制作清晰简洁的学术汇报PPT只需学会这几招

笔记本: b论文写作

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作者: beyourselfwb@163.com

- 1、大纲清晰
- 2、多种字体颜色
- 3、使用母语(中文)
- 4、模型方面,不同模块使用红框圈起来表示
- 5、实验结果图表方面,对于信息量大的图表, 在以此列出结论的同时,使用不同底色的背景标注对 应的数据结果
- 6、能用例子尽量用例子,相比于公式和代码,例子 更易于理解
- 7、语言上吐字清晰,语言流畅,起承转合

南开大学的PPT模板非常好!

参考 南开大学 陈少维 PPT

The 58th Annual Meeting of the Association for Computational Linguistics (ACL 2020)



智能信息处理实验室

Synchronous Double-channel Recurrent Network for Aspect-Opinion Pair Extraction

Shaowei Chen, Jie Liu*, Yu Wang, Wenzheng Zhang, Ziming Chi College of Artificial Intelligence, Nankai University, Tianjin, China



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这是非常典型的一个大纲, 四个部分:

- 1、研究背景与动机(包括任务描述、现存问题/挑战)
- 2、提出的方法/模型
- 3、实验分析
- 4、总结



🚺 目录

中容日子

- 一、研究背景与研究动机
- 二、同步双通道循环神经网络
- 三、实验分析
- 四、总结

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背景与动机

同步双通道循环神经网络

实验分析

总结

□ 意见实体抽取:

- > 旨在抽取评价方面集合和 (或) 评价词集合
- » 许多工作关注于:
 - Aspect term extraction
 - · Opinion term extraction
 - · Aspect and opinion term co-extraction
- > 忽略了评价方面和评价词之间对应关系的建模
 - Nice-looking 和 delicious 均表达正向情感
 - 从外观和味道两个角度
 - 准确建模对应关系可以支撑后续更细粒度的意见挖掘任务
 - 意见二元组情感分类
 - 意见二元组聚类

Review:

The food was nice-looking and delicious.

The result of Opinion Entity Extraction:

Aspect: {food}

Opinion Expression: {nice-looking, delicious}

The result of Aspect-Opinion Pair Extraction:

{food, nice-looking} {food, delicious}

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> > 3

■ 意见二元组抽取 (Aspect-Opinion Pair Extraction, AOPE)

- 相关研究工作较少
- > 三个主要挑战:
 - 如何准确识别对应关系
 - 关系结构复杂
 - 可能存在一对多、多对一、嵌套、交叠等
 - 如何恰当融合意见实体抽取和关系检测两个子任务
 - 相互依赖
 - 如何同步抽取实体和关系,并使得两者相互指导
 - "hot dog" 和 "tasty"
 - 结合实体整体语义有助于识别关系
 - 检测到两个词存在对应关系,则一个应为评价方 面,另一个为评价词

The food and service in this bar are perfect and unforgettable.

The result of Aspect Extraction:

{ food, service }

The result of Opinion Expression Extraction:

Results of Aspect-Opinion Pair Extraction:

(food , perfect) (food , unforgettable)

(service , perfect) (service , unforgettable)

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- 一、研究背景与研究动机
- 二、同步双通道循环神经网络
- 三、实验分析
- 四、总结

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背景与动机

同步双通道循环神经网络

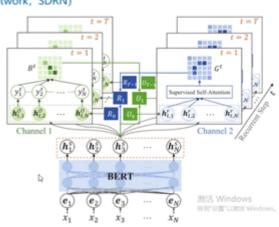
实验分析

总结

■ 基于同步双通道循环神经网络的意见二元组抽取模型

(Synchronous Double-channel Recurrent Network, SDRN)

- > 编码层: BERT
 - 学习更丰富的上下文语义
- > 同步双通道循环网络
 - 意见实体抽取单元: CRF
 - 准确识别实体边界
 - 关系检测单元: Self-Attention
 - 识别复杂的对应关系
 - 信息同步单元
 - 使两通道相互指导、相互促进

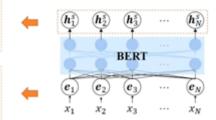


□ 编码层 (Encoding Layer)

