西北工業大學

NORTHWESTERN POLYTECHNICAL UNIVERSITY

基于对比表示学习的因果关系抽取技术研究

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研究背景

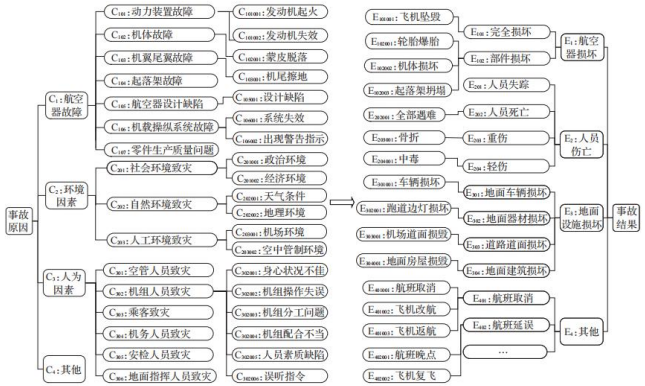
- 人们的社会活动以事件为驱动，事件是社会活动的载体。

  在自然语言处理中，事件作为一种信息表示形式显得十分重要，受到越来越多的重视。事件中包含了大量的内部组成结构（如参与者、时间、地点等）和外部关联（如因果、共指、时序等语义关系）。

- 因果关系在诸多领域发挥着越来越重要的作用

  在**人机交互、航空安全、医学、经济、政治、社会发现和自然科学**等领域应用日益增长

“将因果关系整合到人工智能中是一件大事！”——Yoshua Bengio



航空安全领域本体因果关系主要概念的构成

人机对话中文本关系信息抽取

精神疾病成因分析

突发生物安全事件成因分析

研究背景

- 什么是因果关系?

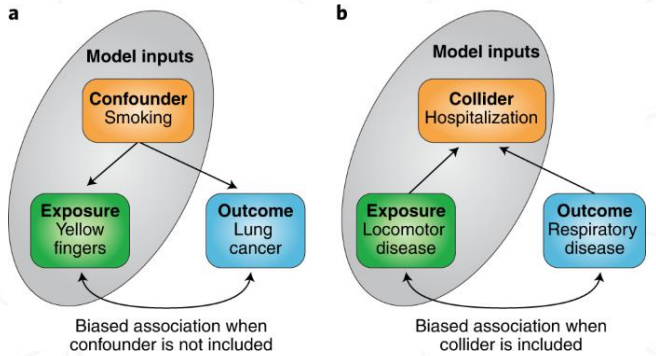
  因果关系是一种由现象A导致现象B发生的单向关系。

- 现有的因果研究有哪些?
  - 因果分析（Causal Analysis）
  - 因果推断（Causal Inference）
  - 因果关系抽取 （Causality Extraction）

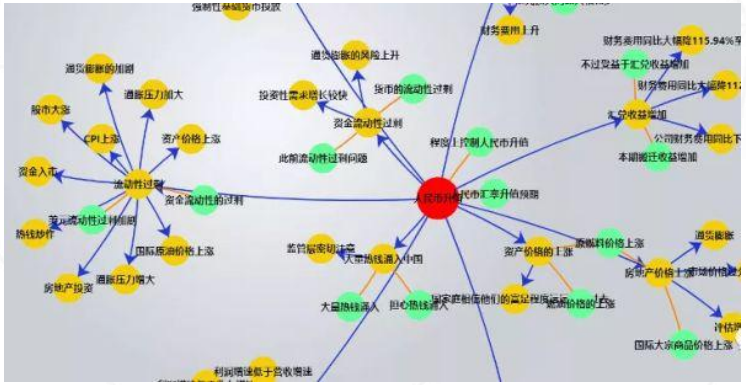
- 现有的因果关系组织形式?

I got so depressed because I lost my favorite toy.

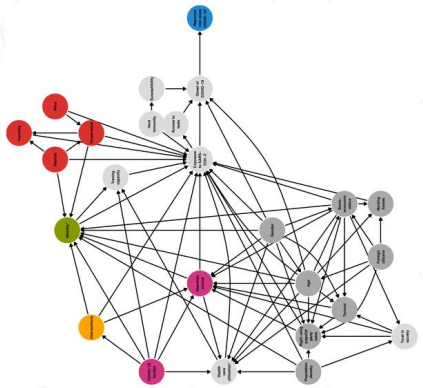
{[lost my favorite toy], C-E, [depressed]}



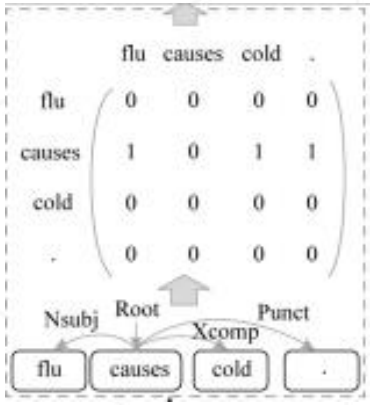
因果推断



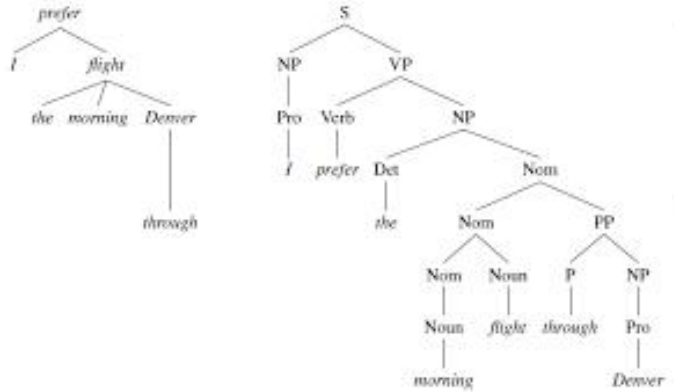
因果分析知识图谱



Causal Graph



稀疏矩阵



语法依存树

研究背景

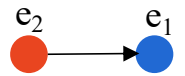
因果关系的类型有哪些?

