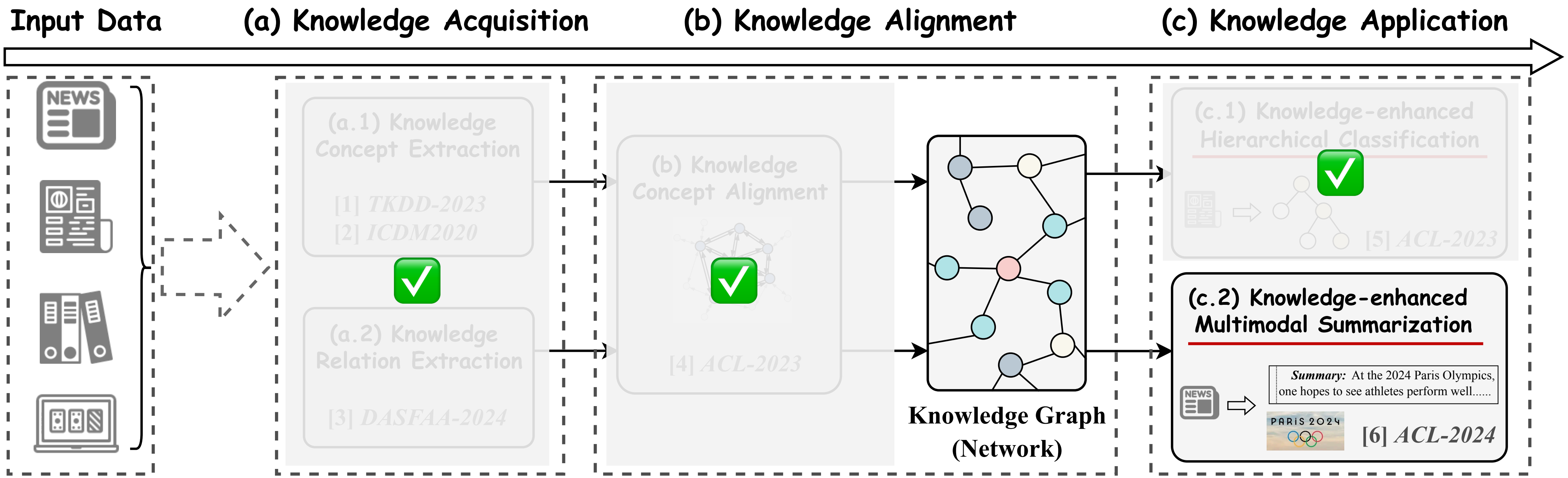
Knowledge Application

- Knowledge-aware NLP techniques
  - Knowledge Acquisition
  - Knowledge Alignment
  - Knowledge ***Application***



Knowledge Application

☐ Knowledge-enhanced Multimodal Summarization

- Given the source text and corresponding source images, MSMO aims to produce a multimodal summary with a textual abstract alongside a pertinent image.

Input

Source Images:

Source Text:

An amazing video has shown how the Chinese workers built the world 's longest rail-road steel arch bridge . The Hutong Yangtze River Bridge , crossing the greatest river in China … the closure of an arch on the Tianshenggang Channel Bridge , a section of the Hutong Yangtze River Bridge , on Sunday … The completion of the arch is a critical step in the construction of the massive rail-road bridge …

Output

Multimodal Summary:

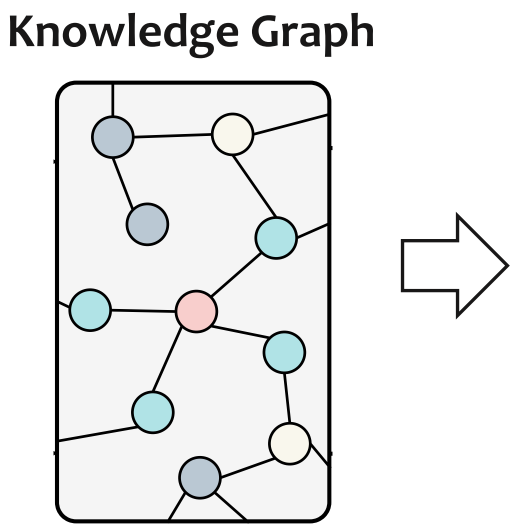
The Hutong Yangtze River Bridge , which cost a whopping # 1.7 billion , is a rail-road steel arch bridge . Amazing footage shows the completion of one steel arch on the massive 6.8-mile-long …