- > BERT 作为编码层,学习丰富的上下文语义
- ▶ 将 BERT 中最后一层 Transformer 的输出作为上下文表示 序列H^s = {h²h²₂,...,h^s_N}
- 词初始向量表示:

$$e_i = e_i^w + e_i^s + e_i^p$$

其中, e_i^v 为词嵌入表示, e_i^s 为段落嵌入表示, e_i^p 为位置 嵌入表示



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背景与动机

同步双通道循环神经网络

实验分析

总结

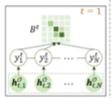
□ 双通道结构 (Double-channel)

- 意见实体抽取单元 (Opinion Entity Extraction Unit)
 - CRF: 准确识别意见实体边界
- 关系检测单元 (Relation Detection Unit)
 - 词级别自注意力机制:识别复杂的对应关系

条件随机场 (CRF):

$$\begin{split} P^t &= H_t^{\mathcal{O}} W_p + b_p \\ S(X,Y^t) &= \sum_{i=1}^N Q_{\mathcal{Y}_{i-1}^t,\mathcal{Y}_i^t} + \sum_{i=1}^N P_{i,\mathcal{Y}_i^t}^t \end{split}$$

$$p(Y^{t}|X) = \frac{\exp(S(X, Y^{t}))}{\sum_{\tilde{Y}^{t} \in Y_{X}^{t}} \exp(S(X, \tilde{Y}^{t}))}$$





t = 1 词级别自注意力机制:

$$g_{i,j}^{t} = \frac{\exp\left(\gamma\left(\boldsymbol{h}_{t,i}^{r}, \boldsymbol{h}_{t,j}^{r}\right)\right)}{\sum_{k=1}^{N} \exp\left(\gamma\left(\boldsymbol{h}_{t,i}^{r}, \boldsymbol{h}_{t,k}^{r}\right)\right)}$$

$$h_{t,1}^r = h_{t,2}^r = \cdots = h_{t,N}^r \gamma (h_{t,i}^r, h_{t,j}^r) = \tanh(h_{t,i}^r W_r^1 + h_{t,j}^r W_r^2) W_r^3$$

$$p(z_{i,j}|x_i,x_j) = \begin{cases} g_{i,j}^t, & \text{if } z_{i,j} = 1\\ 1 - g_{i,j}^t, & \text{if } z_{i,j} = 0 \end{cases}$$

对最后一个循环步构建损失:

$$\mathcal{L}_E = \log \sum\nolimits_{\tilde{Y} \in Y_X^{\mathrm{T}}} \exp \left(S \left(X, \tilde{Y} \right) \right) - S(X, Y)$$

联合学习:

对最后一个循环步构建损失: $\mathcal{L}_R = -\sum_{i=1}^N \sum_{j=1}^N p(z_{i,j}|x_i,x_j) \log \hat{p}(z_{i,j}|x_i,x_j)$

背景与动机

同步双通道循环神经网络

实验分析

总结

□ 信息同步单元 (Synchronization Unit)

- > 实体同步机制 (Entity Synchronization Mechanism, ESM)
 - 计算每个词所属实体的语义表示:

$$u_{t,i} = \sum_{j=1}^{N} \varphi(B_{i,j}^t)h_j^s$$

更新关系检测单元的隐藏表示H^r_t;

$$h_{t+1,i}^r = \sigma(u_{t,i}W_r^4 + h_i^sW_r^5)$$

- > 关系同步机制 (Relation Synchronization Mechanism, RSM)
 - 计算每个词对应的关系语义表示:

$$r_{t,i} = \sum_{j=1}^{N} \varphi\left(\phi(g_{i,j}^{t})\right) h_{j}^{s}$$

更新意见实体抽取单元的隐藏表示H^o:

$$\mathbf{h}_{t+1,i}^{O} = \sigma(\mathbf{r}_{t,i}W_O^1 + \mathbf{h}_i^sW_O^2)$$

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■ 推理层(Inference Layer)

意见实体抽取模块 预测结果: $Y = \{y_1, y_2, ..., y_N\}$

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评价方面集合: $A = \{a_1, a_2, ..., a_{l_A}\}$

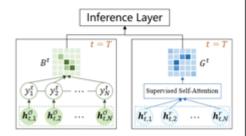
评价词集合: $O = \{o_1, o_2, ..., o_{lo}\}$

对于所有可能的 {评价方面, 评价词} 二元组:

关系检测模块 预测结果 G^T $a = \{x_{i_S^a}, \dots, x_{i_E^a}\}$ $o = \{x_{i_S^a}, \dots, x_{i_E^a}\}$

 $\delta = \frac{1}{2} \bigg(\frac{1}{|a|} \sum_{\substack{k=i_{S}^{a} \\ k=i_{S}^{a}}}^{i_{E}^{a}} \sum_{\substack{l=i_{S}^{a} \\ l=i_{S}^{a}}}^{i_{E}^{a}} g_{k,l} + \frac{1}{|o|} \sum_{\substack{l=i_{S}^{a} \\ l=i_{S}^{a}}}^{i_{E}^{a}} \sum_{\substack{k=i_{S}^{a} \\ k=i_{S}^{a}}}^{i_{E}^{a}} g_{l,k} \bigg)$

当关联程度 δ 高于给定的阈值 δ 时,抽取(a,o)为意见二元组



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30

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实验分析

总结

□ 实验分析

> 数据集

✓来源:

- SemEval Challenge 2014 竞赛
- SemEval Challenge 2015 竞赛
- J.D. Power and Associates Sentiment Corpora
- MPQA version 2.0
- ✓ 对于三个来自 SemEval 竞赛的数据,本文基于 Wang 等人 [1,2] 对评价词的标注结果,进一步手工 标注了评价方面和评价词之间的对应关系。

表1: 数据集统计

Datas	et	#Sent	#A	#O	#R
SemEval-14	Train	3041	3693	3512	2809
Restaurant	Test	800	1134	1014	936
SemEval-14	Train	3045	2359	2500	1535
Laptop	Test	800	653	677	380
SemEval-15	Train	1315	1205	1217	1231
Restaurant	Test	685	542	516	516
JDPA D	Camera	3125	6107	4557	4144
JDPA	Car	6501	8272	11123	8709
MPQA		9471	4676	5849	4823

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[13] Wang W, Pan S J, Dahlmeier D, et al. Coupled MultiLayer Attentions for Co-Extraction of Aspect and Opinion Terms. In: AAAJ, 2017: 3316 ~ 3322.

131 Wang W, Pan S J, Dahlmeier D, et al. Recursive Neural Conditional Random Fields for Aspectbased Sentiment Analysis. In: EMNLP, 2016: 616 ~ 626.

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实验分析

总结

□ 实验分析

➤ 评价指标: 微平均F1值 (Micro-F1)

➤ 对比算法: □

✓ 流水线模型 (Pipeline Model) :

● 意见实体抽取: DE-CNN、HAST、IMN、RINANTE、SPAN

● 关系检测: 采用本文模型 (SDRN) 中的关系检测模块

✓ 联合学习模型 (Joint Model):

● IDF: 基于强制定义因子图的方法

● CRF+ILP: 基于整数线性规划的 CRF 方法

■ LSTM+SLL+RLL: 采用 LSTM 学习语义特征,并设计多个不同的联合损失函数进行模型训练。

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□ 实验分析

- > 实验结果: 意见二元组抽取
 - ✓ SDRN 在全部数据集上均取得了最优性能
 - SDRN、SPAN+RD 和其他对比算法相比,BERT可以学习更丰富的上下文语义
 - 在JDPA、MPQA数据集,SDRN 没有使用手工特征,并取得明显提升

表2: 三个SemEval数据集上意见二元组抽取结果

Models		14-Res	14-Lap	15-Res	
	HAST+RD	73.55	64.05	65.20	
Pipeline DE-CNN+RD IMN+RD SPAN+RD	DE-CNN+RD	71.02	61.11	64.19	
	IMN+RD	73.69	62.98	65.56	
	SPAN+RD	74.17	65.99	67.55	
	RINANTE+RD	74.34	64.17	65.42	
	SDRN w/o ESM	74.60	66.57	69.28	
Joint	SDRN w/o RSM	75.01	66.43	69.33	
Joint	SDRN w/o ESM&RSM	74.28	65.74	67.67	
	SDRN	76.48	67.13	70.94	