- 是否包含因果触发词:
  - 显式因果关系：包含因果连接词
  - 隐式因果关系：不包含因果连接词
- 因果数目:
  - 1→1：1个原因导致1个结果
  - 1→多：1个原因导致多个结果
  - 多→1：多个原因导致多个结果
  - 多→多：多个原因交叉导致的多个结果

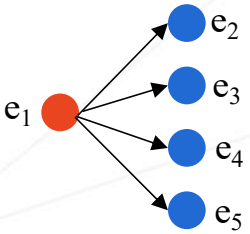
复杂因果

目前因果关系抽取的研究主要集中在简单因果抽取，针对单对因果抽取涌现了各种各样的模型，对复杂因果研究较少。

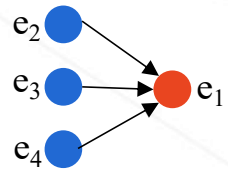
<e1>I don’ t believe in myself</e1>
due to <e2>my anxiety</e2>.



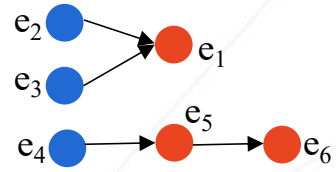
After <e1> the discard and break up</e1>,
i was so <e2> confused </e2>,
<e3> heart broken </e3>,
<e4> horribly jealous </e4>,
<e5> angry </e5>.



I <e1> haven’t been sleeping well </e1>
because i’m <e2> afraid of the dark </e2>,
<e3> sensitive to noise at night </e3>,
and <e4> my thoughts run wild </e4>.



I am so <e1> sad </e1>,
because my <e2> parents got divorced </e2>,
and my little <e3> brother got a fever </e3>.
I am so <e4> tired </e4> that <e5> have
no time to finish my homework </e5>.
So the <e6> teacher criticized me </e6>



图：因果关系的四种类型

研究挑战

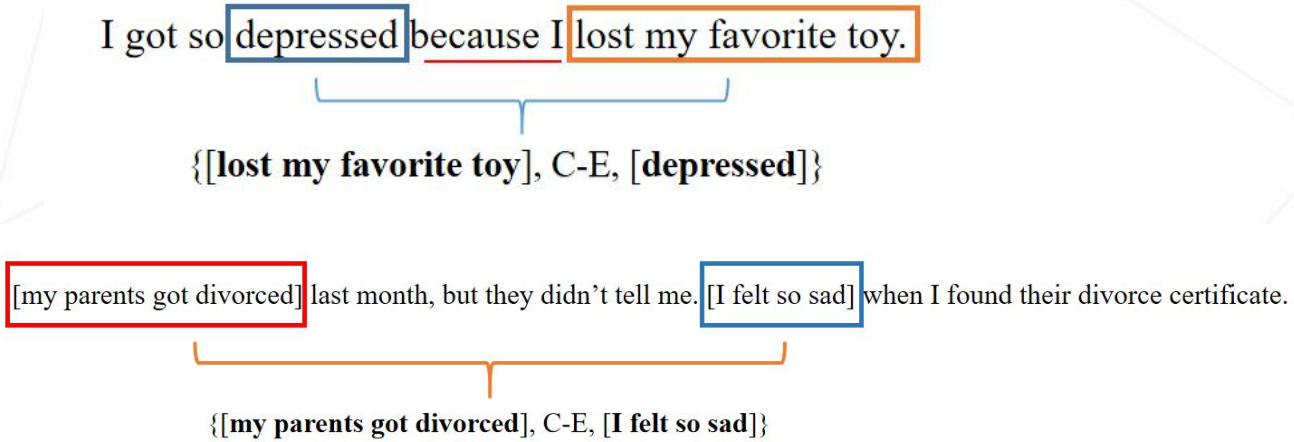
为什么对复杂因果研究较少？

- 缺少数据集：目前的数据集用于简单因果抽取，用于复杂因果抽取的数据集规模小
- 包含多个论元：论元之间的交互关系复杂，研究困难
- 论元长度复杂多样：复杂因果的论元涉及单词、短语以及分句等多种语法单元，难以用统一的模板衡量
- 关系跨度远：论元之间的跨度增大，增加了模型理解文本的难度，很难做出决策
- 无显式连接词：隐式因果占大多数，缺乏因果关系连接词，对抽取造成困难

I am so <e1>sad</e1>, because my <e2>parents got divorced</e2> last month, and my little <e3>brother got a fever</e3>, I must take him to the hospital. I'm so tired that have no time to finish my homework. So the <e4>teacher criticized me</e4> today. I want to <e5>commit suicide</e5>, because I can not breathe in such a <e6>high pressure</e6>, as well as the <e7>loneliness</e7>.

Cause-Effect((e2, e1), (e3, e1), (e4, e1), (e6, e5), (e7,e5))

复杂因果案例



显式因果关系（上）和隐式因果关系（下）

相关工作

因果关系抽取数据集调研

数据集	规模	简单因果	复杂因果	语言	备注
SemEval2010 Task-8	10717	1331	0	English	
BECause	5380	1634	587	English	
ADE	23516	7100	0	English	
SCIFI	5235	924	346	English	Task-8数据集重新标注
CREST	28878	28878	0	English	融合多个数据集
AItlex	81325	6289	0	English	
Chinese Emergency Corpus	332	0	200	Chinese	
ECE Corpus(Gui et al 2016a)	2105	2046	59	Chinese	
航空安全	11392	11302	0	Chinese	955篇航空事故文本

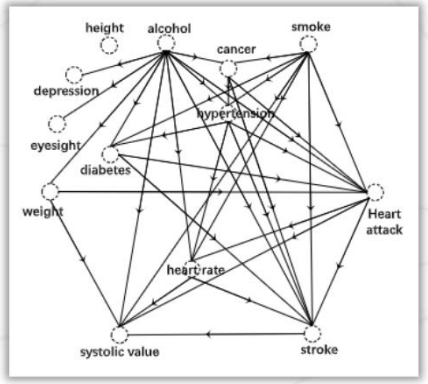
现状：目前用于因果关系研究的数据集包含航空安全、医疗、经济、新闻、情绪分析以及紧急事件等领域，但是现有数据集主要针对简单因果关系，复杂因果关系数据集规模小。

