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Effective Representation Learning for Legal Case Retrieval

Yanran Tang

The University of Queensland

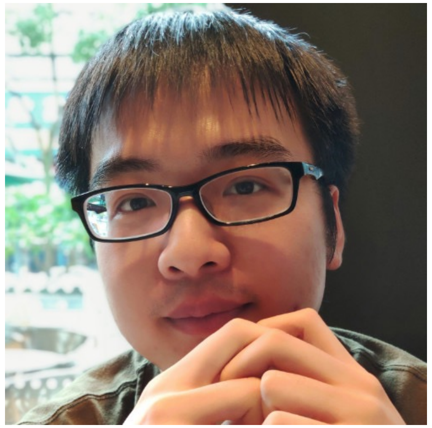
Glasgow IR Seminar

Contents

Team Members

Yanran Tang

EECS, UQ



Dr. Ruihong Qiu

EECS, UQ

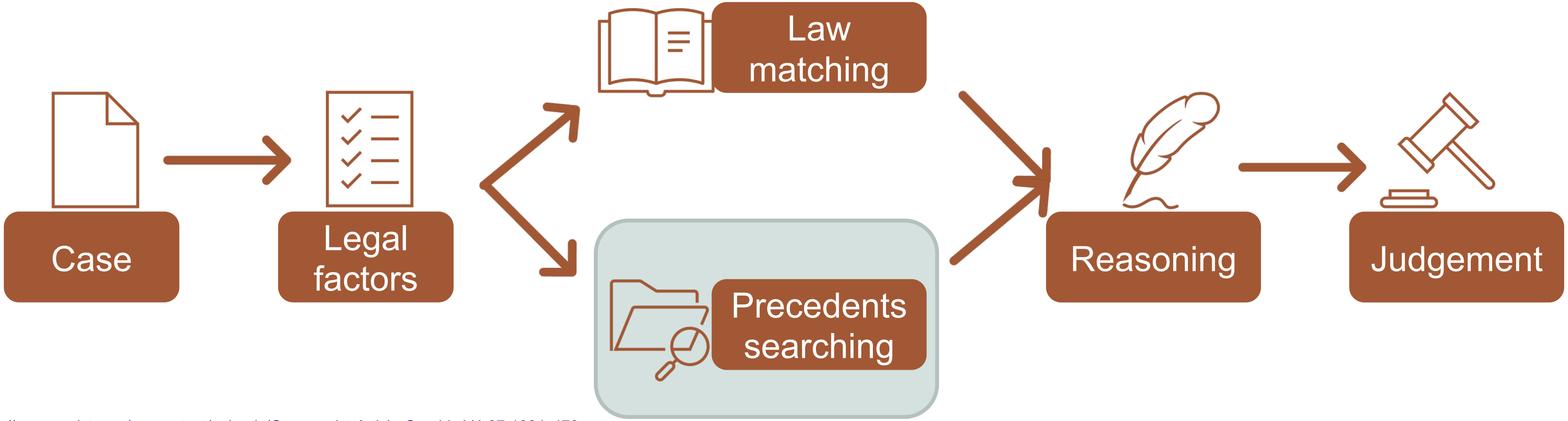
Prof. Xue Li

EECS, UQ

Prof. Helen Huang

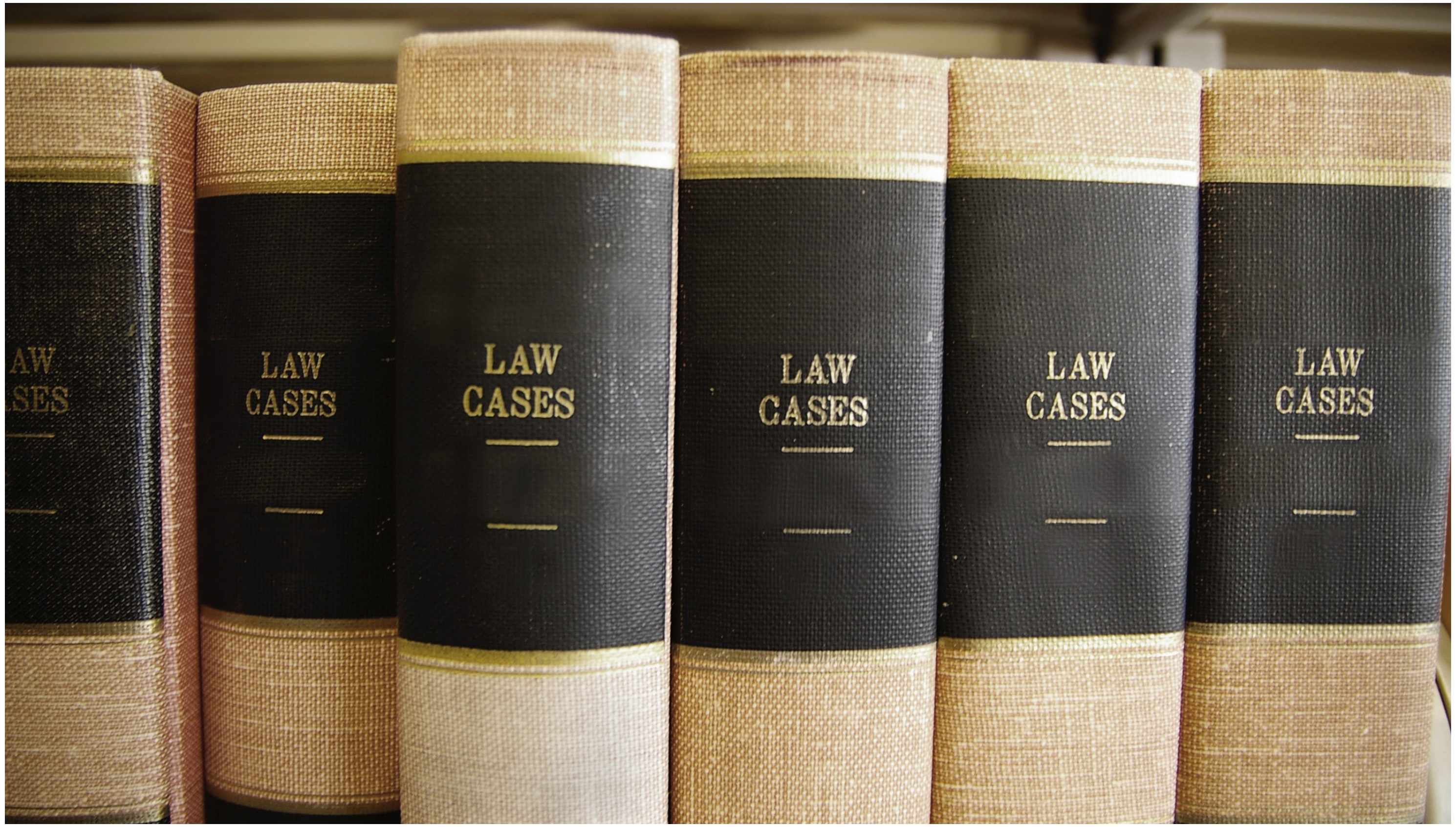
EECS, UQ

How Judges Make a Judgement



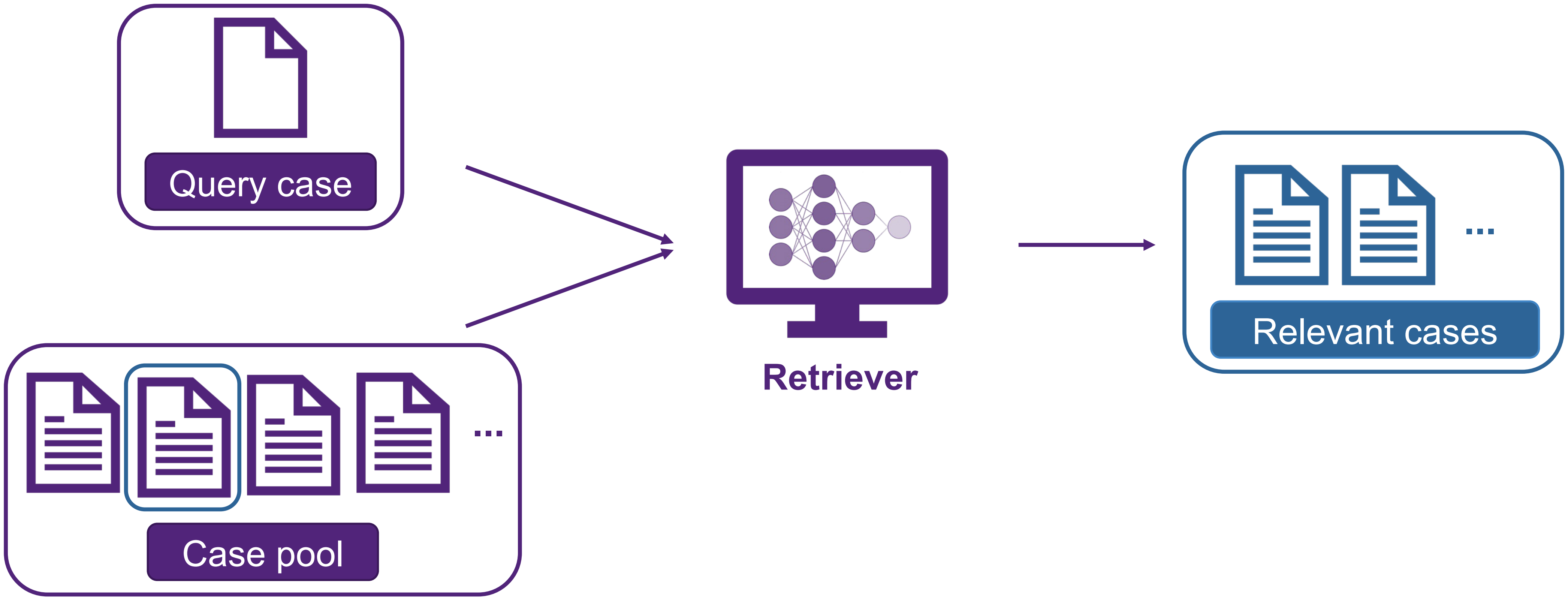
https://grammarist.com/wp-content/uploads/Grammarist-Article-Graphic-V4-87-1024x478.png