表3: JDPA、MPQA数据集上意见二元组抽取结果

Models	JDPA Camera	JDPA Car	MPQA
IDF Pipeline	21.5	26.6	N/A
IDF Joint	14.1	16.1	N/A
CRF+ILP	N/A	N/A	57.04
LSTM+SLL+RLL	N/A	N/A	54.98
SDRN	48.63	47.85	63.95

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实验分析

总结

□ 实验分析

- > 实验结果: 意见二元组抽取 (消融实验)
 - 单纯加深网络层数,相较于流水线的方法缺乏竞争力
 - 采用关系同步单元 (RSM) 或实体同步单元 (ESM) ,模型性能会有所提升
 - 当同时采用两个同步单元时,模型取得了最优的性能

表4: 三个SemEval数据集上意见二元组抽取结果

	Models	14-Res	14-Lap	15-Res
	HAST+RD	73.55	64.05	65.20
	DE-CNN+RD	71.02	61.11	64.19
Pipeline	IMN+RD	73.69	62.98	65.56
	SPAN+RD	74.17	65.99	67.55
	RINANTE+RD	74.34	64.17	65.42
	SDRN w/o ESM	74.60	66.57	69.28
Joint	SDRN w/o RSM	75.01	66.43	69.33
Joint	SDRN w/o ESM&RSM	74.28	65.74	67.67
	SDRN	76,48	67.13	70.94

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背景与动机

同步双通道循环神经网络

实验分析

总结

□ 实验分析

- > 实验结果: 意见实体抽取
 - 与关系检测模块进行联合训练,可以提升意见实体抽取的性能
 - aspect and opinion term co-extraction 模型优于 aspect term extraction 模型

表5: 三个SemEval数据集上意见实体抽取结果

Models	14-	Res	14-	Lap	15-	Res
Models	A	0	A	0	A	0
WDEmb (Yin et al., 2016)	84.97	N/A	75.16	N/A	69.73	N/A
RNCRF [†] (Wang et al., 2016)	84.93	84.11	78.42	79.44	67.74	67.62
CMLA [†] (Wang et al., 2017)	85.29	83.18	77.80	80.17	70.73	73.68
HAST (Li et al., 2018)	85.61	85.46*	79.52	78.58*	71.46	70.77*
DE-CNN (Xu et al., 2018)	85.20	81.99*	81.59	76.34*	68.28	68.56*
IMN† (He et al., 2019)	83.33	85.61	127.96	77.51	70.04	71.94
SPAN (Hu et al., 2019)	86.20*	86.52*	80.67*	82.07*	73.65*	79.13*
GMTCMLA [†] (Yu et al., 2019)	84.50	85.20	78.69	79.89	70.53	72.78
RINANTE [†] (Dai and Song, 2019)	86.45	85.67	80.16	81.96	69.90	72:09. Windows
SDRN	89.49	87.84	83.67	82.25	74.05	79.65

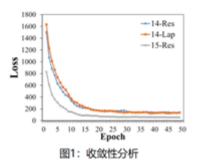
□ 实验分析

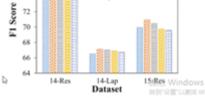
- > 实验结果: 收敛性分析 + 参数敏感性分析
 - 通常在 15 个 epoch 左右达到收敛,收敛速度较快
 - 随着循环步数的增加,模型的性能呈现先增加后趋于平稳(或轻微下降)的趋势,最优的结果出现在

76

74

72





Step = 1

Step = 5

Step = 2

图2:参数敏感性分析

同步双通道循环神经网络

实验分析

总结

□ 实验分析

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> 实验结果: 样例分析

流水线模型: 错误传导

◆ SDRN w/o ESM&RSM: 缺乏信息交互、难以应对复杂关系

表5: 样例分析

Reviews	SPAN+RD	SDRN w/o ESM&RSM	SDRN
1. The receiver was full of [superlatives] _{1,2} for the [quality] ₁ and [performance] ₂ .	(quality, superlatives) (performance, superlatives)	(receiver, superlatives) (quality, superlatives) (performance, superlatives)	(quality, superlatives) (performance, superlatives)
 The [selection of food]₁ is [excellent]₁, and the [atmosphere]₂ is [great]₂. 	(selection, excellent) X (food, excellent) X (atmosphere, great)	(selection of food, excellent) (atmosphere, great)	(selection of food, excellent) (atmosphere, great)
3. The [bartenders] ₁ and the [managers] ₂ are really [nice] _{1,2} and the [decor] _{3,4,5} is very [comfy] ₃ and [laid-back] ₄ , all the while being [trendy] ₅ .	(bartenders, nice) (managers, nice) (decor, comfy) (decor, trendy)	(bartenders, nice) (managers, nice) (decor, comfy) (-, laid-back) X (decor, trendy)	(bartenders, nice) (managers, nice) (decor, comfy) (decor, laid-back) (decor, trendy)