相关工作

➢ 简单因果关系抽取

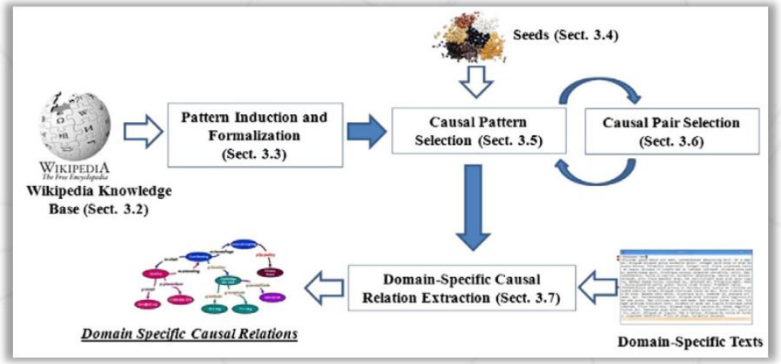
模式匹配

Causal Graph[2]



COMPUT BIOL MED 2019

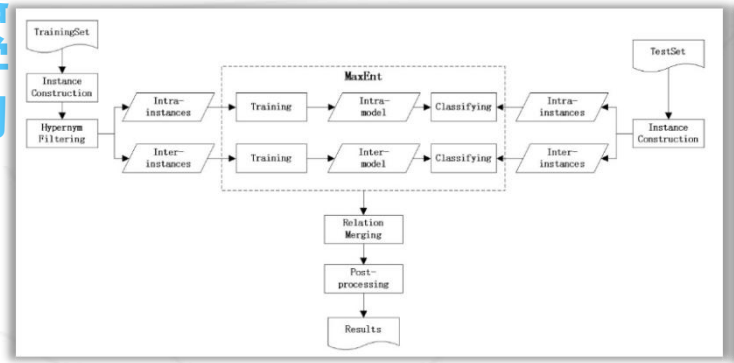
Causal Pattern[3]



DATA KNOWL ENG 2013

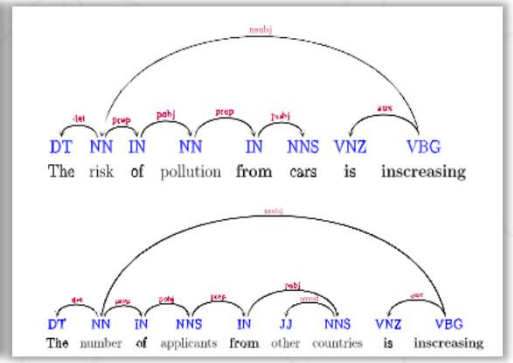
机器学习

Maximum Entropy[5]



Database 2020

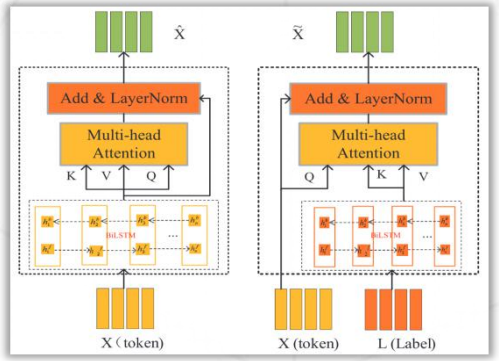
RHNB[4]



Neurocomputing 2016

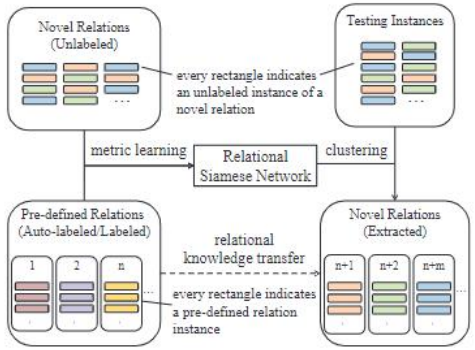
深度学习

CMAN[6]



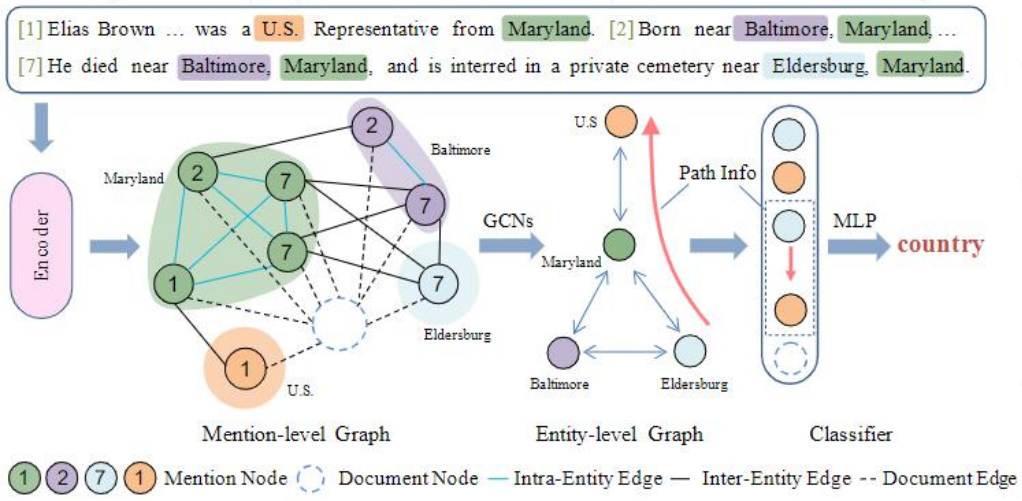
IJCAI 2020

RSN[8]



EMNLP 2019

GAIN[7]