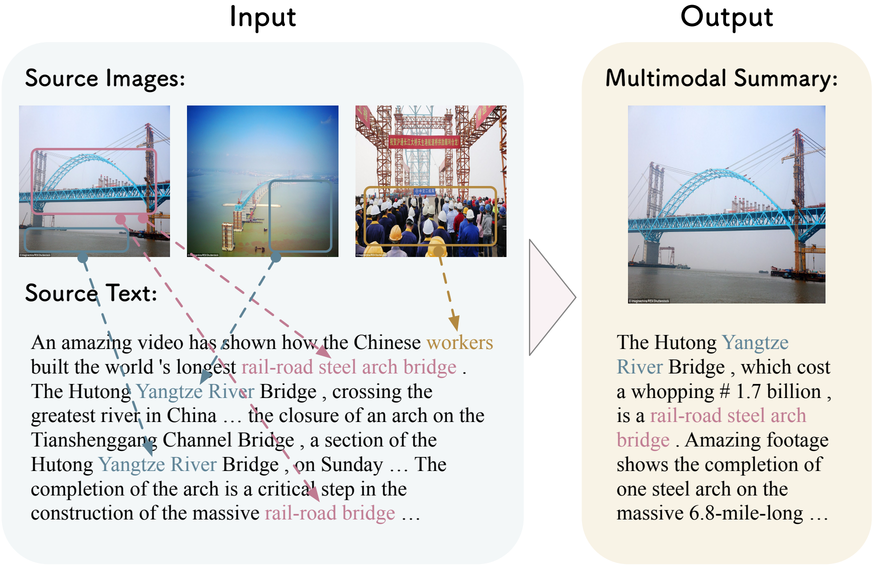
Leveraging Entity Information for Cross-Modality Correlation Learning: The Entity-Guided Multimodal Summarization, ACL2024

Knowledge Application

Related Work

- Previous studies focus on text and image representations. However, ***visual objects*** typically align with ***knowledge concepts*** in the text, which can be related through KGs
- Utilize KGs to mine the ***knowledge concepts*** from input text