A Huge Collection of Cases



https://www.lesaonline.org/family-law-25-discover-the-latest-case-law/

Legal Case Retrieval Workflow



Legal Cases

Lafond v. **Muskeg Lake Cree Nation** (2008), 330 F.T.R. 60 (FC) → **Parties**: plaintiff & defendant

Summary:
Lafond was elected as a councillor to the Muskeg Lake Cree Nation Band Council. After receiving complaints regarding Lafond, the band's chief suspended Lafond from his duties. Lafond sought judicial review. → **Case Summaries**

(Not every case)

…

In the recent decision of **FRAGMENT_SUPPRESSED**, the Federal Court of Appeal, when confronted with a jurisdictional challenge where a Chief had been removed from office, noted that: → **Citation**

…

For these reasons, the application for judicial review of Chief Ledoux's **decision** will be allowed. → **Judgement**

Related work

Related Work in Information Retrieval

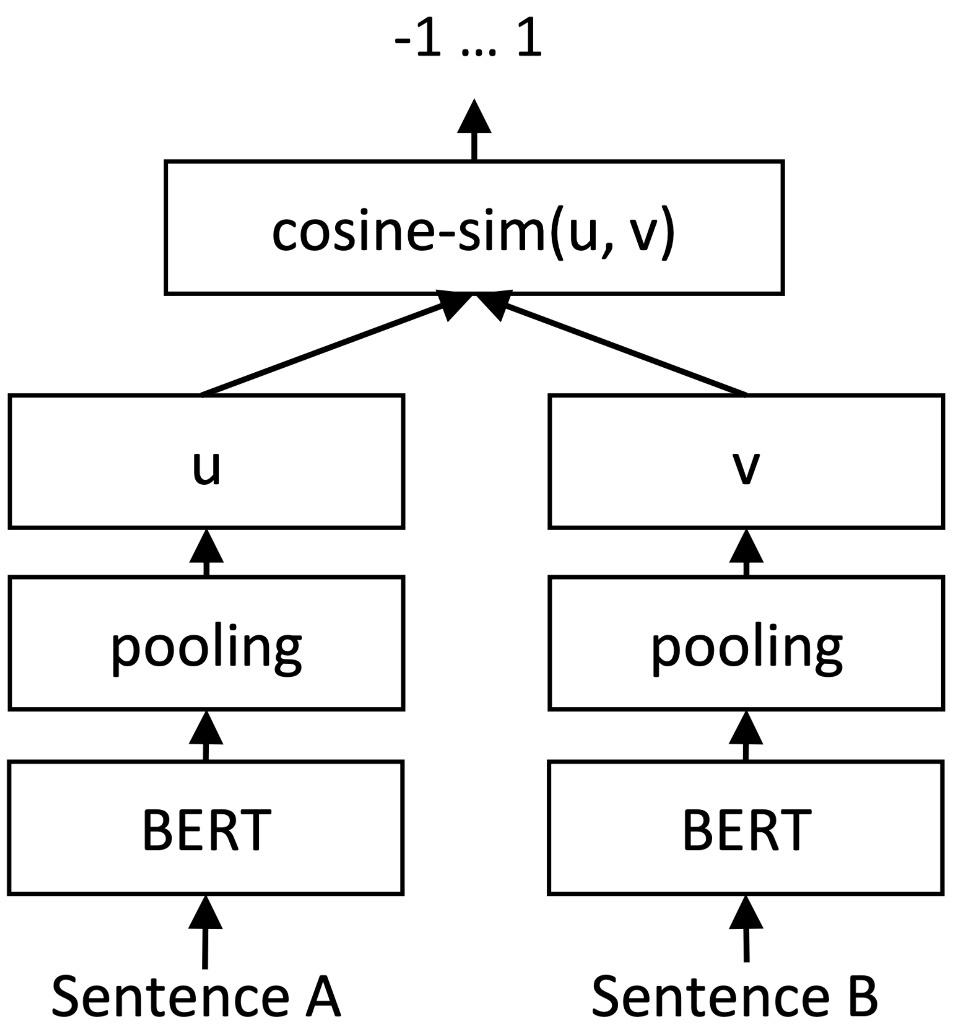
- **Sparse Retrieval**
  – TF-IDF [1]
  – BM25 [2]
  – LMIR [3]

[1] Gerard Salton and Christopher Buckley. “Term-weighting approaches in automatic text retrieval”, Information Processing & Management, 1988
[2] Stephen E Robertson and Steve Walker, “Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval”, In SIGIR, 1994
[3] Fei Song and W Bruce Croft, “A general language model for information retrieval”, In CIKM,1999

Related Work in Information Retrieval

- **Dense Retrieval**
  - Sentence-BERT [4] :

    Sentence embedding of a query interacts with sentence embedding of a document.

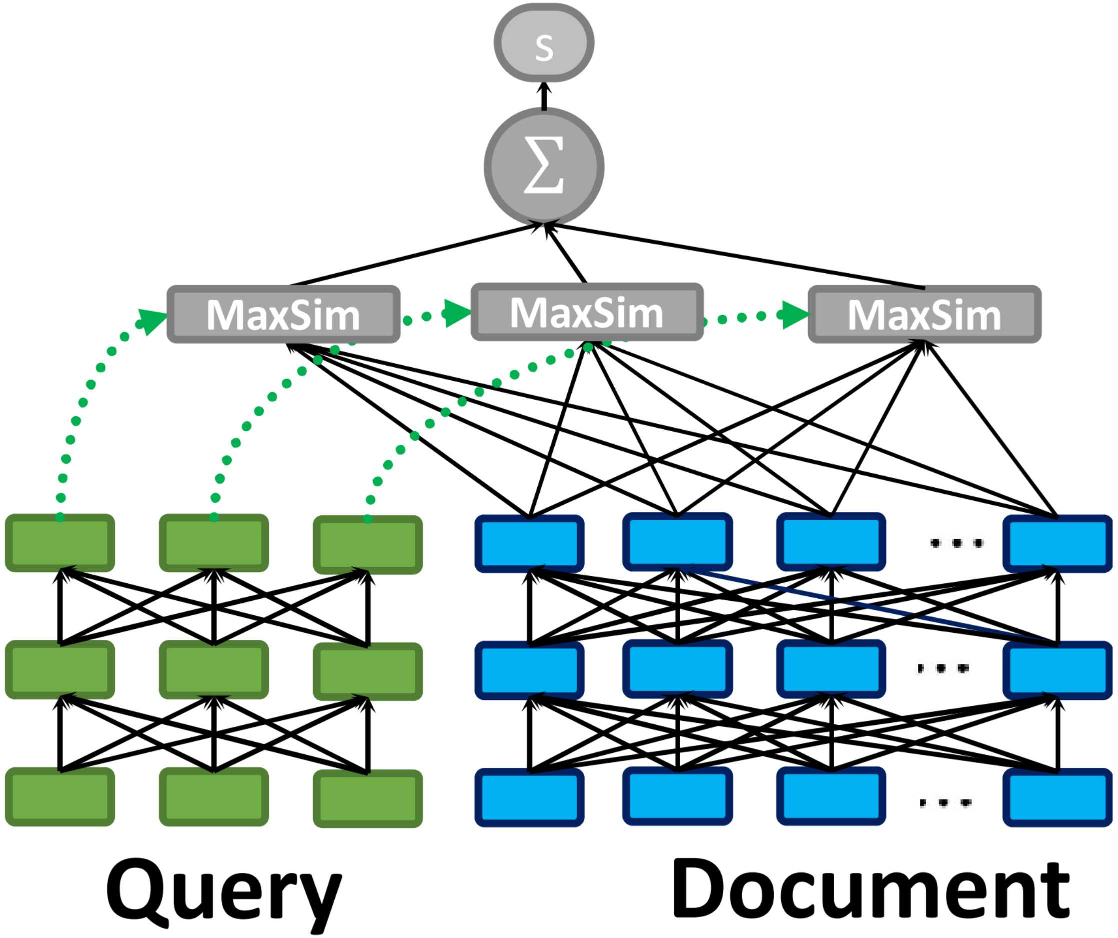


[4] Nils Reimers, Iryna Gurevych, "Sentence BERT: Sentence Embeddings using Siamese BERT-Networks", In EMNLP, 2019

Related Work in Information Retrieval

- **Dense Retrieval**
  - ColBERT [5] :

    Every **word embedding** of a query interacts with all word embeddings of a document.



[5] Omar Khattab, Matei Zaharia, "ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT", In SIGIR, 2020

Summary

- Pros
  - High accuracy on normal IR tasks
  - Easy to apply on LCR

- Cons
  - No legal **expert knowledge**
  - For sparse retrieval: No **semantic**, which is very important for revealing legal relationship
  - For dense retrieval: Cases are **too long** to directly utilized dense information retrieval models.

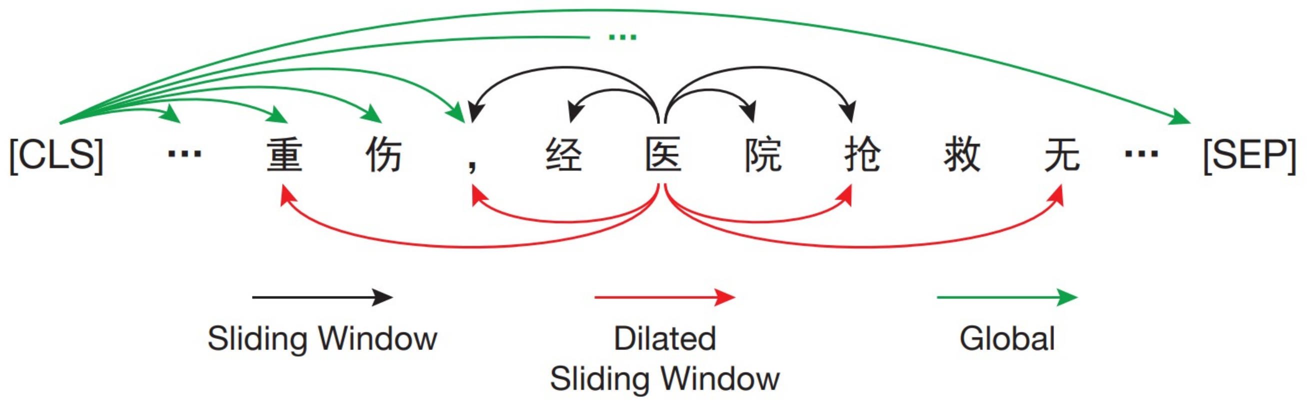
Related Work in Legal Case Retrieval

- **Legal pre-trained model**
  - LEGAL-BERT [6] :
    - Pretrained with a large number of English legal corpus
    - 12 GB of diverse English legal text
    - Totally 355k pieces of UK legislation, European legislation and us court cases, etc.