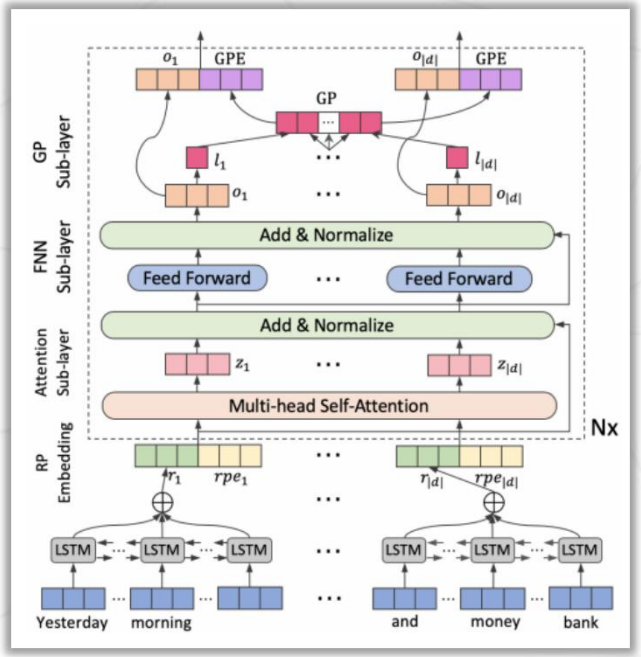


EMNLP 2020

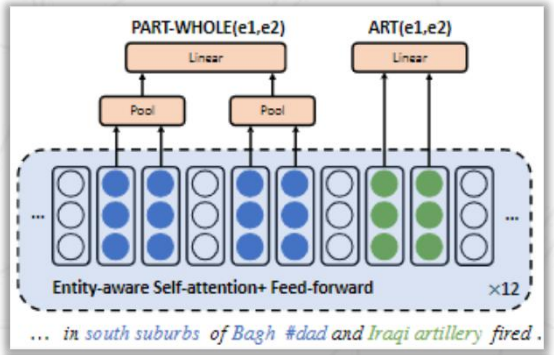
相关工作

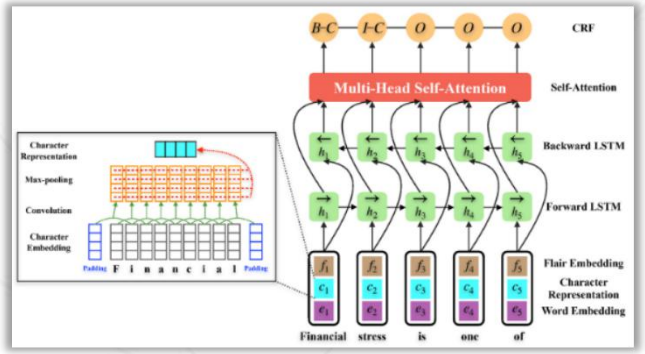
➢ 复杂因果关系抽取

Transformer[9] ACL 2019

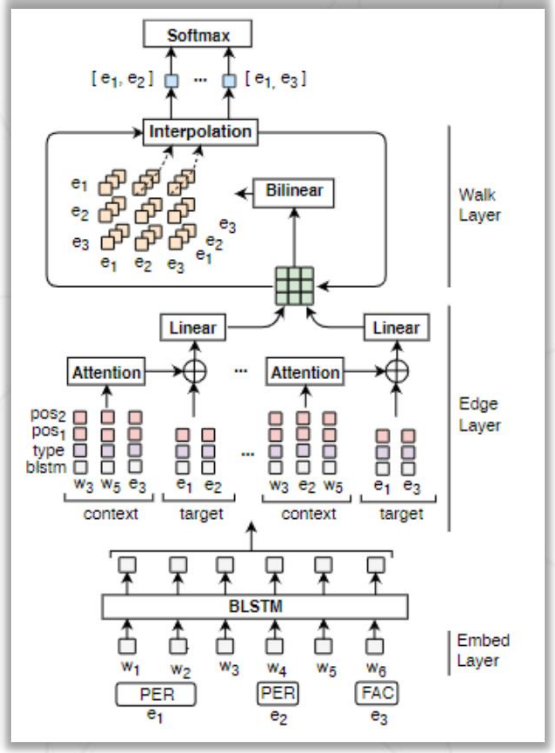


RTHN[9] IJCAI 2019



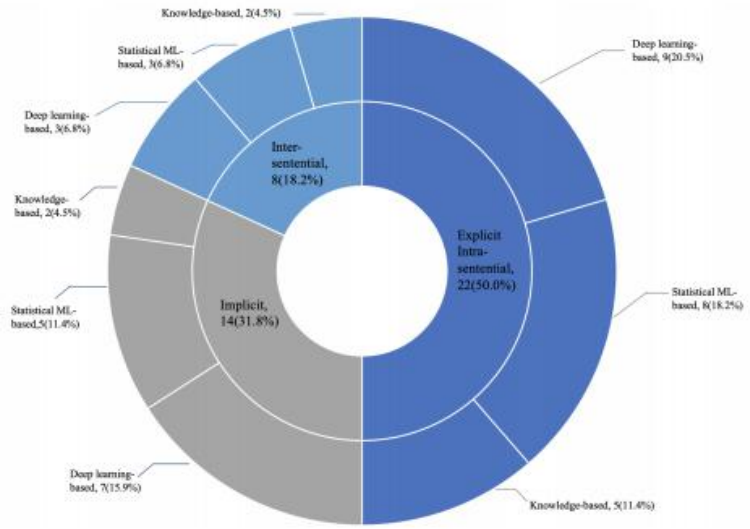


SCITE[11] Neurocomputing 2021



Walk-based[9]

