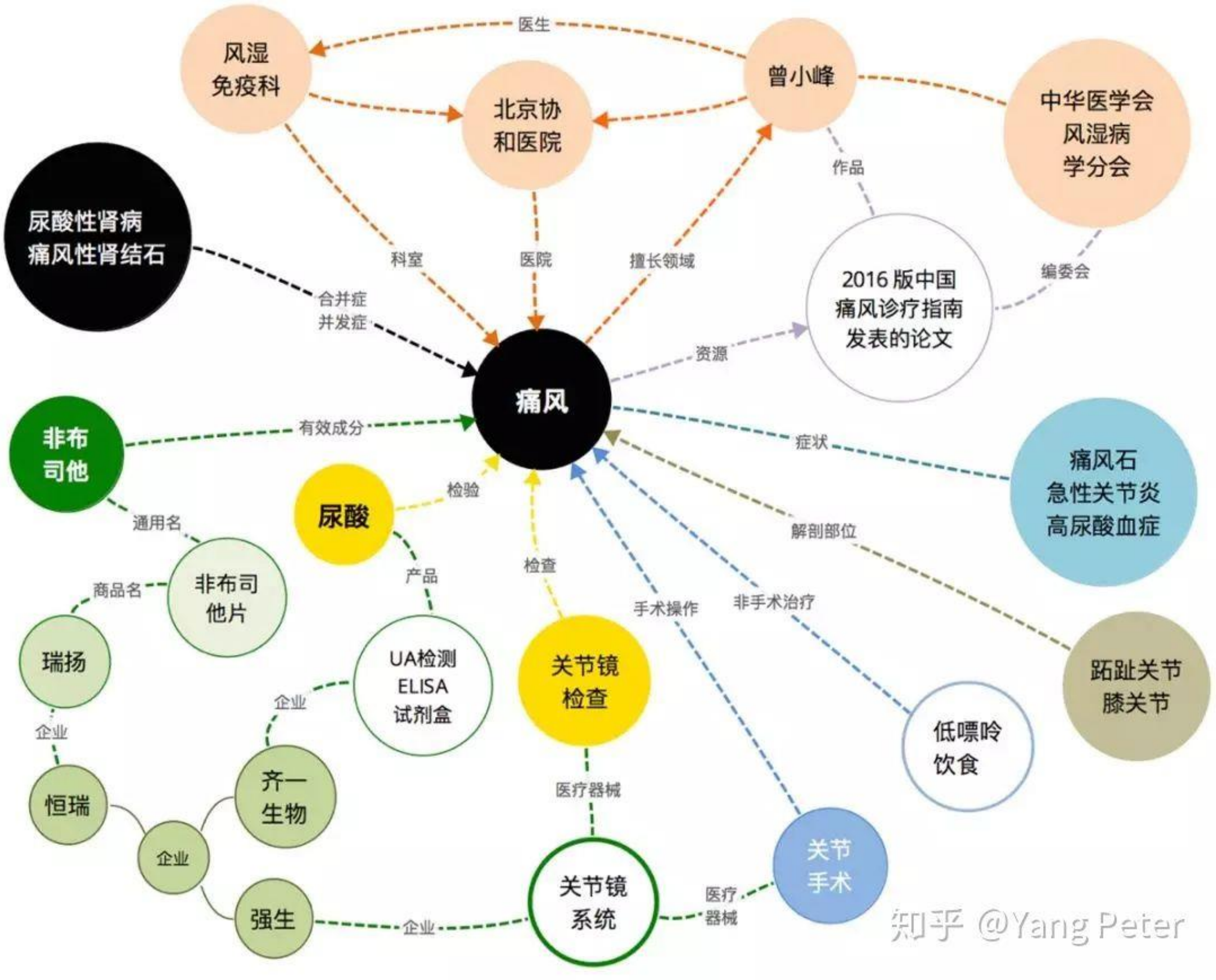
Joint Extraction of Relations and Entities