[6] Ilias Chalkidis, Manos Fergadiotis, Prodromos Malakasiotis, Nikolaos Aletras, Ion Androutsopoulos, "LEGAL-BERT: The Muppets straight out of Law School", In EMNLP (Findings), 2020

Related Work in Legal Case Retrieval

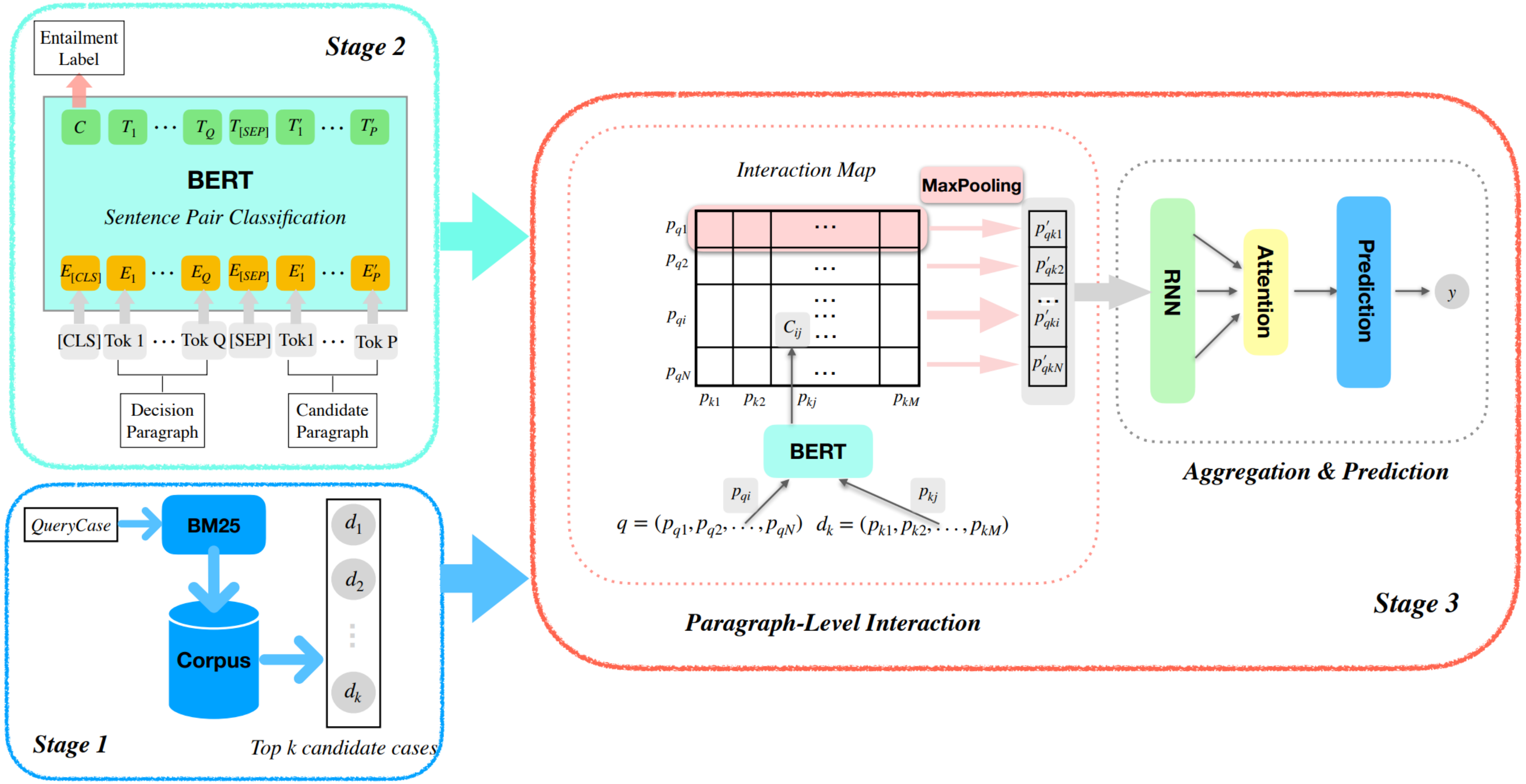
- **Legal pre-trained model**
  - Lawformer [7] :
    - Pretrained with Chinese legal corpus
    - Based model: Longformer
    - Combination of the three types of attention mechanism



[7] Chaojun Xiao, Xueyu Hu, Zhiyuan Liu, Cunchao Tu and Maosong Sun, “Lawformer: A pre-trained language model for chinese legal long documents”, AI Open, 2021

Related Work in Legal Case Retrieval

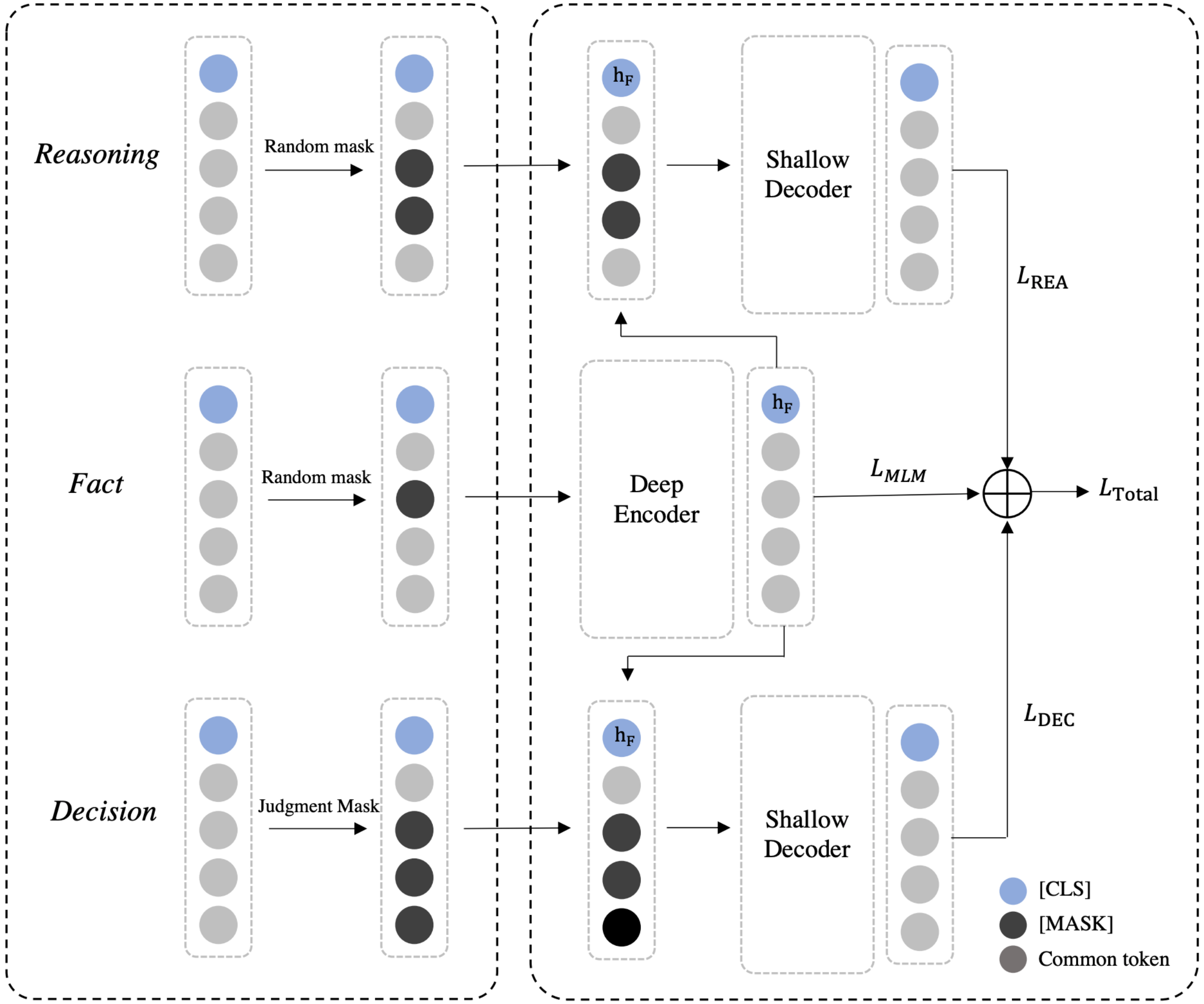
- **Bert-based model**
  - BERT-PLI [8]
    - Encode paragraphs with BERT
    - Paragraph-level interaction



[8] Yunqiu Shao, Jiaxin Mao, Yiqun Liu, Weizhi Ma, Ken Satoh, Min Zhang and Shaoping Ma, “BERT-PLI: Modeling Paragraph-Level Interactions for Legal Case Retrieval”, In IJCAI, 2020

Related Work in Legal Case Retrieval

- **Bert-based model**
  - SAILER [9]
    - Dividing cases into legal sections
    - Generation pretraining



[9] Haitao Li, Qingyao Ai, Jia Chen, Qian Dong, Yueyue Wu, Yiqun Liu, Chong Chen, Qi Tian, "SAILER: Structure-aware Pre-trained Language Model for Legal Case Retrieval", In SIGIR, 2023

Summary

- Pros
  - Better accuracy with semantics by **legal corpus pre-training**
  - Dividing case text for **lengthy** problem

- Cons
  - Case text dividing → loss of legal **context** information & case **global** view