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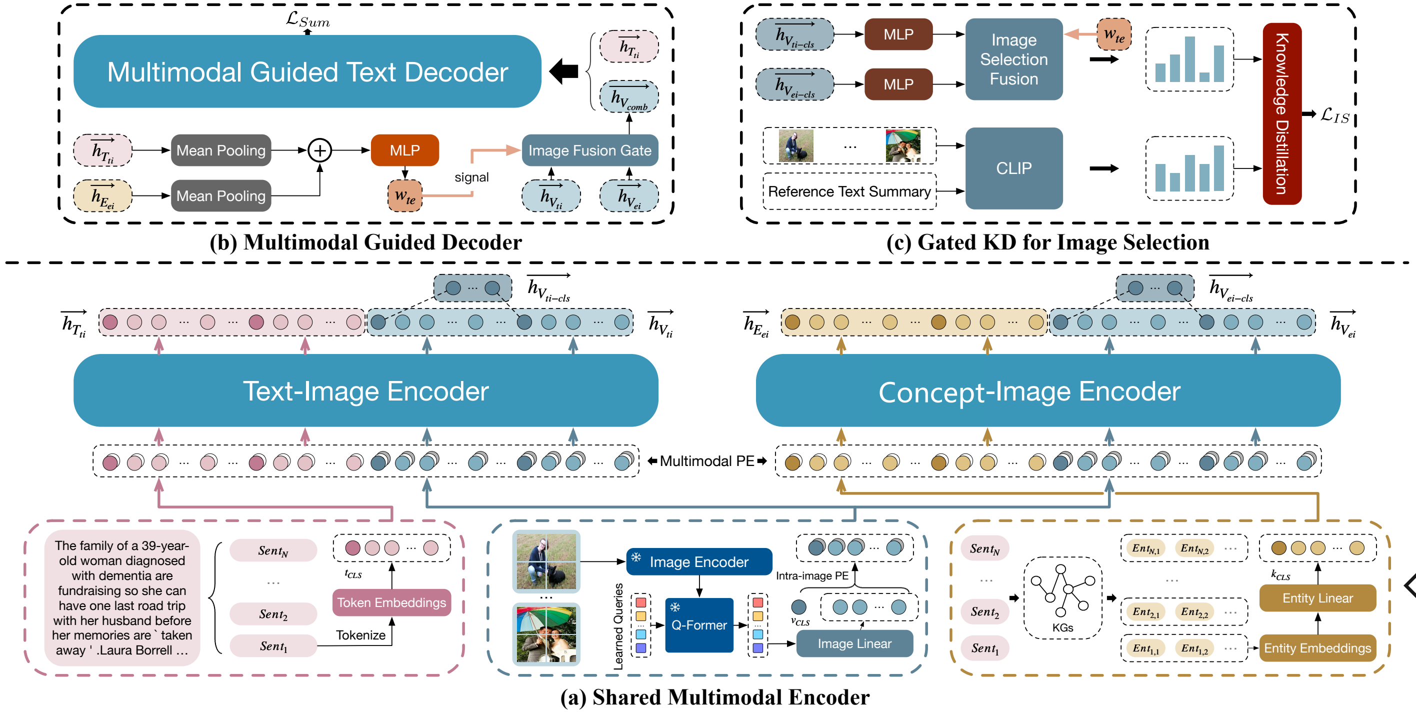
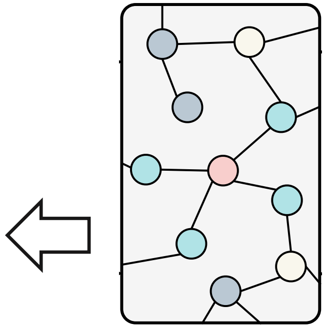
Knowledge Application

Knowledge Concept-Guided Multimodal Summarization model

- Knowledge-enhanced Shared Multimodal Encoder
- Knowledge-enhanced Multimodal Guided Decoder
- Gated Knowledge Distillation for Image Selection





Knowledge Graph

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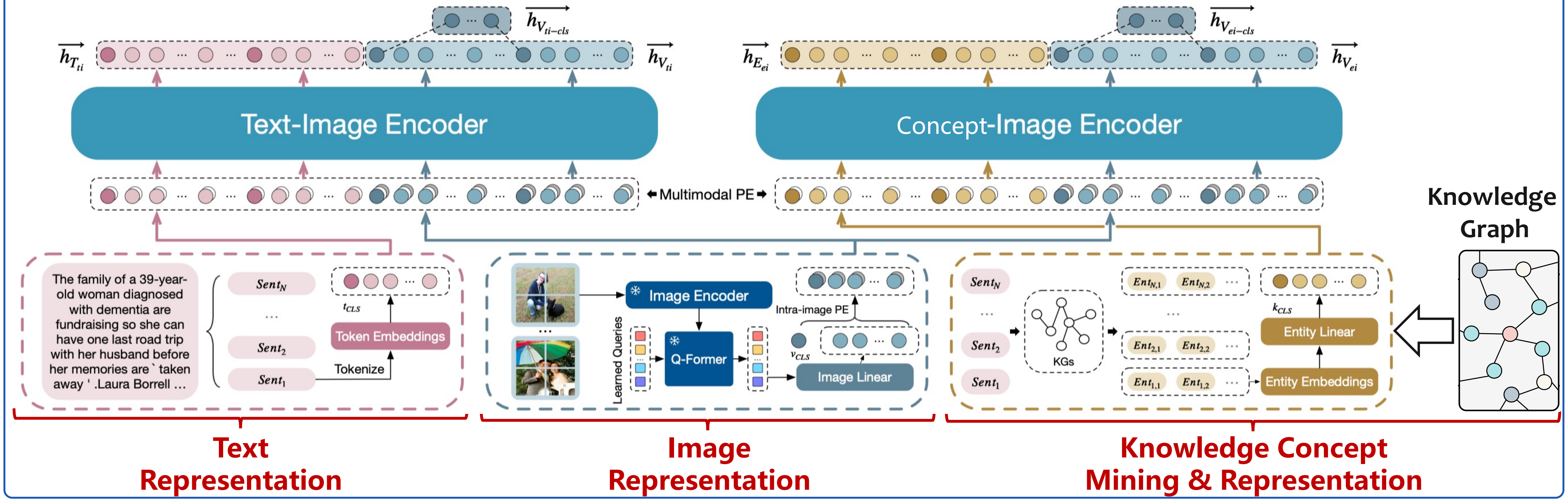
Knowledge Application