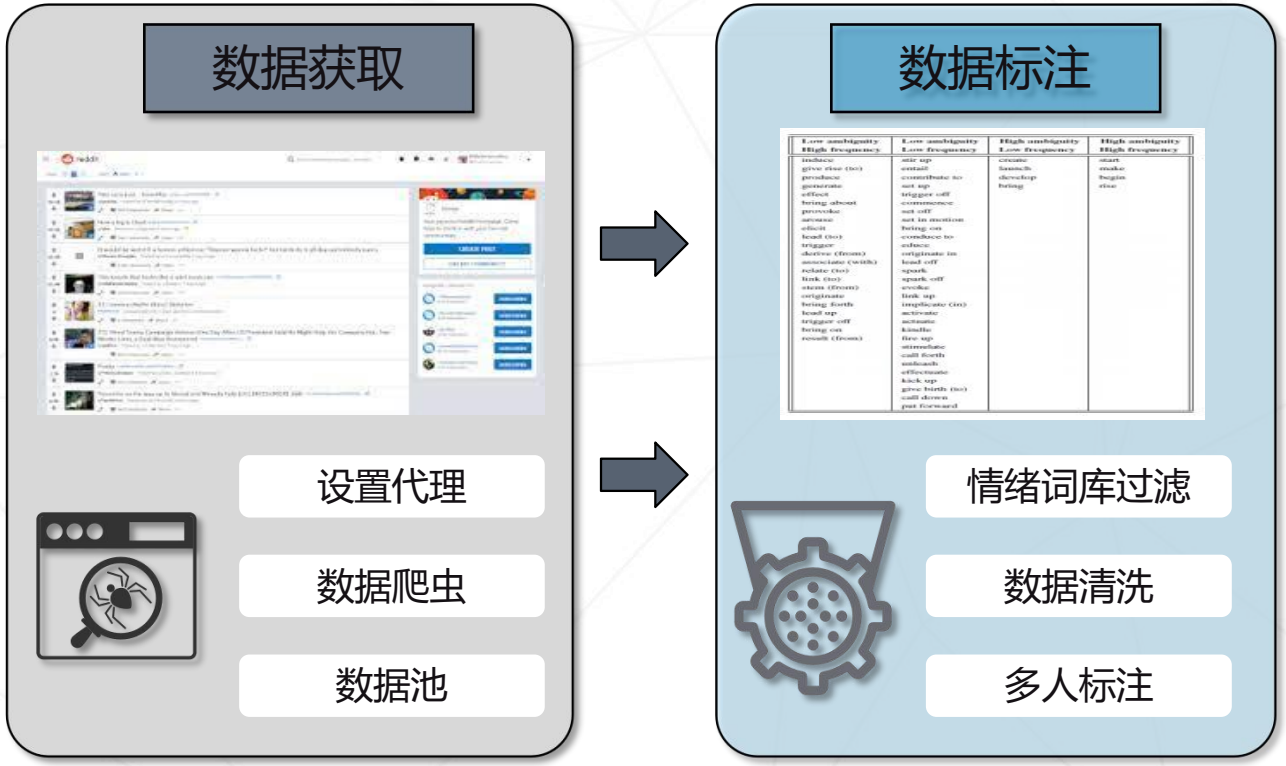
- 目前，研究复杂因果的工作较少，主要分为关系推理、分割文本以及Tag2Triplet的方法
  - 关系推理对因果关系借鉴较少
  - 分割文本不利于句子之间、跨句因果抽取
  - Tag2Triplet需要大量的人工标注工作



解决思路

■ RedditCE数据集构建

采用网络爬虫技术，基于社交媒体Reddit抓取关于12种精神疾病的5w+条文本数据，对其进行筛选、清洗、标注，最终形成35202条复杂因果关系数据集。



I am so <e1>sad</e1>, because my <e2>parents got divorced</e2> last month, and my little <e3>brother got a fever</e3>, I must take him to the hospital. I'm so tired that have no time to finish my homework. So the <e4>teacher criticized me</e4> today. I want to <e5>commit suicide</e5>, because I can not breathe in such a <e6>high pressure</e6>, as well as the <e7>loneliness</e7>.

label: cause-effect((e2,e1),(e3,e1),(e4,e1),(e6,e5),(e7,e5))

type: 3

显/隐: 2/3

标注样例

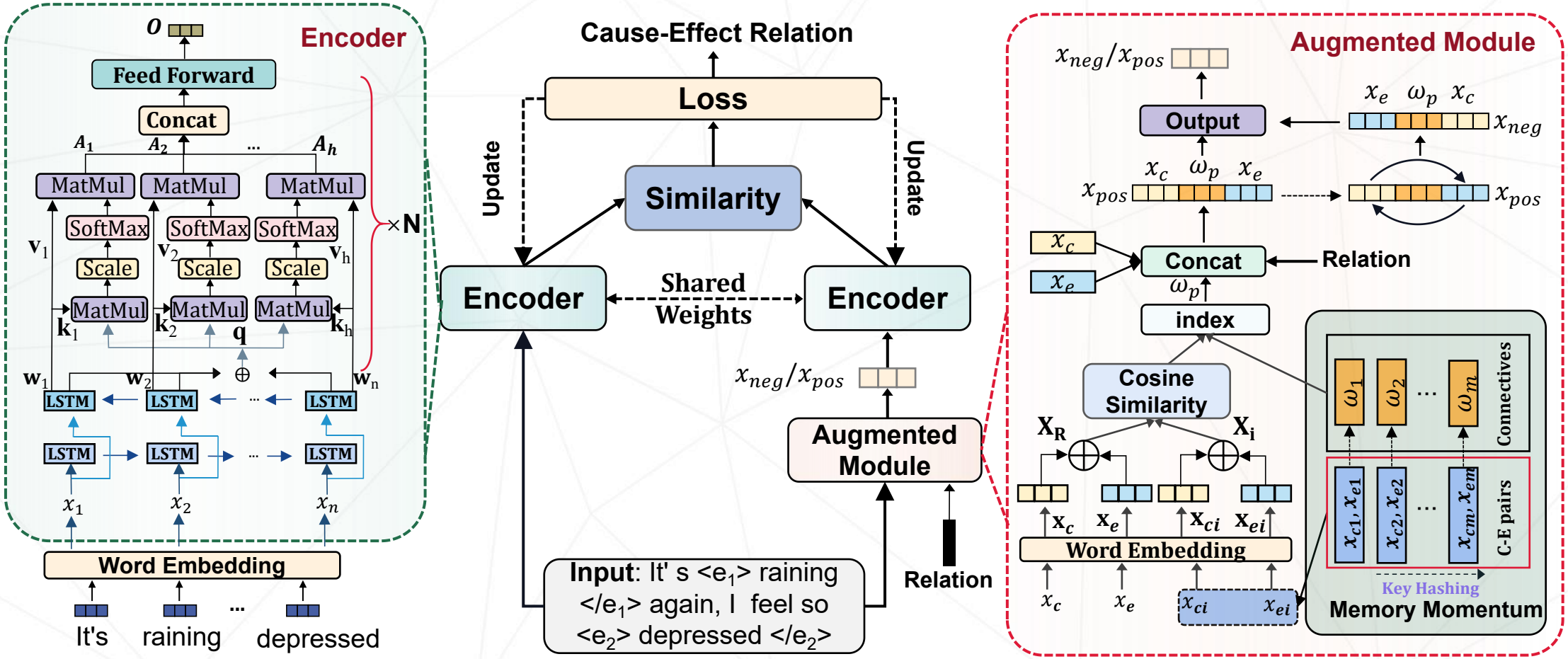
	Single		Multiple		
	train	test	train	test	no cause
RedditCE	21553	5446	18942	4716	15455