Haoran Zhang

ILLINOIS

丁香园



风湿
免疫科
医生
曾小峰
北京协
和医院
中华医学会
风湿病
学分会
作品
尿酸性肾病
痛风性肾结石
科室
医院
擅长领域
编委会
2016 版中国
痛风诊疗指南
发表的论文
合并症
并发症
资源
痛风
非布
司他
有效成分
症状
痛风石
急性关节炎
高尿酸血症
尿酸
检验
解剖部位
通用名
产品
检查
非布司
他片
商品名
手术操作
非手术治疗
瑞扬
UA检测
ELISA
试剂盒
关节镜
检查
跖趾关节
膝关节
企业
企业
低嘌呤
饮食
齐一
生物
医疗器械
恒瑞
企业
关节镜
系统
关节
手术
医疗
器械
强生
企业
知乎 @Yang Peter

Knowledge Base Question Answering

Mag[i] 鹿目圆

鹿目圆
实体

96

描述

"“神权型魔法少女”的代表" "伟大的魔法少女" "悲惨的角色"
"日本魔法少女题材动画《魔法少女小圆》的女主角之一" "见泷原中学二年级的少女"
"黑暗的本作中最能体现魔法少女精神的角色"

属性 仅显示部分热门信息 · 更多请点击或直接搜索问题

就读于	市立见泷原中学二年级	CV:	悠木碧
又称	圆神	另译	鹿目圆香
好友	志筑仁美	战力	112
武器	长弓	母亲	鹿目询子
职业	魔导士	同班同学	佐仓杏子

标签 仅显示部分来源充分的信息 · 点击可显示详情

角色 魔法少女 人物 主角 魔女 少女 女主角 作品 动画角色
主角人物 初中生 动漫人物 动画主角 动画人物 女孩

主要学习来源

井上新原的日记
www.douban.com · 2018年1月26日

《神域召唤》与《魔法少女小圆》联动 1月31日上线_网络游戏新闻...
news.17173.com · 2019年1月21日

NGC 6357_互动百科
www.baike.com

辩论！最经典的魔法少女角色是谁？_动漫迷_新浪博客
blog.sina.com.cn · 2018年12月6日

魔法少女小圆同人游戏下载_魔法少女小圆同人游戏中文版[横版动...
www.downza.cn · 2018年6月22日

日本动漫迷万人票选“最有魅力的魔法少女”Top20名单出炉 - A9VG...
www.a9vg.com · 2016年5月13日

魔法记录手游中文版-魔法记录国服版v1.0 安卓版-腾牛安卓网
www.qqtn.com · 2018年8月6日

DeNA卡牌类《魔娘X勇者》即将将登场[多图] - 海外 - 游戏鸟
www.youxiniao.com · 2014年4月28日

魔法少女（ACGN作品的女性角色特征）_百度百科
baike.baidu.com · 2018年5月27日

盘点动漫中三位非常悲惨的女主角，主角光环居然也会无效
new.qq.com

Outline

- Task
- Pipeline
- Table Filling
- Tagging
- Seq2Seq

Pipeline

Entity Extraction → Relation Extraction

S-GPE O O O O B-GPE E-GPE

Bi-LSTM CRF

Illinois is located in the United States

LOCATE_IN

CNN

Illinois is located in the United States

- Cons: “it prohibits the interactions between components. Errors in the upstream components are propagated to the downstream components without any feedback.” (Li and Ji., 2014)

Task definition

- Input: plain text
- Output: [triplet1, triplet2,…]
- Eg.

Illinois is located in the United States. -> [<Illinois, LOCATE_IN, United States>]

Table Filling

- **TF-MTRNN**(P Gupta et al., 2016)
  - Diagonal: entity extraction
  - Other: relation extraction

- Time Complexity: $O(length^2)$
- How to deal with multi-token entites?