背景与动机

同步双通道循环神经网络

实验分析

总结

□ 总结

- > 本文关注于意见二元组抽取 (AOPE) 任务
- ➤ 本文提出了同步双通道循环神经网络模型
- > 通过采用**词级别有监督自注意力机制**可以有效检测复杂的对应关系
- ▶ 通过信息同步单元使两个通道相互指导
- ▶ 论文数据和代码: https://github.com/NKU-IIPLab/SDRN

参考中科院软件所付成 PPT





Hierarchical Matching Network for Heterogeneous Entity Resolution

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Cheng Fu^{1,3}, Xianpei Han^{1,2}, Jiaming He⁴, Le Sun^{1,2}

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May 23, 2020



SCAS Entity Resolution (ER)

 Identifying records of the same entity within one or across multiple data sources





 Identifying records of the same entity within one or across multiple data sources



- · Plays important roles in many tasks
 - · Data mining
 - · Data integration
 - · Knowledge graph completion
 - Knowledge fusion
 - ...

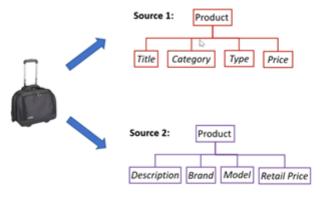
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SCAS Challenges for Heterogeneous Entity Resolution

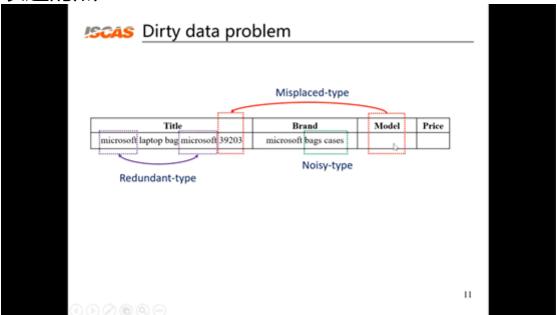
- Schema heterogeneity problem
- Dirty data problem

Schema Heterogeneity Problem

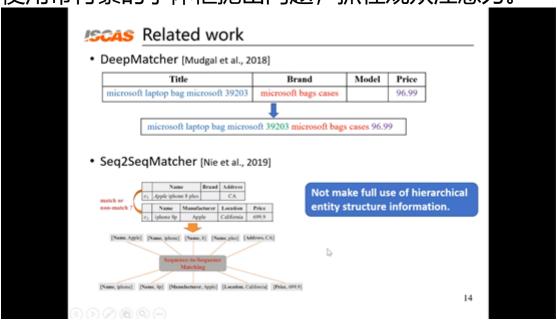
Describe the same entity using different attributes



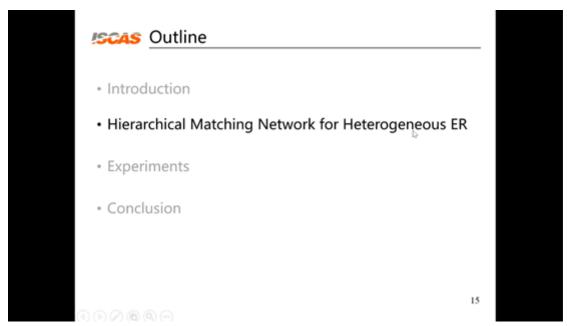
对于不同颜色的使用,使得读者更容易抓住作者想要表达的点!