1→1	1→N	N→1	N→N
11544	864	1071	6288

解决思路

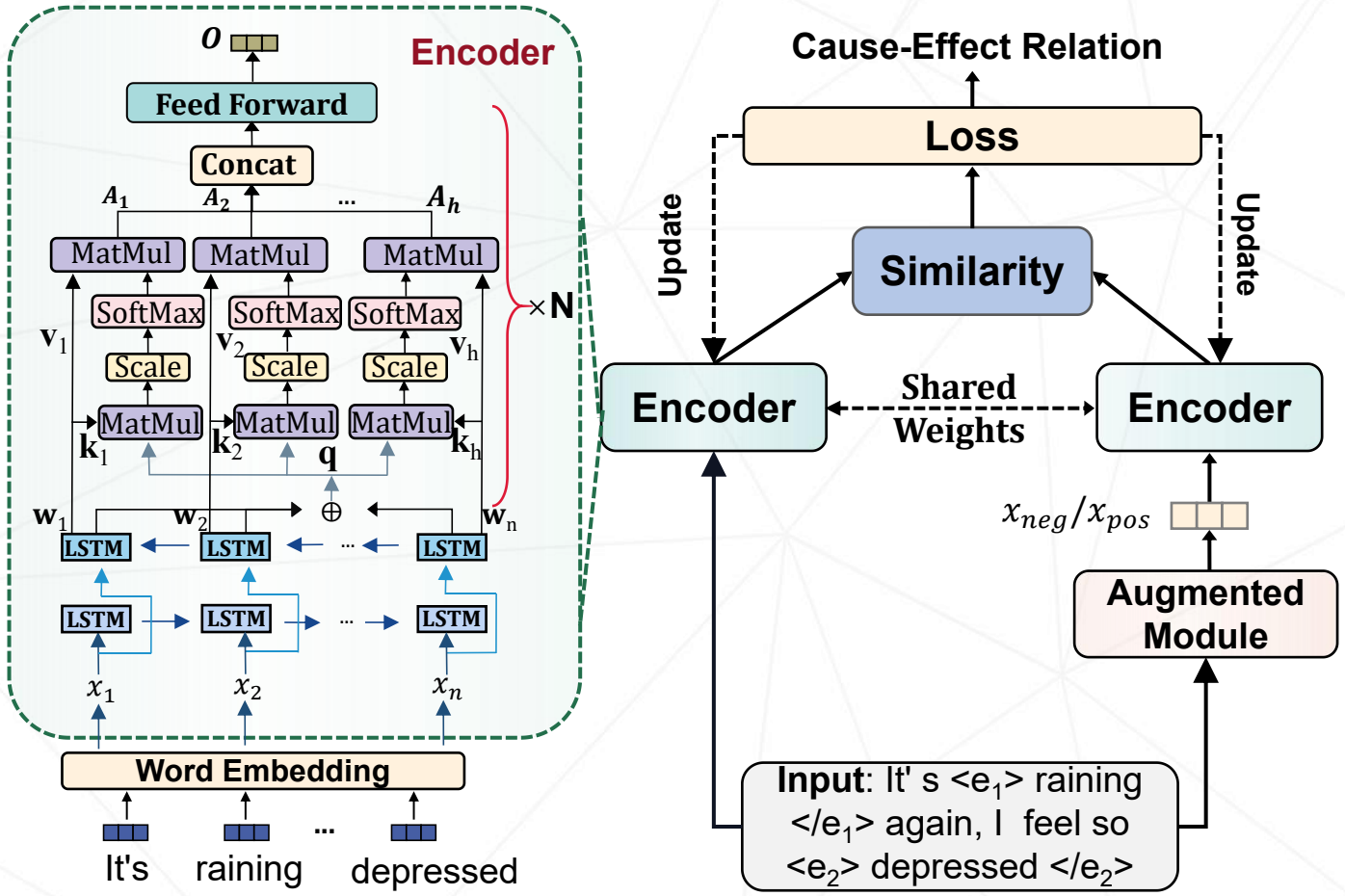
■ 基于对比表示学习的复杂因果关系抽取模型

使用对比表示学习框架，融合BiLSTM-Transformer的深度神经网络学习多对原因和结果之间的复杂交互关系；使用Memory Momentum构造正负样例



解决思路

■ 基于对比表示学习的复杂因果关系抽取模型



- BiLSTM获取分句级别的文本信息获取分句中单词的上下文信息，获得文本的句子级表示
- Transformer捕获BiLSTM所有时间步长中重要的信息。 多头自注意力可以更加关注多对因果之间的信息。
- 增强模块进行数据增强的同时生成正负样例，从而满足对比学习框架的学习需求

$$\overrightarrow{\mathbf{h}}_t = LSTM(\overrightarrow{\mathbf{h}}_{t-1}, \mathbf{x}_t, \mathbf{c}_{t-1})$$
$$\overleftarrow{\mathbf{h}}_t = LSTM(\overleftarrow{\mathbf{h}}_{t-1}, \mathbf{x}_t, \mathbf{c}_{t-1})$$
$$\mathbf{w}_i = [\overrightarrow{\mathbf{h}}_t, \overleftarrow{\mathbf{h}}_t]$$

$$\mathbf{q}_i = ReLU(\mathbf{w}_i \mathbf{W}_Q)$$
$$\mathbf{k}_i = ReLU(\mathbf{w}_i \mathbf{W}_K)$$
$$\mathbf{v}_i = ReLU(\mathbf{w}_i \mathbf{W}_V)$$

$$\mathbf{z}_i = Concat(\mathbf{A}_1, \ldots, \mathbf{A}_h)\mathbf{W}_O$$

$$\mathbf{e}_i = ReLU(\mathbf{z}_i \mathbf{W}_1 + b_1)\mathbf{W}_2 + b_2$$

$$\mathbf{o}_i = Normalize(\mathbf{e}_i + \mathbf{q}_i)$$

解决思路

- 正负样例构造模块

输入： 文本序列 $X=\{\ldots,\langle e_i\rangle x_C,\langle /e_i\rangle,\ldots,\langle e_j\rangle x_e,\langle /e_j\rangle\}$