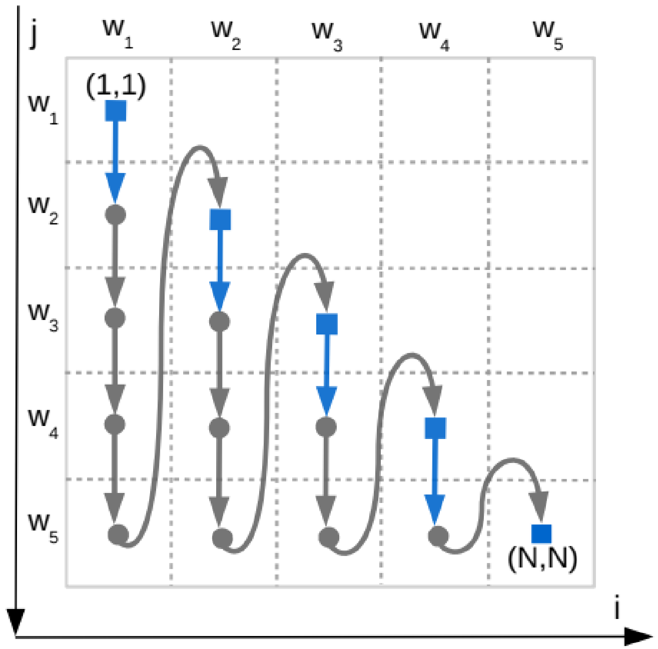


Table Filling

CNN-CRF (H Adel et al.,2017)

	PER	LOC	ORG	Other
PER	KILL	Live_In	Work_For	$\perp$
LOC	Live_In	Located_In	ORG Based_In	$\perp$
ORG	Work_For	ORG Based_In	$\perp$	$\perp$
Other	$\perp$	$\perp$	$\perp$	$\perp$

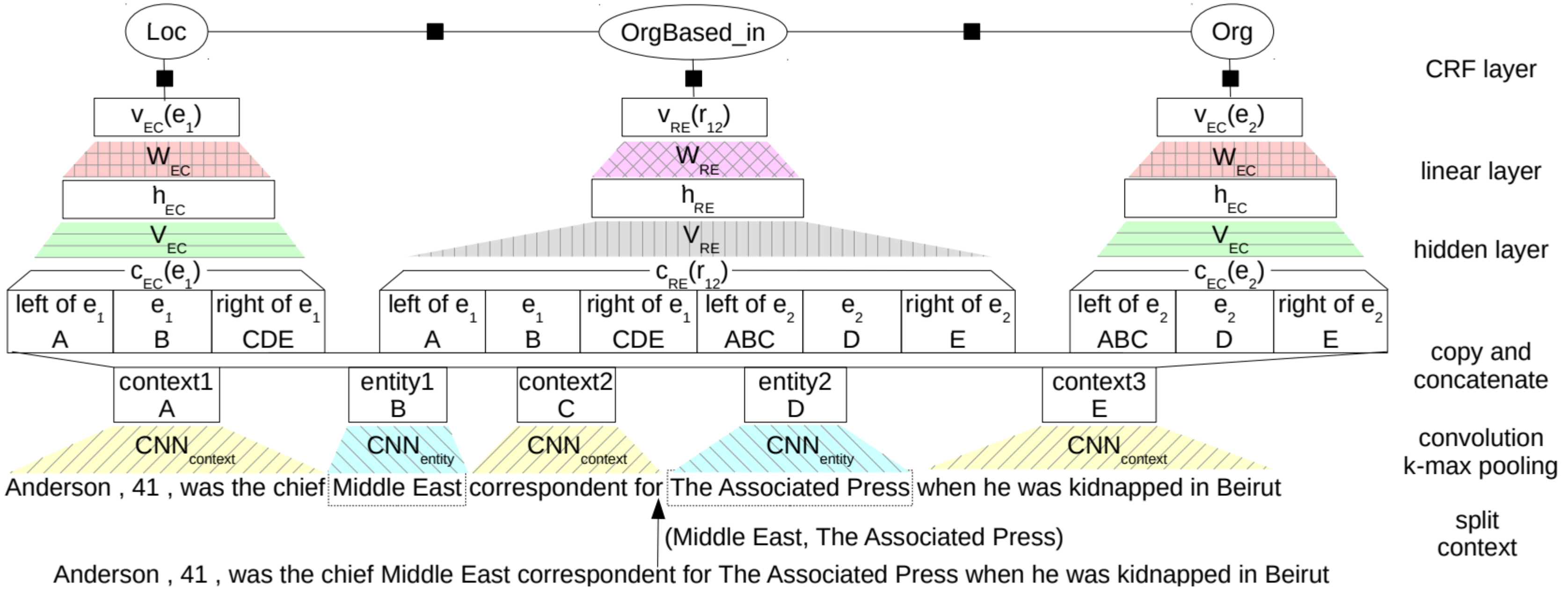


Table Filling

- **Multi-head Selection** (Bekoulis G et al., 2018)