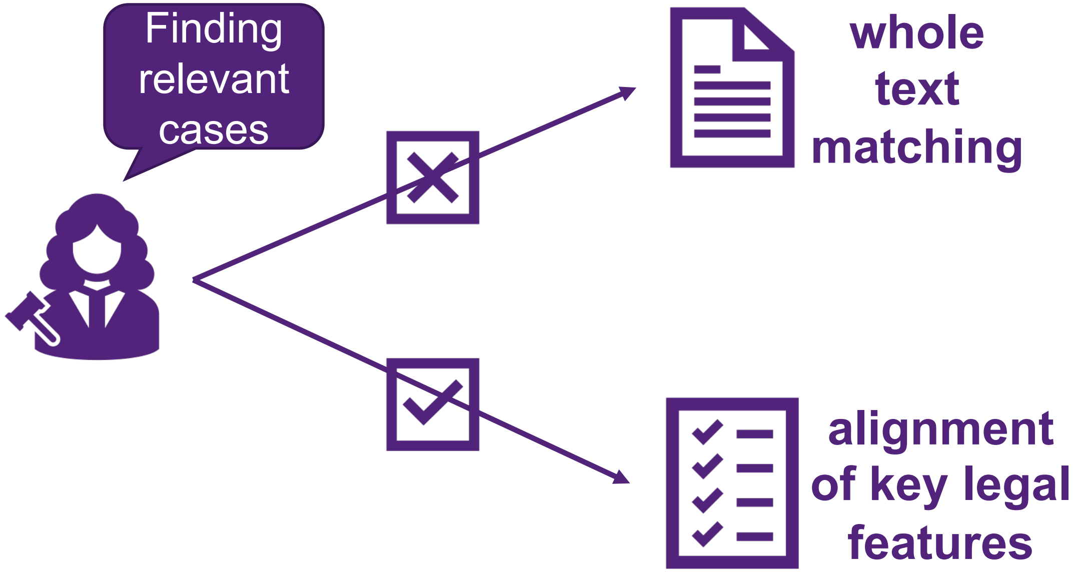
Research 1

PromptCase:
Prompt-based effective input reformulation for legal case retrieval

Yanran Tang, Ruihong Qiu, and Xue Li, “Prompt-Based Effective Input Reformulation for Legal Case Retrieval”, in ADC 2023

Challenges

- Determining factors of relevant cases:



- Input limitation of language models:

  Case needs to be truncated or divided into paragraphs

  → Loss of legal information

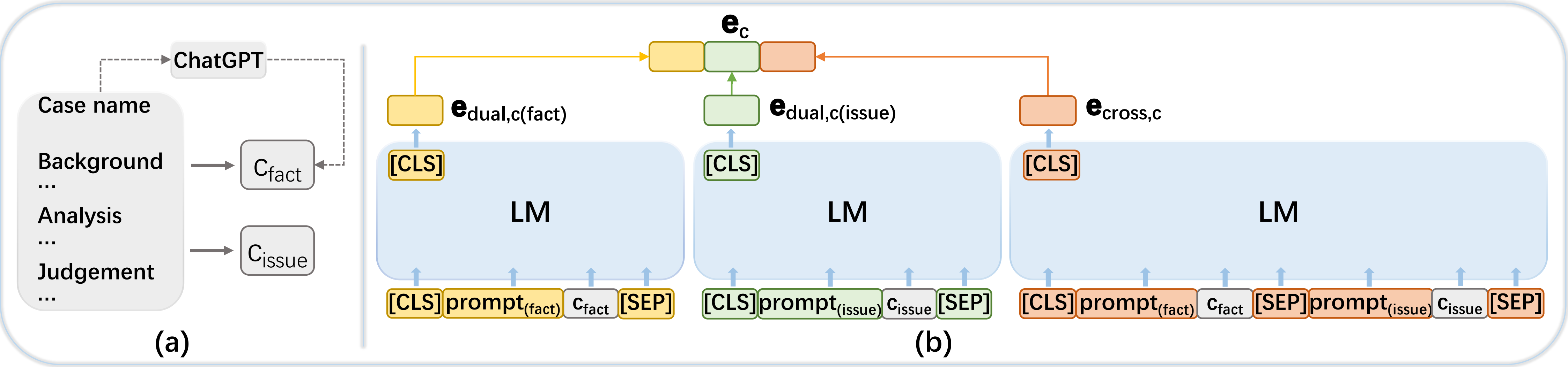
Solution

- **Legal facts** and **legal issues** are considered as the determining factors:
  - Legal facts: Detailed process of a case → Case summary
  - Legal issues: Dispute points between the parties → Precedents / Charges

- **Identify** legal facts and legal issues → Feed into language model

- Use **prompt** to preserve legal context:
  - "The legal facts are: " + legal facts
  - "The legal issues are: " + legal issues

PromptCase Framework



Experiment Setting: Datasets

- English: COLIEE2023 [10]

Lafond v. Muskeg Lake Cree Nation (2008), 330 F.T.R. 60 (FC)

BACKGROUND
On February 13, 2006, the applicant was elected as a councillor to the MLCN Band Council for a term of three years. The respondent Band is located in the province of Saskatchewan and has reserve land ...

ANALYSIS
Does this Court have jurisdiction over the present application?
In order to determine the jurisdiction of the Federal Court in this matter, it is imperative to... Indeed this was recognized by the Federal Court of Appeal in FRAGMENT_SUPPRESSED, where it held that FRAGMENT_SUPPRESSED... Respecting the Government Elections and Related Regulations of the Muskeg Lake Cree Nation (the Election Act) ...

ORDER
For these reasons, the application for judicial review of Chief Ledoux's decision will be allowed.

- Chinese: LeCaRD [11]

李月航容留他人吸毒一案 (Case name)

案件基本情况 (Background)
长乐市人民检察院指控： 1、2017 年 9 月 25 日 22 时许，被告人李月航在其租住的长乐市某街道某村某公寓房间内，容留王某吸食甲基苯丙胺（俗称"冰毒"）。 2、2017 年 10 月 19 日晚，被告人李月航在其租住的长乐市某街道某村某公寓房间内，容留王某... **经审理查明**： 1、2017 年 9 月 25 日 22 时许，被告人李月航在其租住的长 ...

裁判分析过程 (Analysis)
本院认为，被告人李月航多次为他人吸食毒品提供场所，其行为已构成容留他人吸毒罪。长乐市人民检察院指控的罪名成立，应依法追究被告人李月航的刑事责任。被告人李月航因涉嫌吸毒被公安机关抓获，主动向公安机关供述了尚未被掌握的其容留他人吸毒的犯罪事实，视为自动投案，系自首，依法可从轻处罚；被告人李月航被公安 ...

判决结果 (Judgement)
被告人李月航犯容留他人吸毒罪，判处拘役五个月，并处罚金人民币三千元。

[10] https://sites.ualberta.ca/~rabelo/COLIEE2023/
[11] Yixiao Ma, Yunqiu Shao, Yueyue Wu, Yiqun Liu, Ruizhe Zhang, Min Zhang, Shaoping Ma, "LeCaRD: A Legal Case Retrieval Dataset for Chinese Law System". In SIGIR, 2021

Experiment Setting

Baselines

- BM25
- BERT [12]
- Lawformer
- LEGAL-BERT
- Mono-T5 [13]
- SAILER

Metrics

- Precision
- Recall
- F1
- Macro F1
- Mean Average Precision (MAP)
- Mean Reciprocal Rank (MRR)
- Normalized Discounted Cumulative Gain (NDCG)

Two-stage experiments

- Top 10 retrieved cases by BM25 as the first stage result

[12] Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”, In NAACL-HLT, 2019
[13] Rodrigo Frassetto Nogueira, Zhiying Jiang, Ronak Pradeep, Jimmy Lin, “Document Ranking with a Pretrained Sequence-to-Sequence Model”, In EMNLP (Findings), 2020

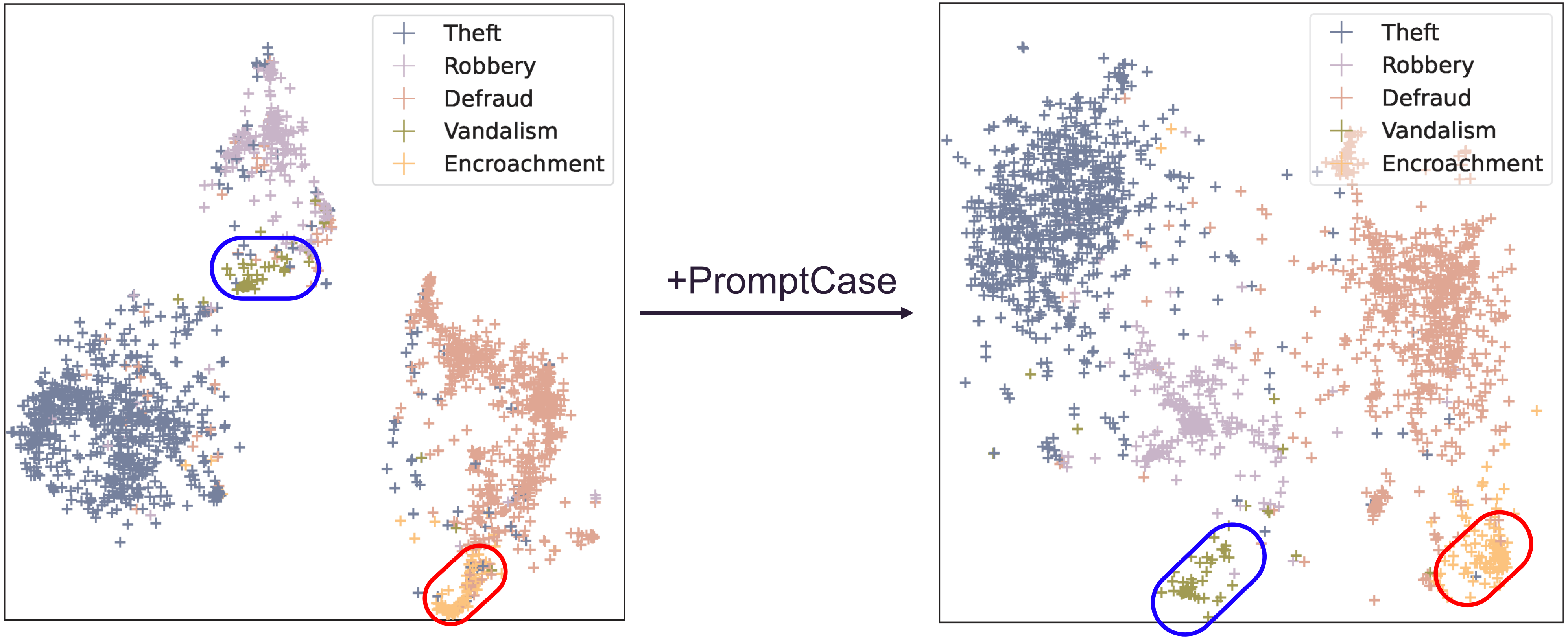
Overall Performance

Methods	LeCaRD@5						
	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5
BM25	40.0	19.2	26.0	30.5	58.3	48.5	45.9
+PromptCase	41.3	19.9	26.8	31.7	60.6	58.8	65.2
BERT	38.7	18.6	25.1	26.7	57.4	54.3	61.0
+PromptCase	46.2	22.2	30.0	35.4	64.4	61.2	67.9
Lawformer	29.0	13.9	18.8	19.5	43.6	41.9	48.2
+PromptCase	38.9	18.7	25.3	30.7	62.0	59.7	64.0
SAILER	46.7	22.5	30.4	37.1	67.9	65.4	70.1
+PromptCase	51.6	24.8	33.5	43.0	71.1	67.6	74.2
Two-stage SAILER	47.8	23.0	31.1	36.1	67.3	64.4	70.6
+PromptCase	51.0	24.6	33.2	38.7	70.7	67.9	73.5