输出： 正负样例

Step 1： 初始化 Memory Momentum，以<原因，结果，连接词>形式存储；

Step 2： 获得输入中的因果对 $R=(x_C,x_e)$，并连接 $X_R=Concat(x_C,x_e)$

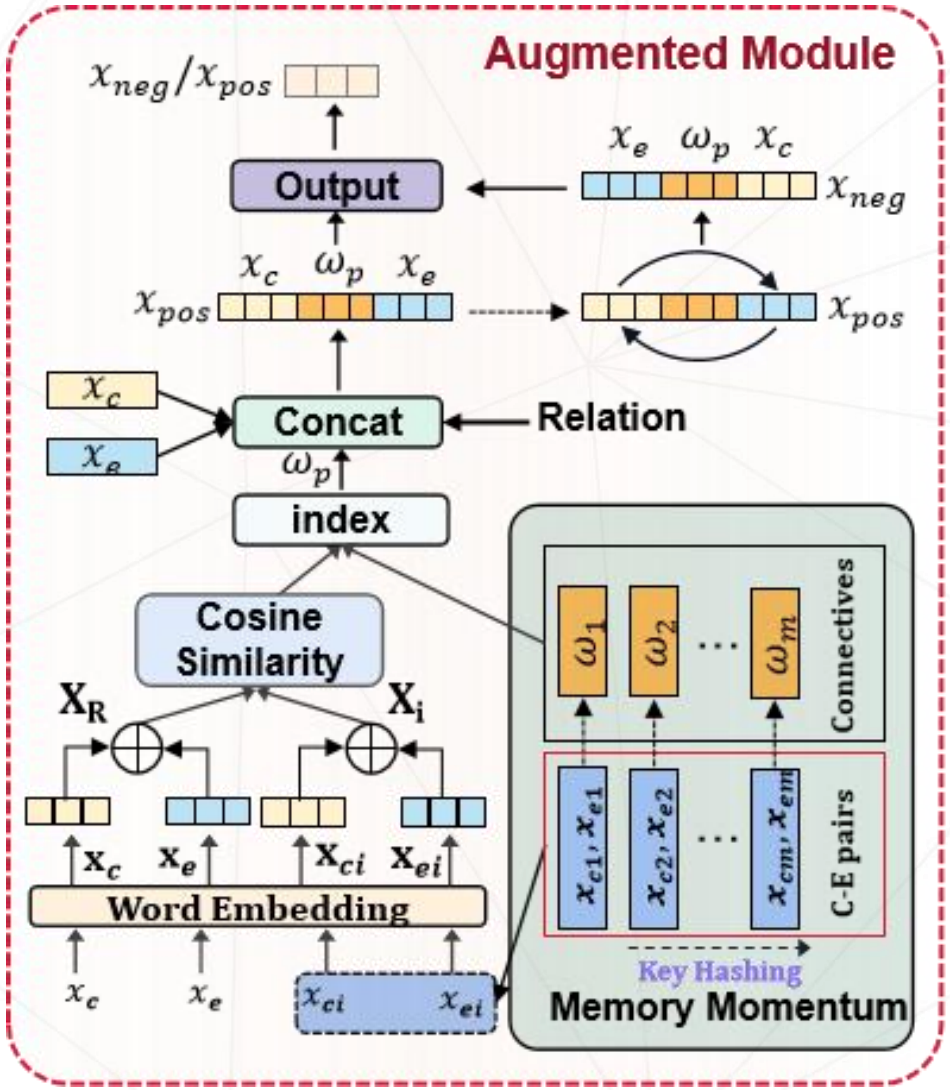
Step 3： 与 Memory Momentum 中的论元对 $X_i=Concat(X_{ci},X_{ei})$ 进行相似度匹配；

Step 4： 获得最合适连接词构造正样例 $X_{pos}=\langle x_C,\omega_p,x_e\rangle$

Step 5： 调换正样例的因果位置得到负样例 $X_{neg}=\langle x_e,\omega_p,x_C\rangle$

$$S_i=\frac{X_R\cdot X_i}{\|X_R\|\cdot\|X_i\|}$$

$$p=index(\max_{i\in[0,m]}(S_i))$$



实验结果

➢ 与现有模型的对比结果

选取涵盖CNN，BiLSTM，Attention在内的5个Baseline，并对深度模型进行替换，进行性能评估，结果如下：

Model	RedditCE				SCIFI				CREST	
	1 → 1		N → N		1 → 1		N → N		1 → 1	
	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)
TextCNN (Li and Mao, 2019)	71.26	77.14	-	-	87.57	96.87	-	-	71.64	**81.92**
RCNN (Lai et al., 2015)	70.80	78.43	75.89	71.12	89.57	96.87	73.08	**98.08**	59.13	73.96
PCNN (Lai et al., 2015)	78.36	71.48	-	-	79.75	80.48	-	-	47.67	36.00
BiLSTM (Bekoulis et al., 2018)	79.35	84.21	-	-	88.52	**97.52**	-	-	67.99	79.46
BiLSTM-ATT (Zhao et al., 2021) (Li et al., 2021)	84.29	**93.71**	79.58	80.19	88.33	**97.09**	73.87	94.85	58.84	74.36
CL-Transformer	67.10	50.37	68.66	58.99	84.57	81.63	75.60	61.29	68.52	57.39
CL-CNN	82.39	80.37	75.81	77.54	92.68	90.82	93.10	91.40	76.19	76.64
CL-RNN	**89.65**	89.44	**87.60**	**88.26**	**94.83**	93.87	**95.72**	94.62	**80.35**	80.79
N2NCause	**93.26**	**93.33**	**90.09**	**90.72**	**96.66**	95.92	**96.55**	**95.70**	**83.79**	**83.74**