2019 Language and Intelligence Challenge   Log in

Overview   Dataset   Submission   Winners & Leaderboard   News

Final Evaluation Leaderboard   Online Evaluation Leaderboard

Rank	Model	Precision	Recall	F1	Submit Time
1	[知识工场] BERT(ensemble) gdm 复旦大学	0.8975	0.8886	0.893	2019/5/20
2	[variant bert+multi head selection] (ensemble) littlebert 个人	0.8962	0.8886	0.8924	2019/5/20
3	[ERNIE CTagging + MultiSub Reviewer] (ensemble) Kill_Thread Ecole X	0.8976	0.8852	0.8914	2019/5/20

http://lic2019.ccf.org.cn/kg

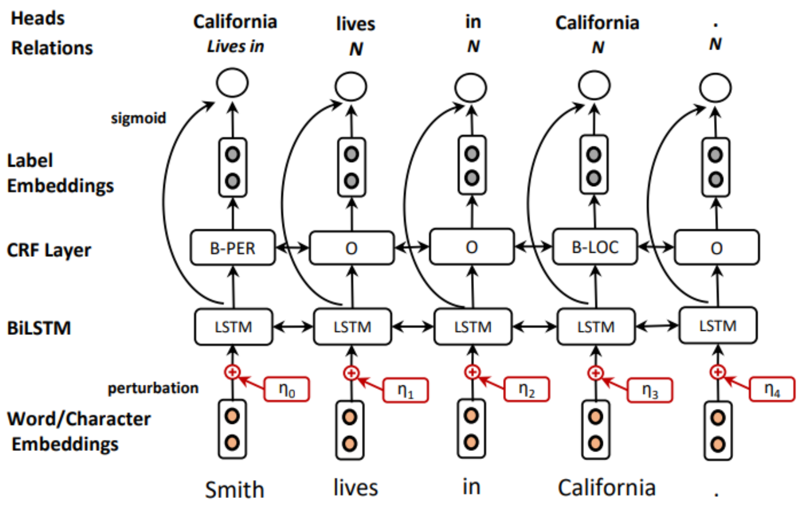
Table Filling

- **Multi-head Selection** (Bekoulis G et al., 2018)
- Cons:
  - Complexity (space): $O(batch \times length^2 \times relation)$
  - Imbalanced classification

(batch, hidden, length) -> (batch, hidden, length, length)

$$P(head = word_j, label = r_k | tail = word_i)$$

0	Marc	B-PER	['N']	[0]
1	Smith	I-PER	['lives_in','works_for']	[5,11]
2	lives	O	['N']	[2]
3	in	O	['N']	[3]
4	New	B-LOC	['N']	[4]
5	Orleans	I-LOC	['N']	[5]
6	and	O	['N']	[6]
7	is	O	['N']	[7]
8	hired	O	['N']	[8]
9	by	O	['N']	[9]
10	the	O	['N']	[10]
11	government	B-ORG	['N']	[11]
12	.	O	['N']	[12]



Tagging

- NovelTagging (Zheng S et al., 2017)