Knowledge-enhanced Shared Multimodal Encoder

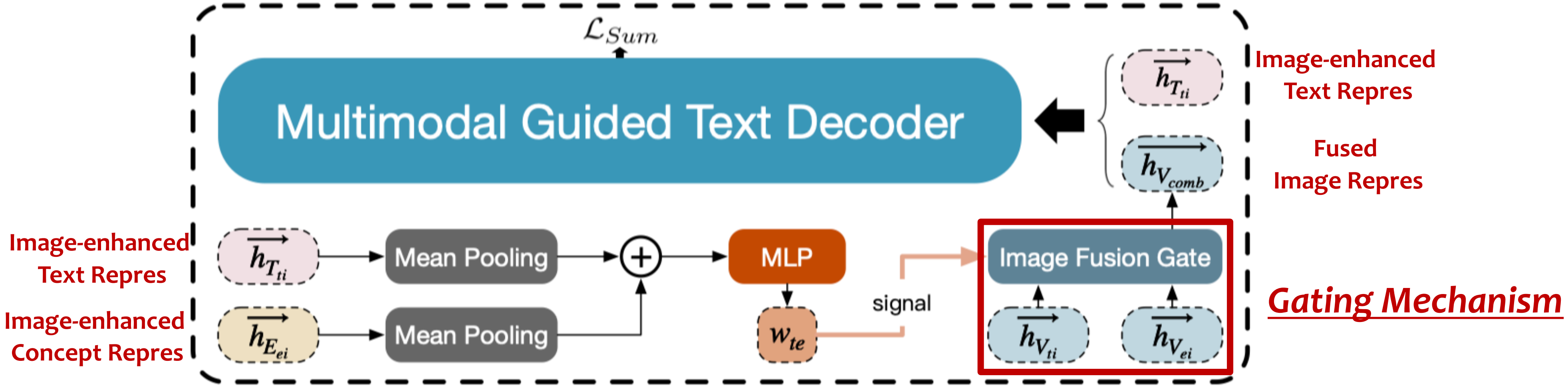
- Mine ***knowledge concepts*** from KGs
- Expands BART to two weight-sharing encoders for ***text***, ***image***, and ***knowledge concept*** interactions.



Knowledge Application

Knowledge-enhanced Multimodal Guided Decoder

- Uses a ***Gating Mechanism*** to integrate text-enhanced image, and ***knowledge concept-enhanced*** image representations for text summarization, enhancing the semantic relevance of generated summaries.



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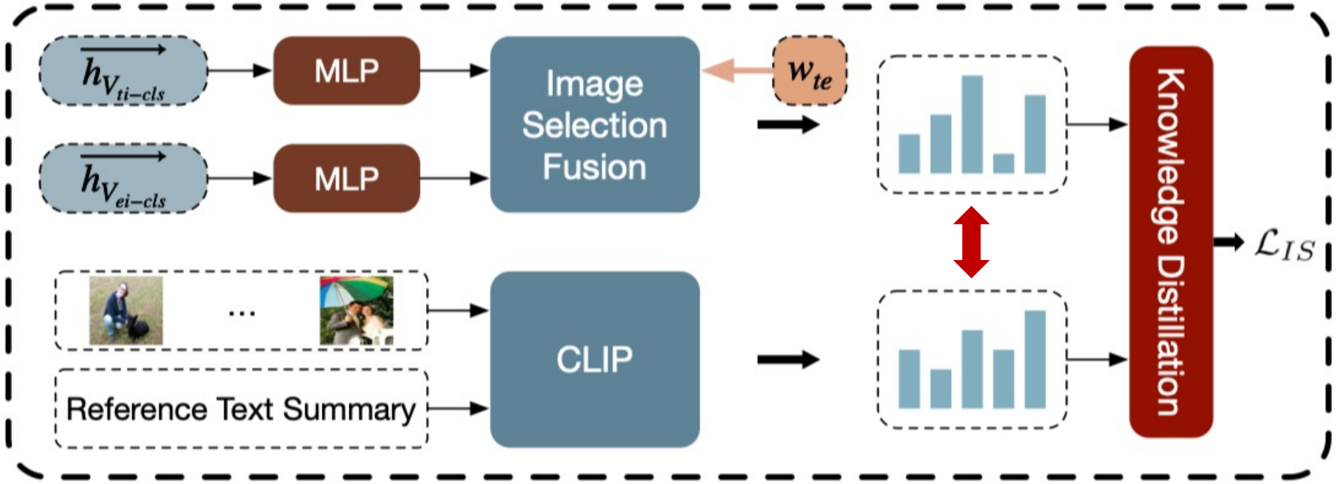
Knowledge Application