Methods	COLIEE2023						
	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5
BM25	16.5	30.6	21.4	22.2	23.1	20.4	23.7
+PromptCase	17.0	31.5	22.1	23.0	24.2	21.6	24.4
BERT	2.07	3.84	2.69	2.57	5.51	5.48	6.25
+PromptCase	2.38	4.42	3.10	3.02	6.33	6.25	7.21
LEGAL-BERT	4.64	8.61	6.03	6.03	11.4	11.3	13.6
+PromptCase	4.83	8.96	6.28	6.44	13.4	13.4	15.5
MonoT5	0.38	0.70	0.49	0.47	1.17	1.33	0.61
+PromptCase	0.56	1.05	0.73	0.72	1.63	1.43	0.89
SAILER	12.8	23.7	16.6	17.0	25.9	25.3	29.3
+PromptCase	16.0	29.7	20.8	21.5	32.7	32.0	36.2
Two-stage SAILER	19.6	32.6	24.5	23.5	37.3	36.1	40.8
+PromptCase	21.8	36.3	27.2	26.5	39.9	38.7	44.0

- Plug-and-play and improve consistently

PromptCase Case Study



After utilising PromptCase, case embeddings evenly distributed corresponding to 5 charges as 5 clusters.

Conclusion of Research 1

- **Legal facts** and **legal issues** are determining factors for legal case retrieval.

- **PromptCase** effectively encodes the legal features.

Research 2

CaseGNN:
Graph neural networks for legal case retrieval with text-attributed graphs

Yanran Tang, Ruihong Qiu, Yilun Liu, Xue Li, and Zi Huang, “CaseGNN: Graph Neural Networks for Legal Case Retrieval with Text-Attributed Graphs”, in ECIR 2024.

Challenges

- Legal **structural** information:
  - High-order interactions of **elements** in a case: parties, crime activities and evidences
- **Lengthy** legal text limitation:

Datasets	LeCaRD	COLIEE2023
Language	Chinese	English
Avg. length/case	8,275	5,566
Largest length of cases	99,163	61,965
Avg. relevant cases/query	10.33	2.69

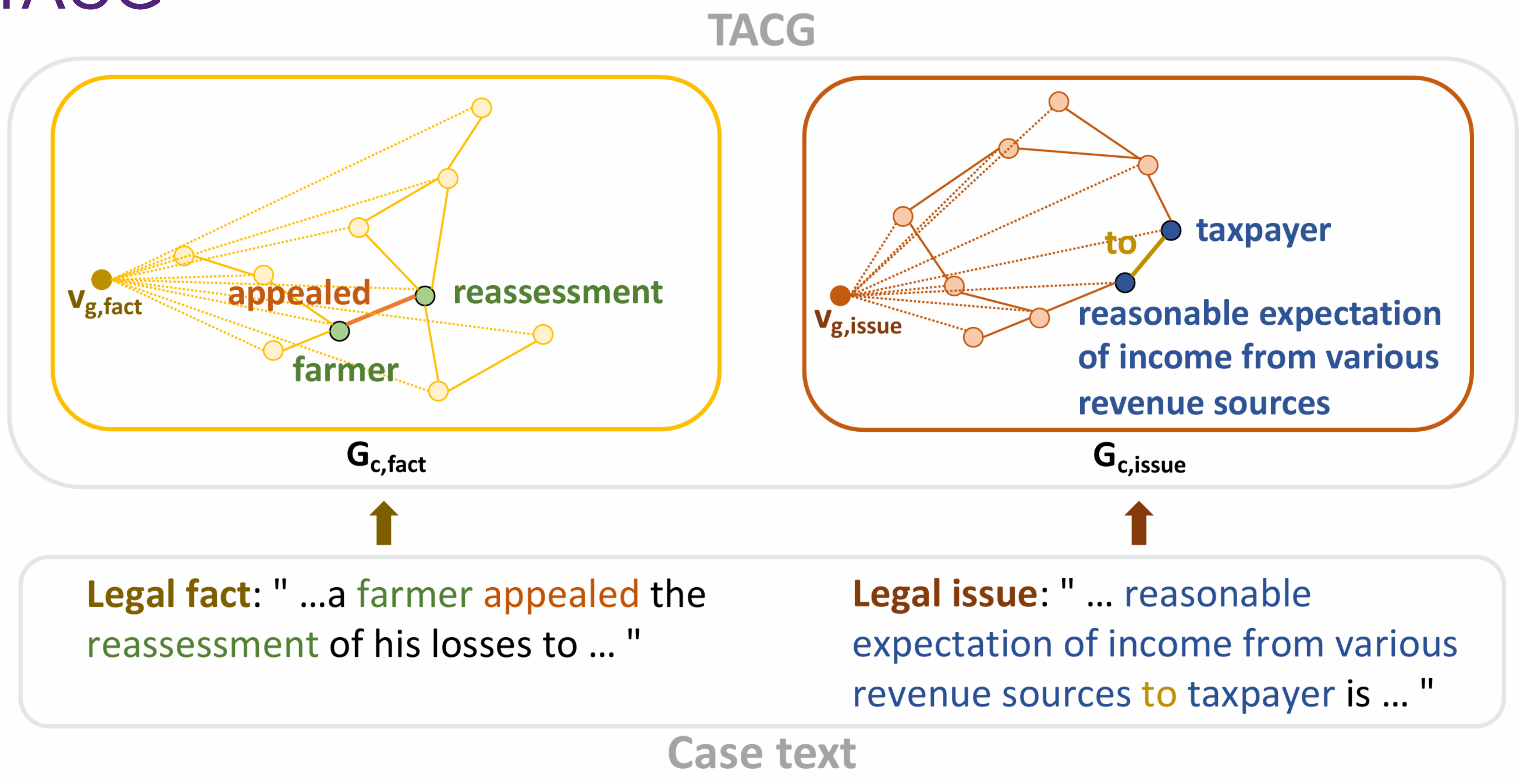
Solution

- Graph is an effective data structure to incorporate **structural** information for legal cases.

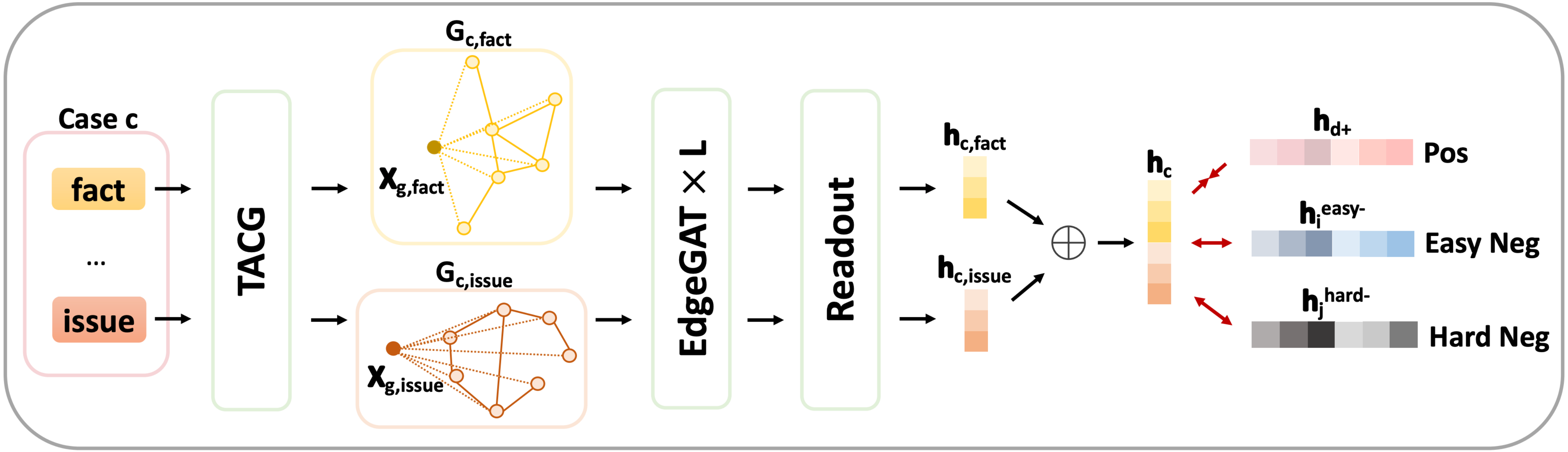
- Transform a legal case into a **Text-Attributed Case Graph (TACG)**.

- An **Edge Graph Attention Layer (EdgeGAT)** and a readout function are proposed to obtain a graph level case representation.