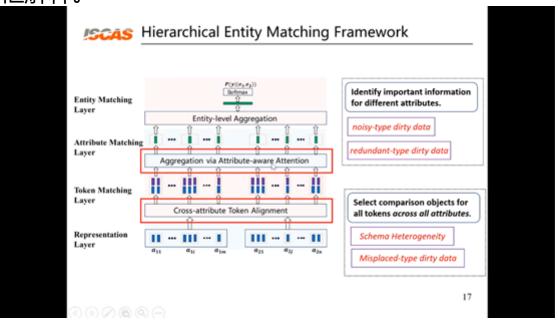
使用带背景的字体框抛出问题, 抓住观众注意力。



对于大纲,只突出显示马上要介绍的章节,其他的置灰。



分模块介绍模型,红框标记,右边对应不同颜色文本 框解释。



实验部分,表信息量较大时,抛出结论,使用颜色背景标记出对应数据

Experimental Results

For heterogeneous ER

Type	Dataset			F1 sco		$\Delta F1$	$\Delta F1'$	
.,,,,		Magellan	Deep- Matcher	MPM	Seq2Seq- Matcher	HierMatcher		
	Walmart-Amazon2	37.4	53.8	-	68.3	68.5	+14.7	+0.2
Dirty	DBLP-ACM ₂	91.9	98.1	-	98.4	98.1	+0.0	-0.3
-	DBLP-Scholar ₂	82.5	93.8	-	94.1	94.5	+0.7	+0.4
	Average	-	-	-	-		+5.1	+0.1
	Walmart-Amazon3(1-n)	-	67.1	-	75.6	80.7	+13.6	+5.1
Unterconnections	Walmart-Amazon4(n-n)	-	63.4	- 1	74.7	81.4	+18.0	+6.7
Heterogeneous	Walmart-Amazon5(n-n)	-	66.5	-	74.4	81.0	+14.5	+6.6
	Average	- 0		-	-	-	+15.4	+6.1
		Incommon Million						

Aligned attribute based

HierMatcher can effectively solve the schema heterogeneity and dirty data problems in ER.

20



Experimental Results

Type	Dataset	F1.sc	ore	
	Dataset	HierMatcher -ave	HierMatcher	
	Walmarr-Amazon1	77.1	81.6	
(I.m., ann., ann.	Amazon-Google	70.0	74.9	
Homogeneous	DBLP-ACM ₁	98.1	98.8	-2.6
	DBLP-Scholar ₁	94.9	95.3	
	Average		-	
	Walmarr-Amazon2	61.4	68.5	
Dirty	DBLP-ACM ₂	97.3	98.1	-2.8
	DBLP-Scholar ₂	93.9	94.5	210
	Average			
	Walmarr-Amazony(1-n)	67.5	80.7	
Unterconnection	Walmarr-Amazon ₄ (n-n)	67.6	81.4	-13.0
Heterogeneous	Walmarr-Amazony(n-n)	69,0	81.0	10.0
	Average		-	

Effectively identifying important information for each attribute is critical for ER.