Gated Knowledge Distillation for Image Selection

- Uses CLIP to generate ***soft labels*** for image selection via ***knowledge distillation***, improving image relevance for summarization by compensating for missing annotations.

Text-enhanced Image Repres

Concept-enhanced Image Repres



$$\mathcal{P}_p(p,\tau) = \frac{\exp(\frac{g(p)}{\tau})}{\sum_{p\in P}\exp(\frac{g(p)}{\tau})},$$

$$\mathcal{Q}_p(S_t,p,\tau) = \frac{\exp(\frac{l(S_t,p)}{\tau})}{\sum_{p\in P}\exp(\frac{l(S_t,p)}{\tau})},$$

$$\mathcal{L}_{IS} = KL(\mathcal{P}||\mathcal{Q}) = -\sum_{p\in P}\mathcal{P}_p \cdot \ln\frac{\mathcal{Q}_p}{\mathcal{P}_p}$$

Leveraging Entity Information for Cross-Modality Correlation Learning: The Entity-Guided Multimodal Summarization, ACL2024

Knowledge Application

Experiments

Datasets

- ✓ Multimodal Summarization with Multimodal Output (MSMO)

Statistics	Train	Valid	Test
#Samples	293,965	10,355	10,261
#AvgTokens(A)	720.87	766.08	730.80
#AvgTokens(S)	70.12	70.02	72.16
#AvgImgs	6.56	6.62	6.97

Baseline Methods

- ✓ Textual Summarization Methods:
  - BertAbs, BertExtAbs, BART
- ✓ Multimodal Summarization Methods:
  - ATG, MOF, UniMS …