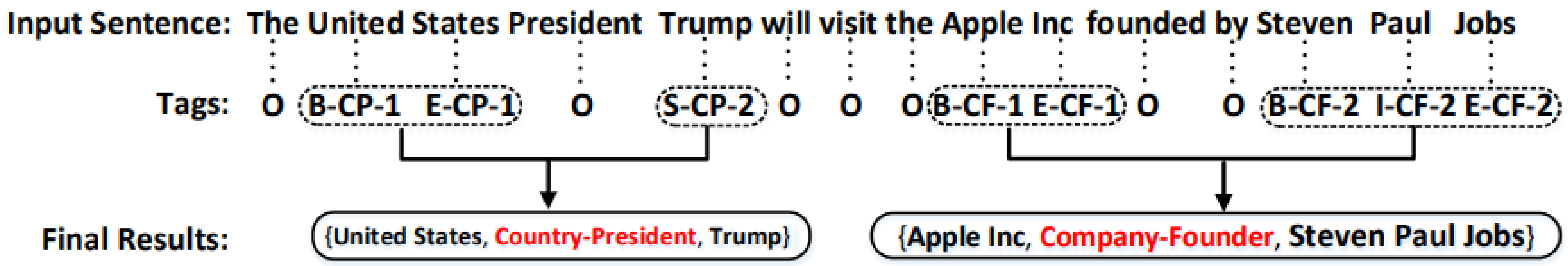
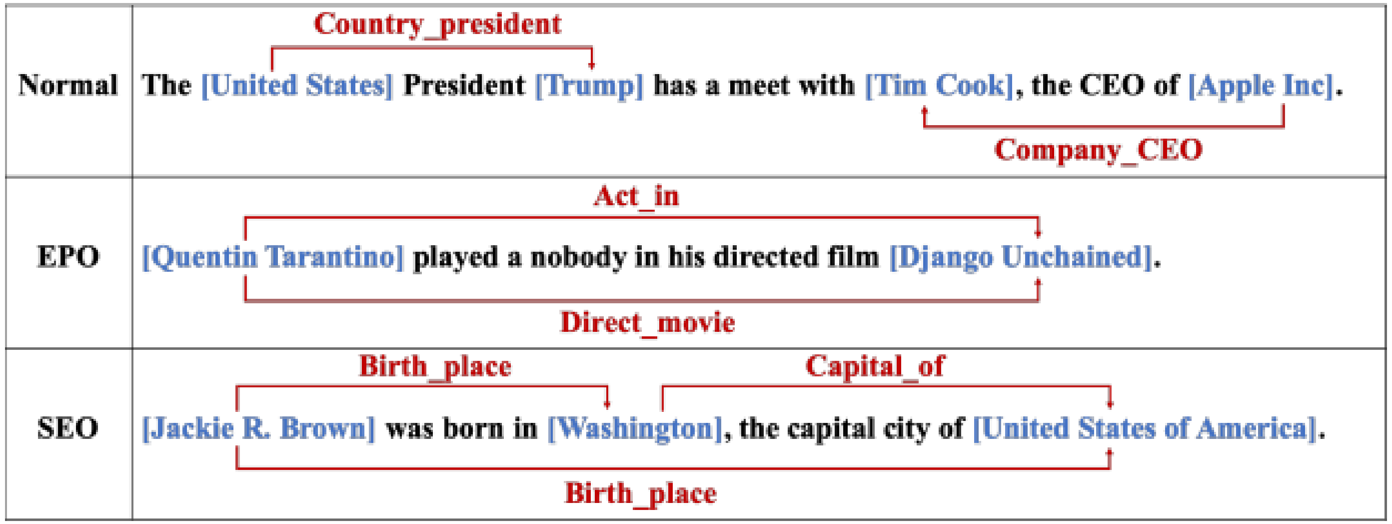


Figure 2: Gold standard annotation for an example sentence based on our tagging scheme, where "CP" is short for "Country-President" and "CF" is short for "Company-Founder".

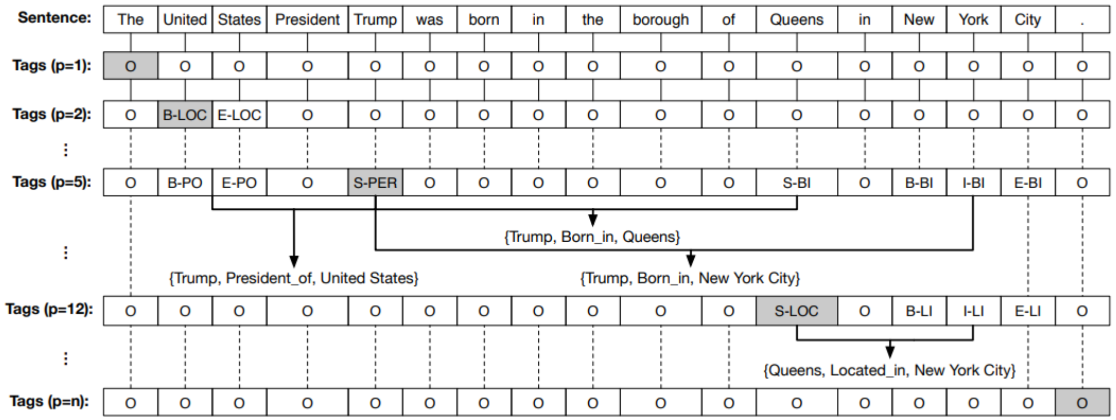
Tagging

- NovelTagging (Zheng S et al., 2017)
- Cons: Overlapping Relations?