TACG


TACG
$v_{g,fact}$
appealed
reassessment
farmer
$G_{c,fact}$
to
taxpayer
$v_{g,issue}$
reasonable expectation
of income from various
revenue sources
$G_{c,issue}$
Legal fact: " ...a farmer appealed the reassessment of his losses to ... "
Legal issue: " ... reasonable expectation of income from various revenue sources to taxpayer is ... "
Case text

CaseGNN Framework



Experiment Setting

- Metrics and baselines: follow PromptCase

- Datasets:
  - COLIEE2022 [14] and COLIEE2023
  - LeCaRD is not used due to no sufficient foundational and open-sourced relation extraction tool for Chinese

Datasets	COLIEE2022		COLIEE2023	
	train	test	train	test
# Query	898	300	959	319
# Candidates	4415	1563	4400	1335
# Avg. relevant cases	4.68	4.21	4.68	2.69
Avg. length (# token)	6724	6785	6532	5566
Largest length (# token)	127934	85136	127934	61965

[14] https://sites.ualberta.ca/~rabelo/COLIEE2022/

Overall Performance

Methods	COLIEE2022							COLIEE2023						
	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5
One-stage														
BM25	17.9	21.2	19.4	21.4	23.6	25.4	33.6	16.5	30.6	21.4	22.2	23.1	20.4	23.7
LEGAL-BERT	4.47	5.30	4.85	5.38	7.42	7.47	10.9	4.64	8.61	6.03	6.03	11.4	11.3	13.6
MonoT5	0.71	0.65	0.60	0.79	1.39	1.41	1.73	0.38	0.70	0.49	0.47	1.17	1.33	0.61
SAILER	16.6	15.2	14.0	16.8	17.2	18.5	25.1	12.8	23.7	16.6	17.0	25.9	25.3	29.3
PromptCase	17.1	20.3	18.5	20.5	35.1	33.9	38.7	16.0	29.7	20.8	21.5	32.7	32.0	36.2
CaseGNN (Ours)	**35.5**±0.2	**42.1**±0.2	**38.4**±0.3	**42.4**±0.1	**66.8**±0.8	**64.4**±0.9	**69.3**±0.8	**17.7**±0.7	**32.8**±0.7	**23.0**±0.5	**23.6**±0.5	**38.9**±1.1	**37.7**±0.8	**42.8**±0.7
Two-stage														
SAILER	**23.8**	25.7	24.7	25.2	43.9	42.7	48.4	19.6	32.6	24.5	23.5	37.3	36.1	40.8
PromptCase	23.5	25.3	24.4	**30.3**	41.2	39.6	45.1	**21.8**	36.3	**27.2**	26.5	39.9	38.7	44.0
CaseGNN (Ours)	22.9±0.1	**27.2**±0.1	**24.9**±0.1	27.0±0.1	**54.9**±0.4	**54.0**±0.5	**57.3**±0.6	20.2±0.2	**37.6**±0.5	26.3±0.3	**27.3**±0.2	**45.8**±0.9	**44.4**±0.8	**49.6**±0.8

- **CaseGNN** outperforms other baselines.
- CaseGNN is based on PromptCase, the newly proposed **graph-based** framework can significantly enhance the performance.

Conclusion of Research 2

- Legal **structural** information is important and can be utilised by **graph neural network**.

- Case graphs help avoid **lengthy** case text and **preserve** legal context.

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Research 3

CaseGNN++:
Graph Contrastive Learning for Legal Case Retrieval with Graph Augmentation

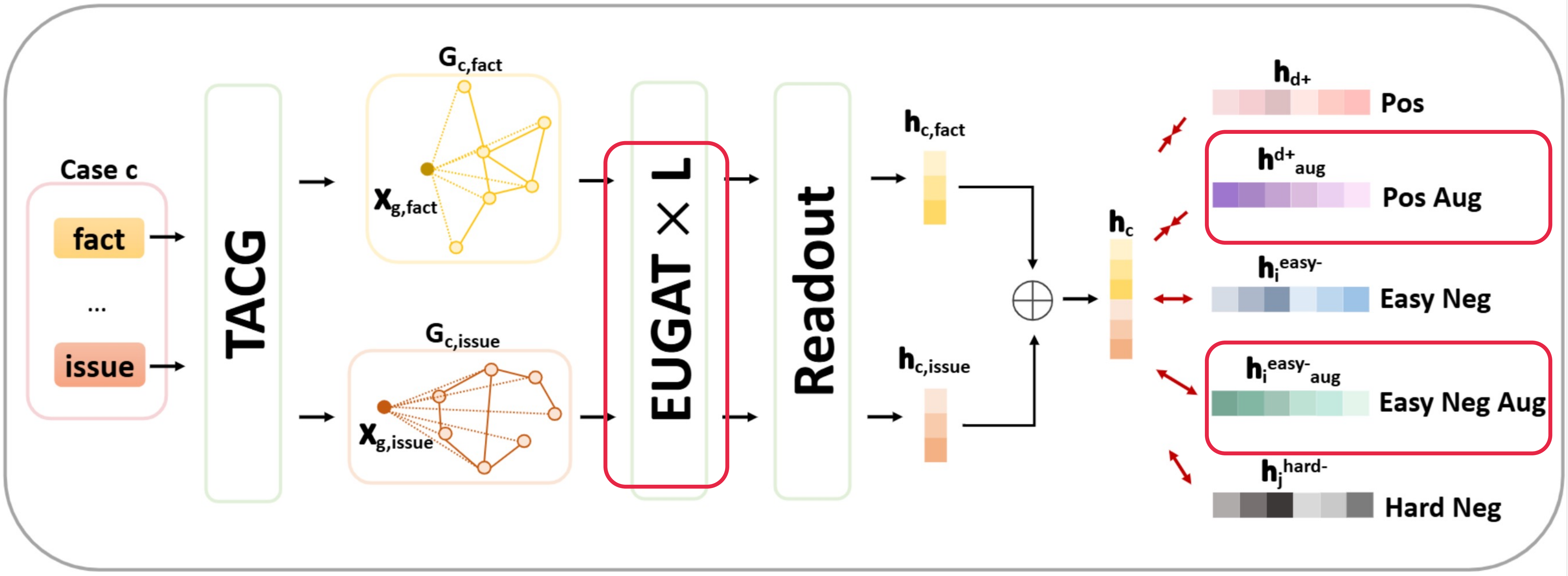
Yanran Tang, Ruihong Qiu, Yilun Liu, Xue Li and Zi Huang, “CaseGNN++: Graph Contrastive Learning for Legal Case Retrieval with Graph Augmentation”, CoRR abs/2307.11572, 2024

Challenges

- The underutilization of rich **edge information** within text-attributed case graphs limits CaseGNN to generate informative case representation

- The **inadequacy of labelled data** in legal datasets hinders the training of CaseGNN model.

CaseGNN++ Framework



- Edge-update graph attention layer (EUGAT)
  - Comprehensively update node and edge features during graph modelling
- Graph contrastive learning & graph augmentation:
  - Edge dropping
  - Feature masking: node or edge feature

Overall Performance

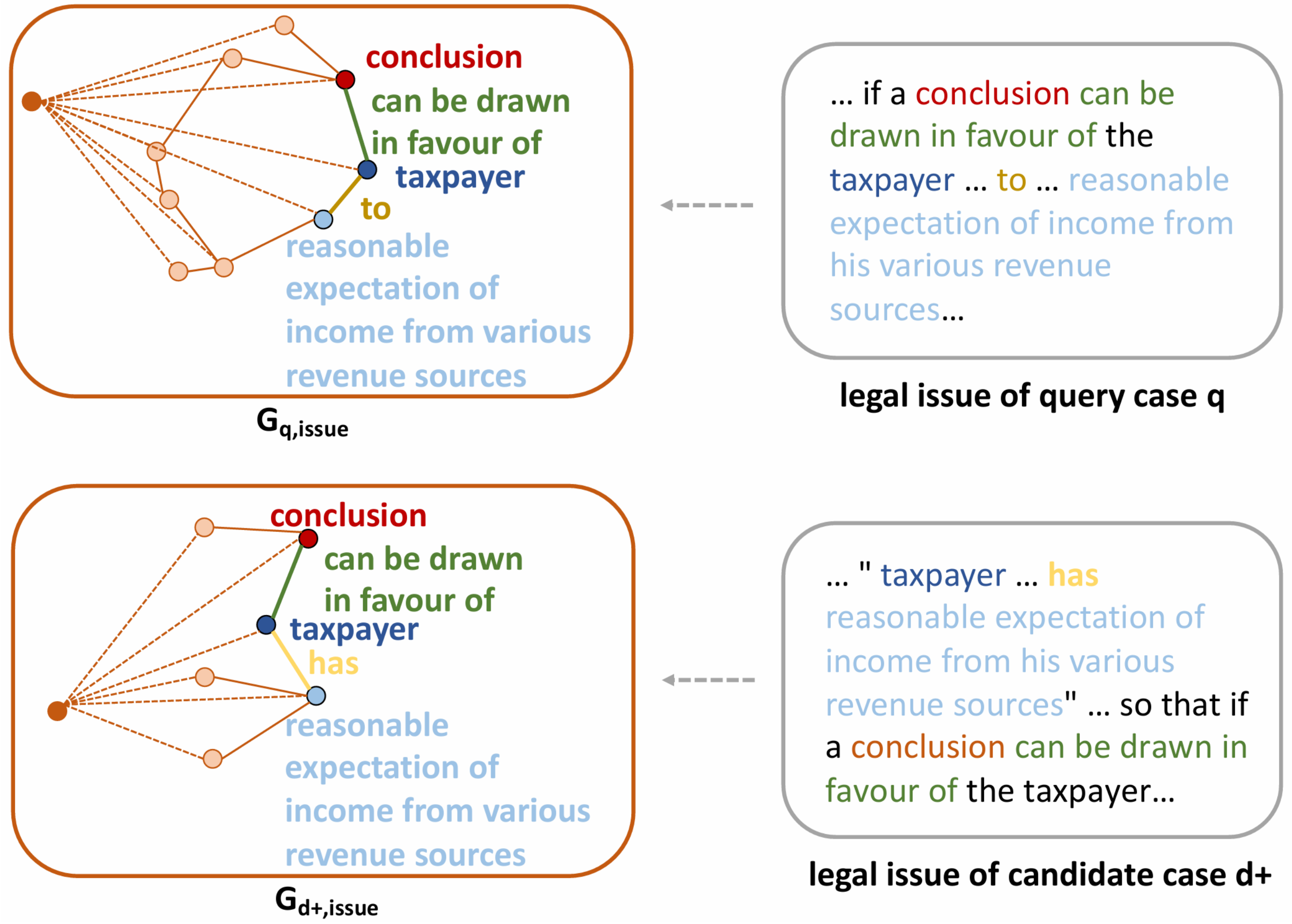
Methods	COLIEE2022						
	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5
One-stage							
BM25	17.9	21.2	19.4	21.4	23.6	25.4	33.6
LEGAL-BERT	4.47	5.30	4.85	5.38	7.42	7.47	10.9
MonoT5	0.71	0.65	0.60	0.79	1.39	1.41	1.73
SAILER	16.6	15.2	14.0	16.8	17.2	18.5	25.1
PromptCase	17.1	20.3	18.5	20.5	35.1	33.9	38.7
CaseGNN (Ours)	35.5±0.2	42.1±0.2	38.4±0.3	42.4±0.1	66.8±0.8	64.4±0.9	69.3±0.8
CaseGNN++ (Ours)	**36.5**±0.6	**43.3**±0.7	**39.6**±0.6	**43.8**±0.7	**68.1**±1.1	**65.3**±1.1	**70.8**±1.1
Two-stage							
SAILER	23.8	25.7	24.7	25.2	43.9	42.7	48.4
PromptCase	23.5	25.3	24.4	**30.3**	41.2	39.6	45.1
CaseGNN (Ours)	22.9±0.1	27.2±0.1	24.9±0.1	27.0±0.1	54.9±0.4	54.0±0.5	57.3±0.6
CaseGNN++ (Ours)	**24.8**±0.1	**29.4**±0.1	**26.9**±0.1	29.3±0.1	**55.6**±0.6	**54.3**±0.3	**58.1**±0.3