Baselines

模块替换

[1]红色表示该项指标的最好结果；蓝色表示次好结果

[2]CL-Transformer/CNN/RNN表示模型采用的深度学习模型分别是Transformer/CNN/RNN

实验结果

- 不同损失函数对实验结果的影响

对比损失：$\mathcal{L}_{con} = Y \cdot \frac{1}{2} d^2 + (1 - Y) \cdot \frac{1}{2} \max(0, (t - d))^2$

MSE：$\mathcal{L}_{mse} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$

有监督对比损失：$\mathcal{L}_{scl} = (1 - \lambda) L_{con} + \lambda L_{mse}$

Model	Loss	RedditCE				SCIFI			
		$1 \to 1$		$N \to N$		$1 \to 1$		$N \to N$	
		F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)
CL-RNN	MSE	90.31	90.19	86.86	87.68	92.85	91.84	92.72	91.40
	MAE	82.21	81.48	83.11	85.21	94.02	92.86	94.55	93.55
	SCL	89.65	89.44	87.60	88.26	**94.83**	**93.87**	**95.72**	**94.62**
CL-Transformer	MSE	63.09	70.72	62.47	69.71	90.09	88.78	90.91	89.24
	MAE	68.73	75.74	59.00	73.62	92.59	91.84	91.42	90.32
	SCL	67.10	50.37	68.66	58.99	84.57	81.63	75.60	61.29
CL-CNN	MSE	74.32	75.56	71.36	74.64	91.23	89.79	94.44	93.54
	MAE	73.53	72.40	73.65	75.22	83.50	82.65	76.60	76.34
	SCL	82.39	80.37	75.81	77.54	92.68	90.82	93.10	91.40
N2NCause	MSE	**91.59**	**91.67**	**89.51**	**90.14**	87.72	85.71	91.43	90.32
	MAE	70.25	75.37	74.33	72.17	91.74	90.82	92.45	91.40
	SCL	**93.26**	**93.33**	**90.09**	**90.72**	**96.66**	**95.92**	**96.55**	**95.70**

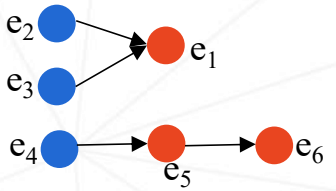
有监督对比损失性能提升明显

案例分析

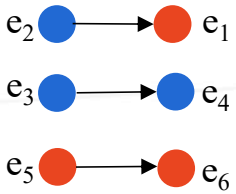
➢ 不同模型抽取复杂因果关系结果示例

为了展示模型对复杂因果关系抽取性能的提升，选取RCNN、BiLSTM-ATT和N2NCause三个模型，多→多的因果关系类型作为测试案例进行分析，结果如下：

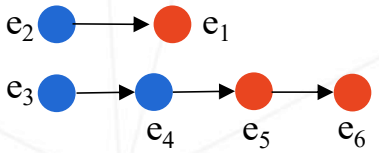
I am so <e_1> sad </e_1>, because my <e_2> parents got divorced </e_2>, and my little <e_3> brother got a fever </e_3>. I am so <e_4> tired </e_4> that <e_5> have no time to finish my homework </e_5>. So the <e_6> teacher criticized me </e_6>



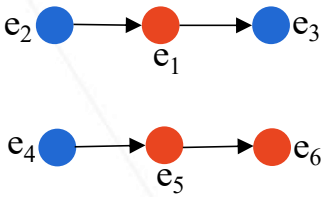
Ground Truth



RCNN



BiLSTM-ATT



N2NCause

✓ RCNN仅识别出2对，错误的认为e_3和e_4也具有因果关系，忽略了e_4和e_5，e_3和e_1的关系

✓ BiLSTM-ATT错误的识别出e3和e4之间的因果关系，但是忽略了e1和e3的关系

✓ N2NCause忽略了e_1与e_3之间的方向性

案例分析

- 模型对方向是否敏感

为了展示模型对方向性是否敏感，选取两个案例，对CL-RNN、CL-Transformer和N2NCause三个模型进行方向敏感性分析，结果如下：

Case 1

<e_1> the vascular dilatation </e_1> was caused by <e_2> the sympathetic </e_2> and <e_3> the course </e_3> of vaso-motor nerves.

$e_2 \rightarrow e_1$
$e_3 \rightarrow e_1$

Positive	CL-RNN	CL-Transformer	N2NCause
$e_2 \rightarrow e_1$	✘	✔	✔
$e_3 \rightarrow e_1$	✘	✔	✔

Negative	CL-RNN	CL-Transformer	N2NCause
$e_1 \rightarrow e_2$	✔	✔	✘
$e_1 \rightarrow e_3$	✔	✔	✘

Case 2

generally it appears that most of <e_1> the damage </e_1> was caused by <e_2> the winds </e_2> and <e_3> the rough seas </e_3>

$e_2 \rightarrow e_1$
$e_3 \rightarrow e_1$

Positive	CL-RNN	CL-Transformer	N2NCause
$e_2 \rightarrow e_1$	✘	✔	✔
$e_3 \rightarrow e_1$	✔	✔	✔

Negative	CL-RNN	CL-Transformer	N2NCause
$e_1 \rightarrow e_2$	✘	✔	✘
$e_1 \rightarrow e_3$	✘	✔	✘

[1] ✔ means that the triplet is recognized as a cause-effect pair; ✘ means that there is no causal relationship.

未来计划

下一步完善目标包括现有实验结果扩充、数据集扩建以及方法提升三方面

2022.08

实验扩充

- 参数选取消融实验
- Memory Momentum改进实验（连接词的丰富）
- 样本复杂度对实验结果的研究（自步学习）
- 目标期刊：TKDE

2022.11

数据集扩建

- 数据集规模扩大（目标数据量10w+）
- 数据集完善度（包括论元标注和因果关系的完备程度）
- 提升复杂因果占比(70%)

2022.12

方法提升

- 对比表示学习样本丰富度提升（主动对比学习）
- 在精神疾病成因分析的具体应用案例
- 解耦表示学习和因果关系抽取的结合

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THANKS

请各位老师多批评指正！