21

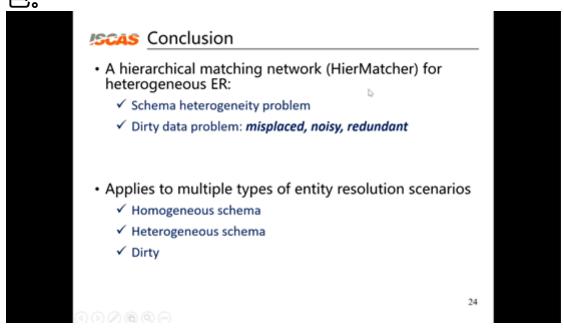


ISCAS Experimental Results

Type	Dutaset	F1 score							
1,544		Magellan	Deep- Matcher	MPM	Seq2Seq- Matcher	HierMatcher -ave	HierMatcher	$\Delta F1$	$\Delta F1'$
	Walmart-Amazon ₁	71.9	67.6	73.6	78.2	77.1	81.6	+8.0	+3.4
Homogeneous	Amazon-Google	49.1	69.3	70.7	61.2	70.0	74.9	+4.2	+13.7
	DBLP-ACM ₁	98.4	98.4		98,9	98.1	98.8	+0.4	-0.1
	DBLP-Scholar ₁	92.3	94.7		95.3	94.9	95.3	+0.6	+0.0
	Average	P-Scholar ₁ 92.3 94.7 - 95.3 94.9 oge		+3.3	+4.3				
	Walmart-Amazon2	37.4	53.8	-	68.3	61.4	68.5	+14.7	+0.2
Dany	DBLP-ACM ₂	91.9	98.1		98.4	97.3	98.1	+0.0	-0.3
	DBLP-Scholar ₂	82.5	93.8		94.1	93.9	94.5	+0.7	+0.4
	Average							+5.1	+0.1
	Walmarr-Amazon3(1-n)		67.1	-	75.6	67.5	80.7	+13.6	+5.1
	Walmart-Amazon4(n-n)		63.4		74.7	67.6	81.4	+18.0	+6.7
Heterogeneous	Walmart-Amazons(n-n)		66.5		74.4	69.0	81.0	+14.5	+6.6
	Average		-	-				+15.4	+6.1

HierMatcher applies to multiple types of ER scenarios.

总结,带√的项目符号很不错,且使用不同字体颜 ^在



参考 北京大学 谢雨汐 PPT

Paper Linic https://arxiv.org/abs/2004.12704
Code Linic https://github.com/WING-NUS/SG-Deep-Question-Generation

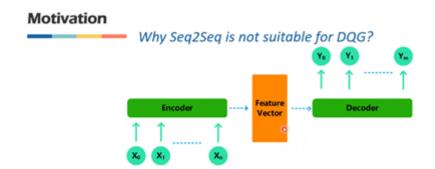


Semantic Graphs for Generating Deep Questions

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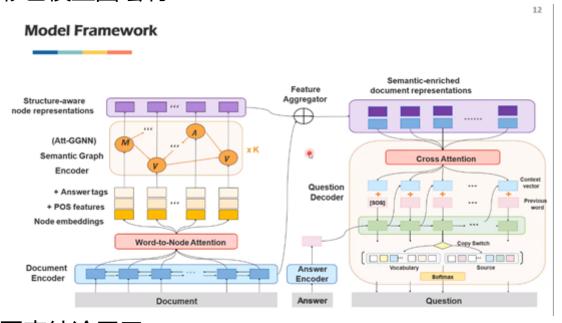
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多种字体颜色的使用



- Seq2Seq directly learns the mapping from unstructured document to question
 - · for DQG, it's hard to directly learn this mapping
- Our model incorporate structured semantic graph to assist question generation
 - · easier for content selection over graph nodes
 - · easier to learn to reason over graph nodes
 - more explainable

彩色模型图绘制



图表结论展示

Performance on Human Evaluation

- Fluency indicates whether the question follows the grammar and accords with the correct logic
- Relevance indicates whether the question is answerable and relevant to the passage
- Complexity indicates whether the question involves reasoning over multiple sentences from the document

Model	Short Contexts		Medium Contexts			Nong Contexts			Average			
Model	Flu. Rel. Cpx		Cpx.	Flu. Rel. Cpx.		Flu. Rel. C		Cpx.	Flu.	Flu. Rel. Cpx		
B4. S2sa-at-mp-gsa	3.76	4.25	3.98	3.43	4.35	4.13	3.17	3.86	3.57	3.45	4.15	3.89
B6. CGC-QG	3.91	4.43	3.60	3.63	4.17	4.10	3.69	3.85	4.13	3.75	4.15	3.94
A2w/o Semantic Graph	4.01	4.43	4.15	3.65	4.41	4.12	3.54	3.88	3.55	3.73	4.24	3.94
A4w/o Multi-Task	4.11	4.58	4.28	3.81	4.27	4.38	3.44	3.91	3.84	3.79	4.25	4.17
P2. DP-Graph	4.34	4.64	4.33	3.83	4.51	4.28	3.55	4.08	4.04	3.91	4.41	4.22
G1. Ground Truth	4.75	4.87	4.74	4.65	4.73	4.73	4.46	4.61	4.55	4.62	4.74	4.67

总结,不同字体颜色突出重点。

Conclusion

- Propose the problem of DQG
 - to generate questions that requires reasoning over multiple disjoint pieces of information
- Utilize semantic graphs
 - · reduce semantic errors significantly
 - · help do content selection by jointly training
 - · facilitate the reasoning process
 - · future direction: incorporation of external knowledge

21