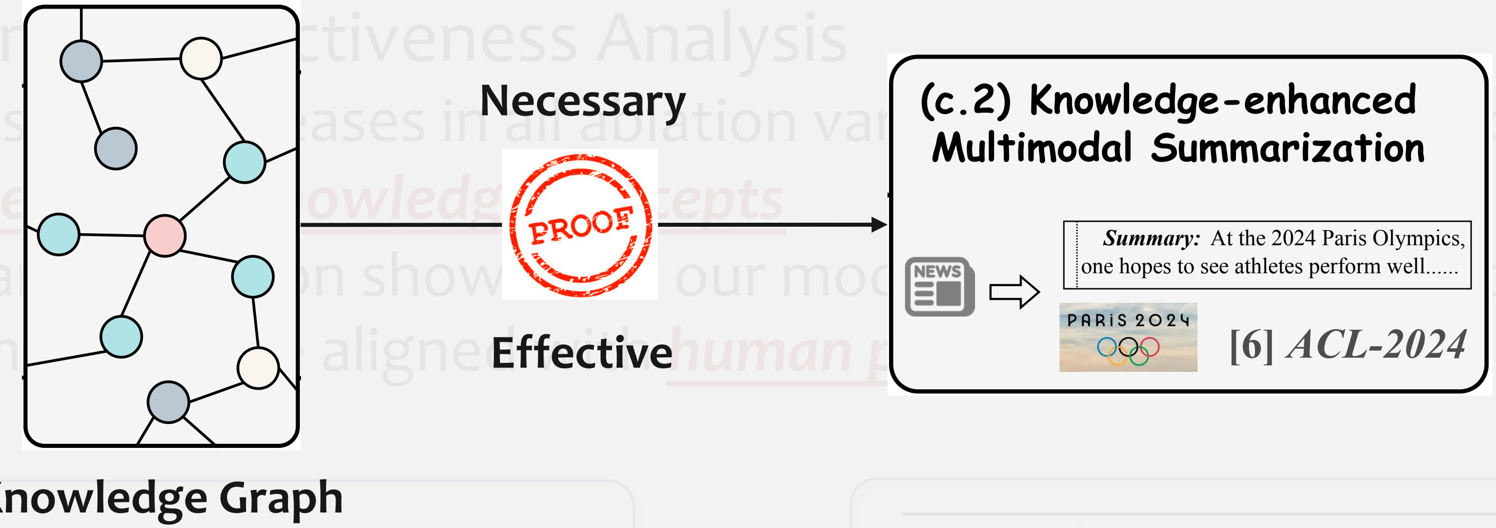
Evaluation Metrics

- ✓ Text: ROUGE-1, ROUGE-2, ROUGE-L
- ✓ Image: Precision

Model	R-1	R-2	R-L	IP
Text Abstractive				
BertAbs*	39.02	18.17	33.20	-
BertExtAbs*	39.88	18.77	38.36	-
BART	42.93	19.95	39.97	-
Multimodal Abstractive				
ATG*	40.63	18.12	37.53	59.28
ATL*	40.86	18.27	37.75	62.44
HAN*	40.82	18.30	37.70	61.83
MOF_{enc}^{RR}*	41.05	18.29	37.74	62.63
MOF_{dec}^{RR}*	41.20	18.33	37.80	65.45
UniMS*	42.94	20.50	40.96	69.38
EGMS	**44.47**	**21.20**	**41.43**	**75.81**

Leveraging Entity Information for Cross-Modality Correlation Learning: The Entity-Guided Multimodal Summarization, ACL2024

Knowledge Application



Leveraging Entity Information for Cross-Modality Correlation Learning: The Entity-Guided Multimodal Summarization

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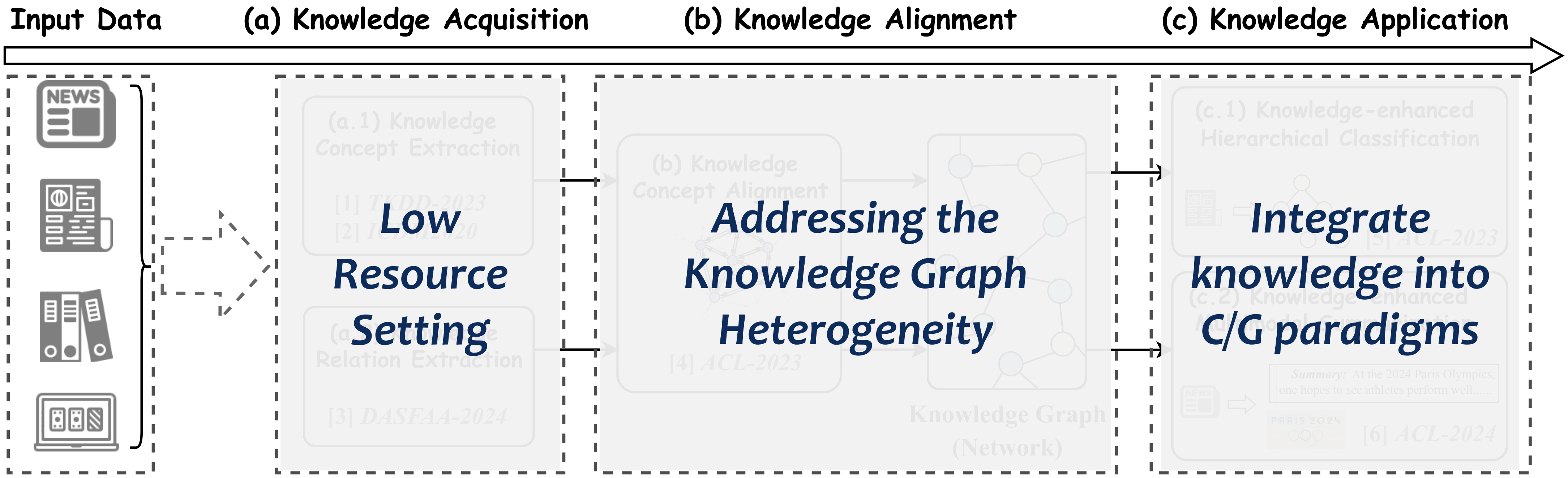
OUTLINE