Overall Performance

Methods	COLIEE2023						
	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5
One-stage							
BM25	16.5	30.6	21.4	22.2	23.1	20.4	23.7
LEGAL-BERT	4.64	8.61	6.03	6.03	11.4	11.3	13.6
MonoT5	0.38	0.70	0.49	0.47	1.17	1.33	0.61
SAILER	12.8	23.7	16.6	17.0	25.9	25.3	29.3
PromptCase	16.0	29.7	20.8	21.5	32.7	32.0	36.2
CaseGNN (Ours)	17.7±0.7	32.8±0.7	23.0±0.5	23.6±0.5	38.9±1.1	37.7±0.8	42.8±0.7
CaseGNN++ (Ours)	**18.2**±0.3	**33.8**±0.4	**23.7**±0.4	**24.3**±0.3	**40.0**±0.2	**38.9**±0.3	**43.8**±0.3
Two-stage							
SAILER	19.6	32.6	24.5	23.5	37.3	36.1	40.8
PromptCase	**21.8**	36.3	**27.2**	26.5	39.9	38.7	44.0
CaseGNN (Ours)	20.2±0.2	37.6±0.5	26.3±0.3	27.3±0.2	45.8±0.9	44.4±0.8	49.6±0.8
CaseGNN++ (Ours)	20.4±0.1	**37.9**±0.2	26.6±0.2	**27.5**±0.2	**45.9**±0.4	**44.5**±0.3	**49.9**±0.3

CaseGNN & CaseGNN++ Case Study

- Successful retrieval by CaseGNN & CaseGNN++ but not by PromptCase.



- Original **text**:

  entities and relationships are **far** from each other. Language models are **not** good at **long dependency**.

- TACG:

  brings multiple entities **together**.

THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

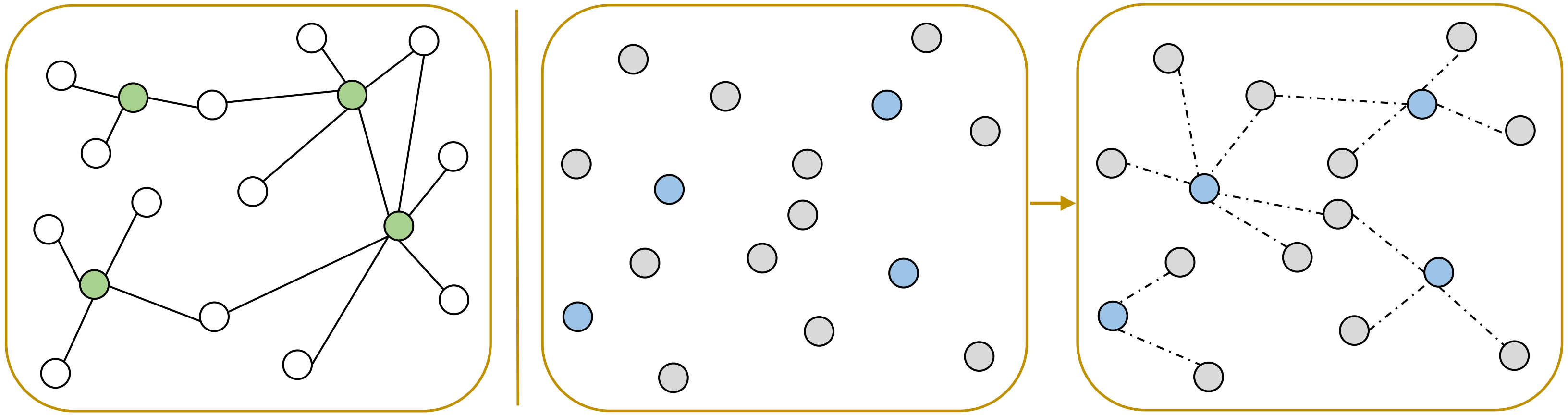
Research 4

CaseLink:
Inductive Graph Learning for Legal Case Retrieval

Yanran Tang, Ruihong Qiu, Xue Li, and Zi Huang, “CaseLink: Inductive Graph Learning for Legal Case Retrieval”, in SIGIR 2024

Challenges

- The **inductive** nature of case reference in legal case retrieval.



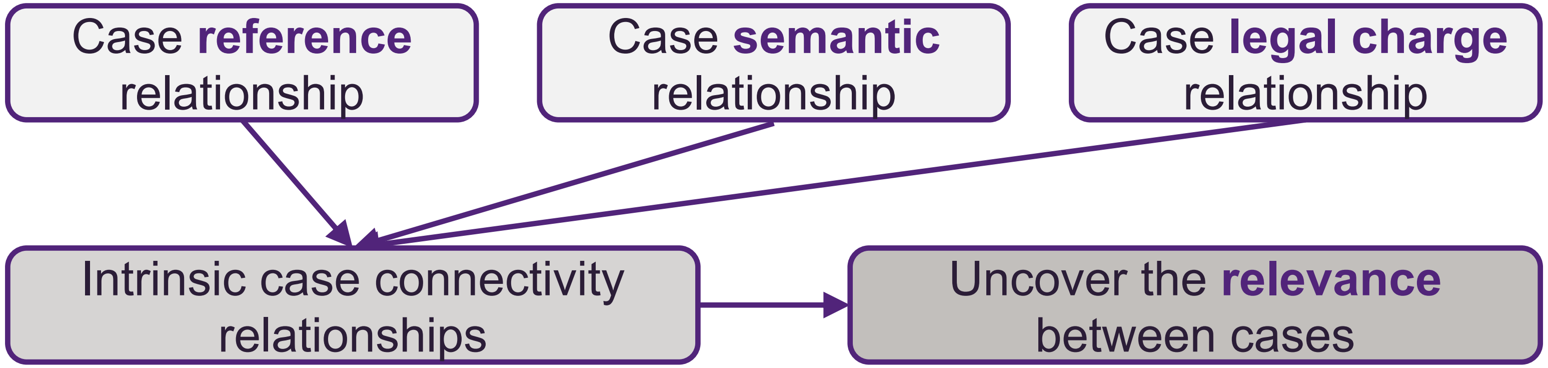
(a) Training set with ground truth edges. **(b) Inductive learning to uncover edges from unseen testing set.**

Figure (a)
- Green node: query cases in training set
- White node: candidate cases in training set
- Solid edges: referenced relation (label)

Figure (b)
- Blue node: query cases in test set
- Grey node: candidate cases in test set
- Dashed edges: predicted referenced relation

Challenges

- The intrinsic case connectivity relationships are important for legal case retrieval.

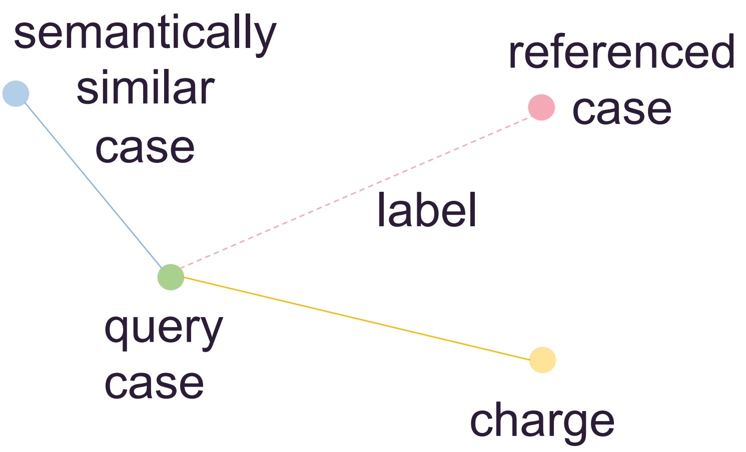


Lafond v. Muskeg Lake Cree Nation (2008), 330 F.T.R. 60 (FC)

BACKGROUND
On February 13, 2006, the applicant was elected as a councillor to the MLCN Band Council for a term of three years. The respondent Band is located in the province of Saskatchewan and has reserve land ...