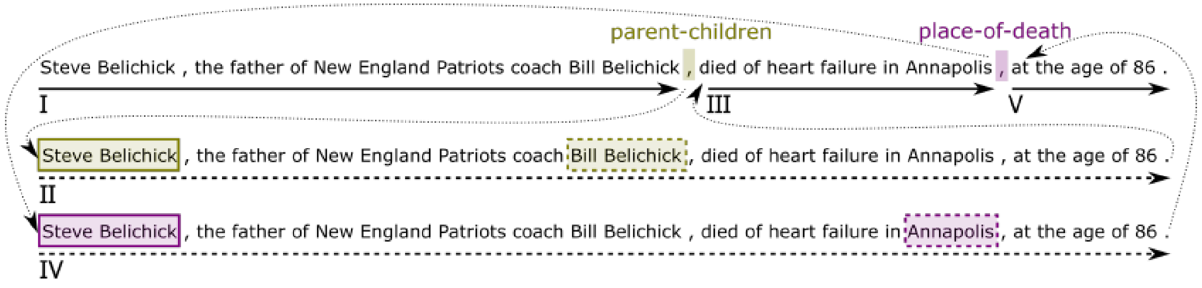
Tagging

(Dai D *et al.*, 2019)

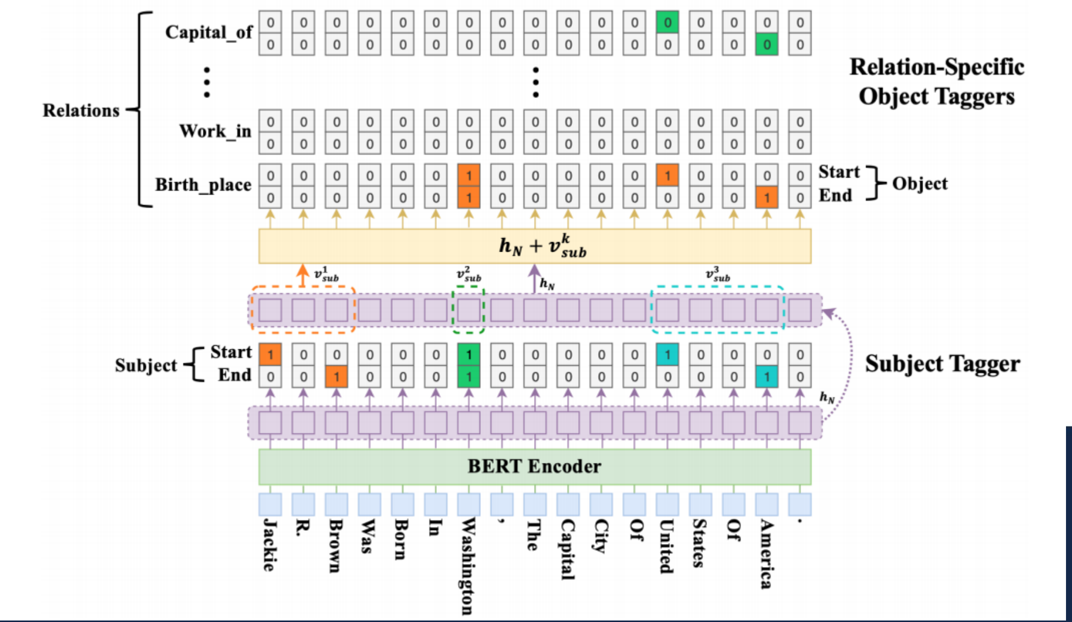


$$P(label = tag_k | tail = word_i, head = word_j)$$

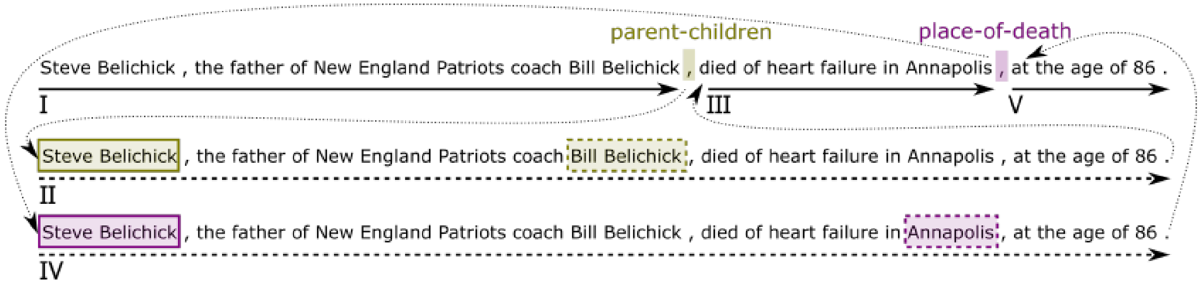
(Takanobu *et al.*, 2019)