CONTENTS

Conclusions

- Knowledge-aware NLP techniques
  - From various documents, build well-organized ***knowledge graphs***
  - Apply these knowledge to mitigate the ***knowledge limitation*** in various downstream tasks

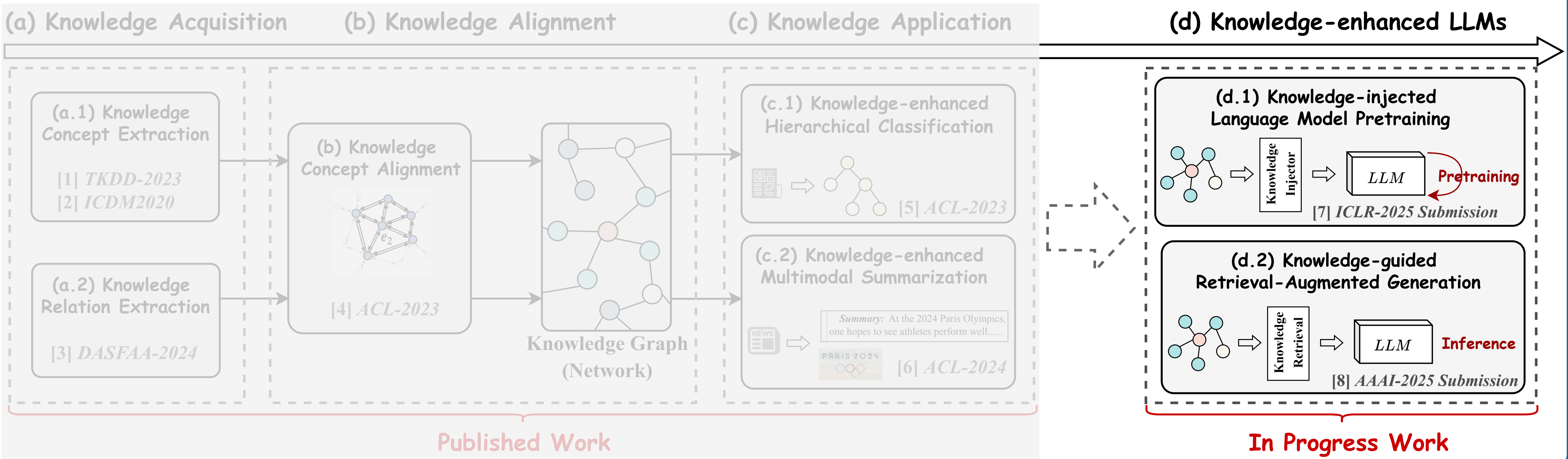


Future Work

- Knowledge-enhance ***LLMs***
  - Knowledge-injected Language Model ***Pretraining/Editing***
    - ✓ Learn while Unlearn: An Iterative Unlearning Framework for GLM [7]
  - Knowledge-guided ***Retrieval Augmented Generation***
    - ✓ A Novel LLM-based Framework for Few-shot Fake News Detection [8]

ICLR-2025 Submission

AAAI-2025 Submission



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[7] Haoyu Tang†, Ye Liu†, Xukai Liu, Kai Zhang, Yanghai Zhang, Qi Liu, Enhong Chen. Learn while Unlearn: An Iterative Unlearning Framework for Generative Language Models. Submitted to ICLR 2025.

[8] Ye Liu, Jiajun Zhu, Kai Zhang, Haoyu Tang, Yanghai Zhang, Xukai Liu, Qi Liu, Enhong Chen. Detect, Investigate, Judge and Determine: A Novel LLM-based Framework for Few-shot Fake News Detection. Submitted to AAAI 2025.

Thank You for Listening！

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