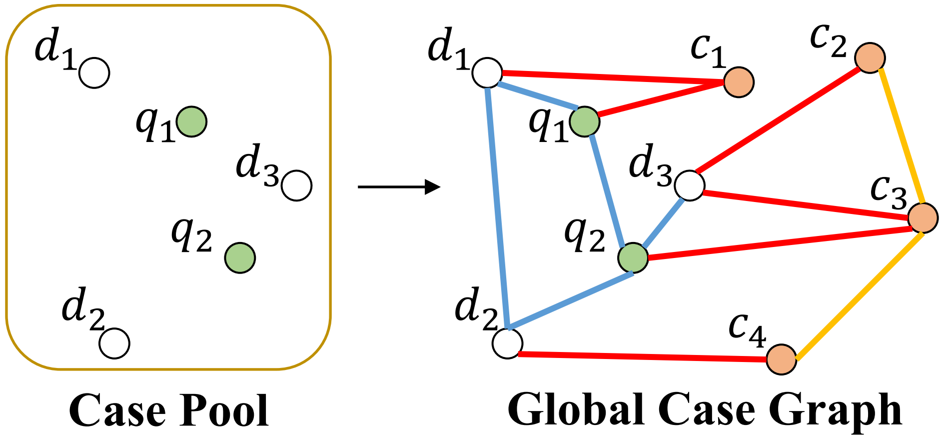
ANALYSIS
Does this Court have jurisdiction over the present application?
In order to determine the jurisdiction of the Federal Court in this matter, it is imperative to... Indeed this was recognized by the Federal Court of Appeal in FRAGMENT_SUPPRESSED, where it held that FRAGMENT_SUPPRESSED... Respecting the Government Elections and Related Regulations of the Muskeg Lake Cree Nation (the Election Act) ..

ORDER
For these reasons, the application for judicial review of Chief Ledoux's decision will be allowed.

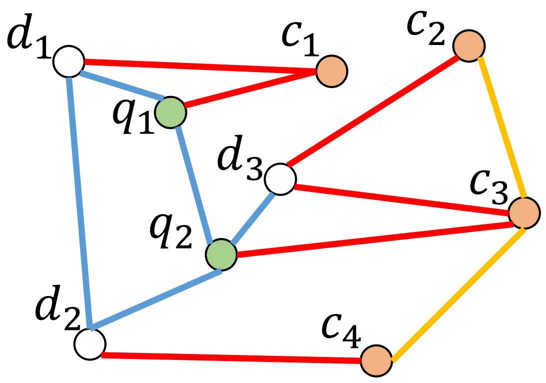


Solution

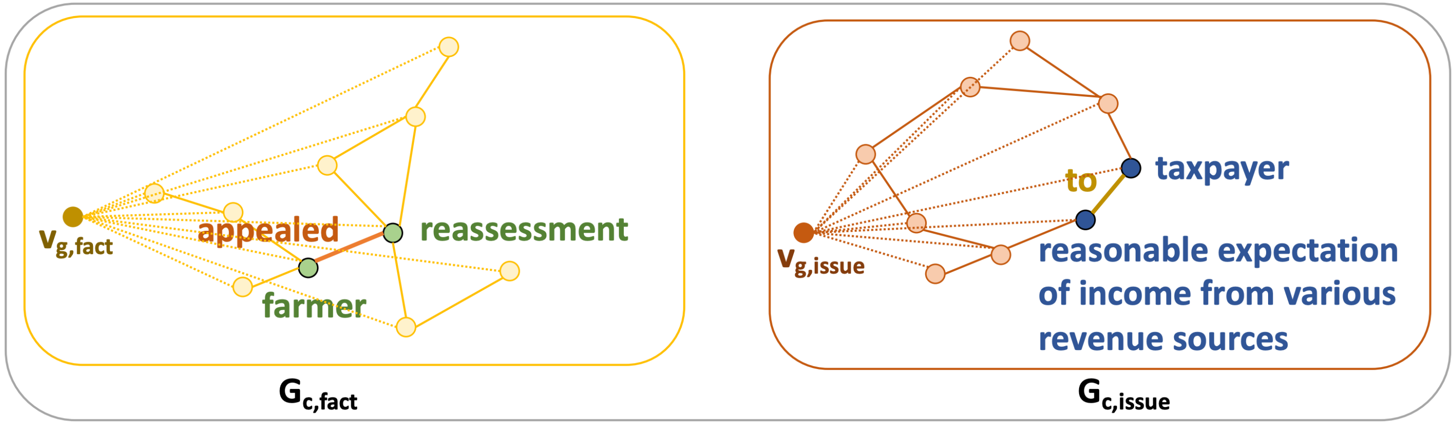
- A pool of cases is converted into a structured graph
  - Case-case bm25 (blue)
  - Case-charge (red)
  - Charge-charge (yellow)



GCG Compared with TACG



GCG



TACG

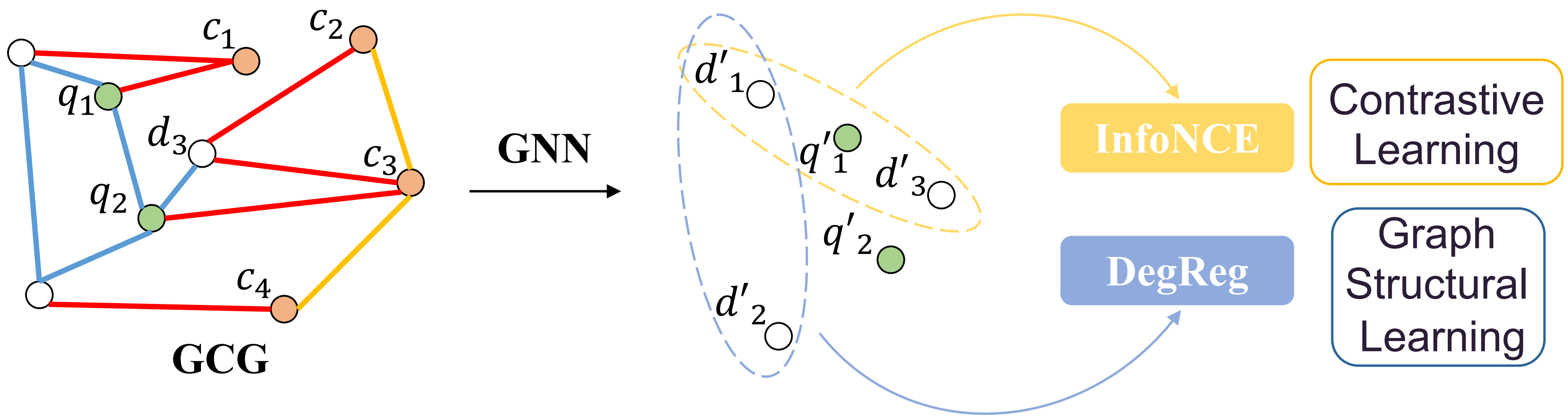
A GCG includes a pool of cases.

Every node is a case.

A TACG stands for a case.

Every node is an entity of the case.

CaseLink Framework



- For query q_1, d_3 is a positive sample and d_1, d_2 are negative samples.
- $\ell = \ell_{\text{InfoNCE}} + \lambda \cdot \ell_{\text{DegReg}}$

Degree Regularisation (DegReg)

- Motivation:
  – Real-world **sparse** situation: candidate case will be only related to a small number of query cases of pool → **low degree**
  – Providing the training signal for **candidate** cases

- $\ell_{\text{DegReg}} = \sum(\hat{A}_{candidate})\downarrow$
  – Minimising the degree of candidate nodes

Experiment

Settings: the same as CaseGNN

Overall performance:

Methods	COLIEE2022							COLIEE2023						
	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5	P@5	R@5	Mi-F1	Ma-F1	MRR@5	MAP	NDCG@5
One-stage														
BM25	17.9	21.2	19.4	21.4	23.6	25.4	33.6	16.5	30.6	21.4	22.2	23.1	20.4	23.7
LEGAL-BERT	4.47	5.30	4.85	5.38	7.42	7.47	10.9	4.64	8.61	6.03	6.03	11.4	11.3	13.6
MonoT5	0.71	0.65	0.60	0.79	1.39	1.41	1.73	0.38	0.70	0.49	0.47	1.17	1.33	0.61
SAILER	16.6	15.2	14.0	16.8	17.2	18.5	25.1	12.8	23.7	16.6	17.0	25.9	25.3	29.3
PromptCase	17.1	20.3	18.5	20.5	35.1	33.9	38.7	16.0	29.7	20.8	21.5	32.7	32.0	36.2
CaseGNN	35.5±0.2	42.1±0.2	38.4±0.3	42.4±0.1	66.8±0.8	64.4±0.9	69.3±0.8	17.7±0.7	32.8±0.7	23.0±0.5	23.6±0.5	38.9±1.1	37.7±0.8	42.8±0.7
CaseLink (Ours)	**37.0**±0.1	**43.9**±0.1	**40.1**±0.1	**44.2**±0.1	**67.3**±0.5	**65.0**±0.2	**70.3**±0.1	**20.9**±0.3	**38.4**±0.6	**27.1**±0.3	**28.2**±0.3	**45.8**±0.5	**44.3**±0.7	**49.8**±0.4
Two-stage														
SAILER	23.8	25.7	24.7	25.2	43.9	42.7	48.4	19.6	32.6	24.5	23.5	37.3	36.1	40.8
PromptCase	23.5	25.3	24.4	30.3	41.2	39.6	45.1	**21.8**	36.3	27.2	26.5	39.9	38.7	44.0
CaseGNN	22.9±0.1	27.2±0.1	24.9±0.1	27.0±0.1	54.9±0.4	54.0±0.5	57.3±0.6	20.2±0.2	37.6±0.5	26.3±0.3	27.3±0.2	45.8±0.9	44.4±0.8	49.6±0.8
CaseLink (Ours)	**24.7**±0.1	**29.1**±0.1	**26.8**±0.1	29.2±0.1	**56.0**±0.2	**55.0**±0.2	**58.6**±0.1	21.0±0.3	**38.9**±0.5	27.1±0.3	**28.2**±0.3	**48.8**±0.2	**47.2**±0.1	**52.6**±0.1

- CaseLink performs the best, better than CaseGNN.
- The performance of graph-based methods (CaseGNN and CaseLink) are significantly better.

Conclusion of Research 4

- Global Case Graph provides effective **connections** among cases.

- **Degree regularisation** can provide effective training signals for candidate cases.

Key Takeaways

- **Structural** legal information is essential for legal case retrieval.

- Both **intra-case** structural information and **inter-case** structural information can highly be beneficial to legal case retrieval.

The University of Queensland
AUSTRALIA

CREATE CHANGE

github.com/yanran-tang

Thank you!

Q & A