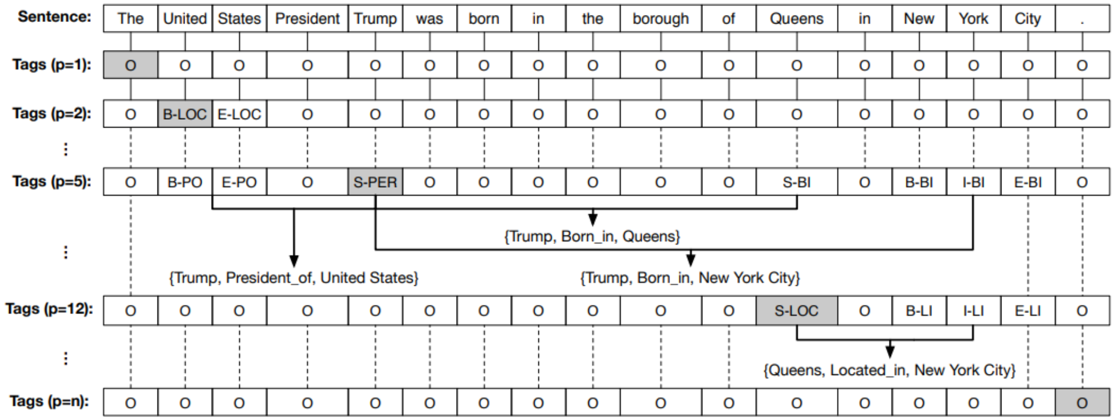
(Zhepei W *et al.*, 2019)



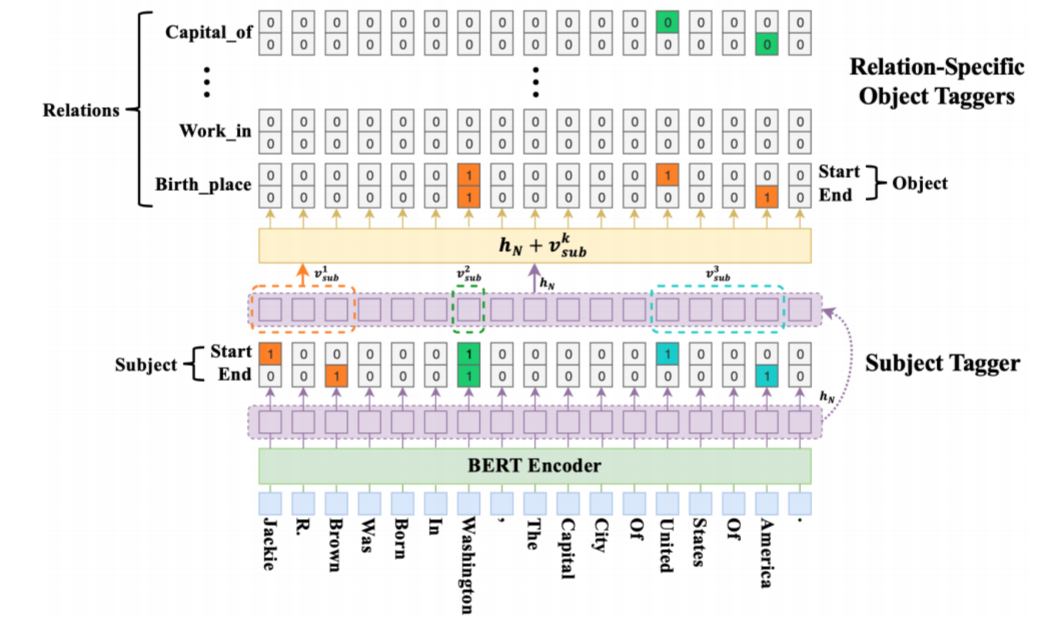
(Takanobu *et al.*, 2019)



(Dai D *et al.*, 2019)



(Zhepei W *et al.*, 2019)

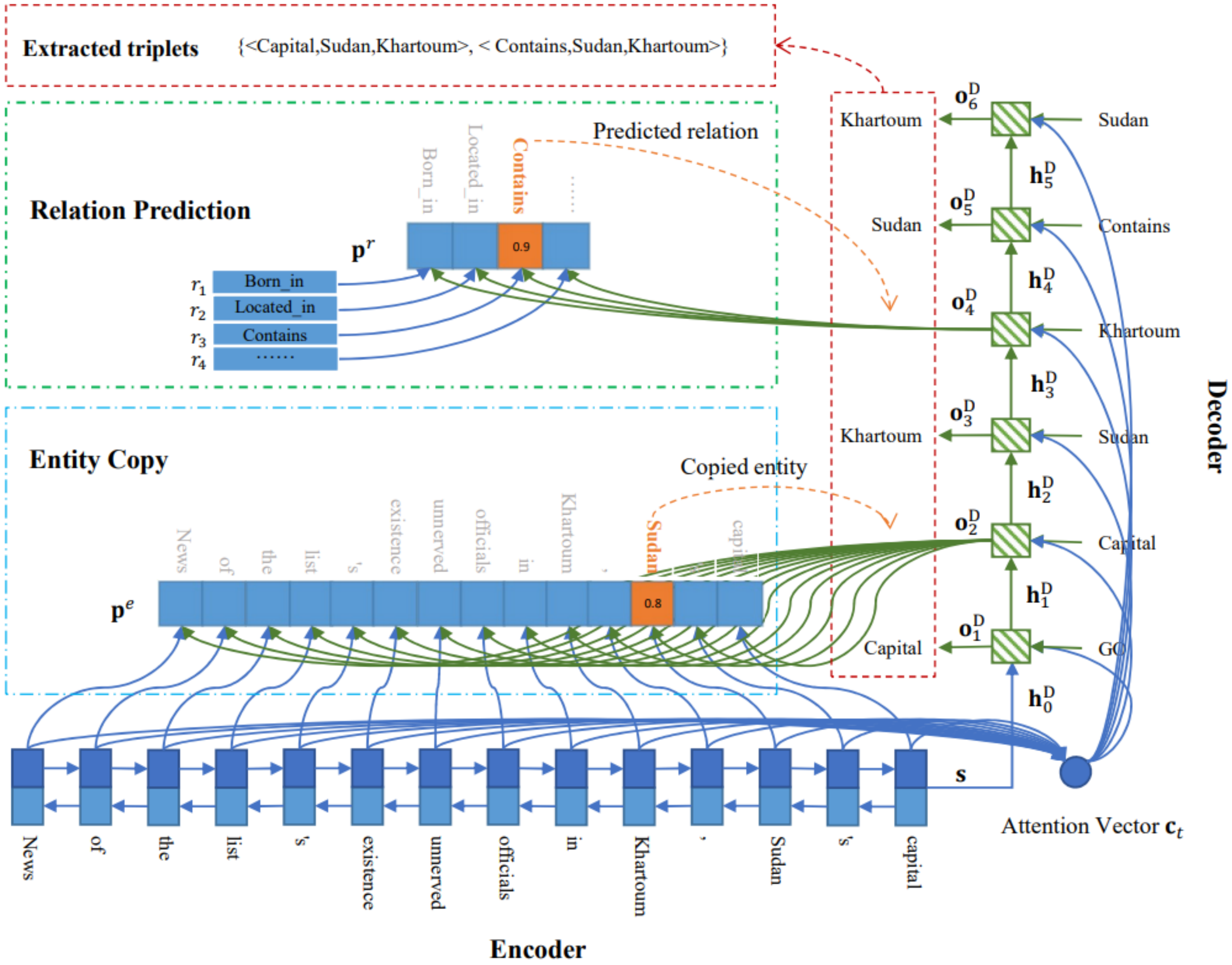


$$P(label = tag_k | tail = word_i, head = word_j)$$

Seq2Seq

- Sequence in, Sequence out -> CopyRE (Zeng X et al.,2018)

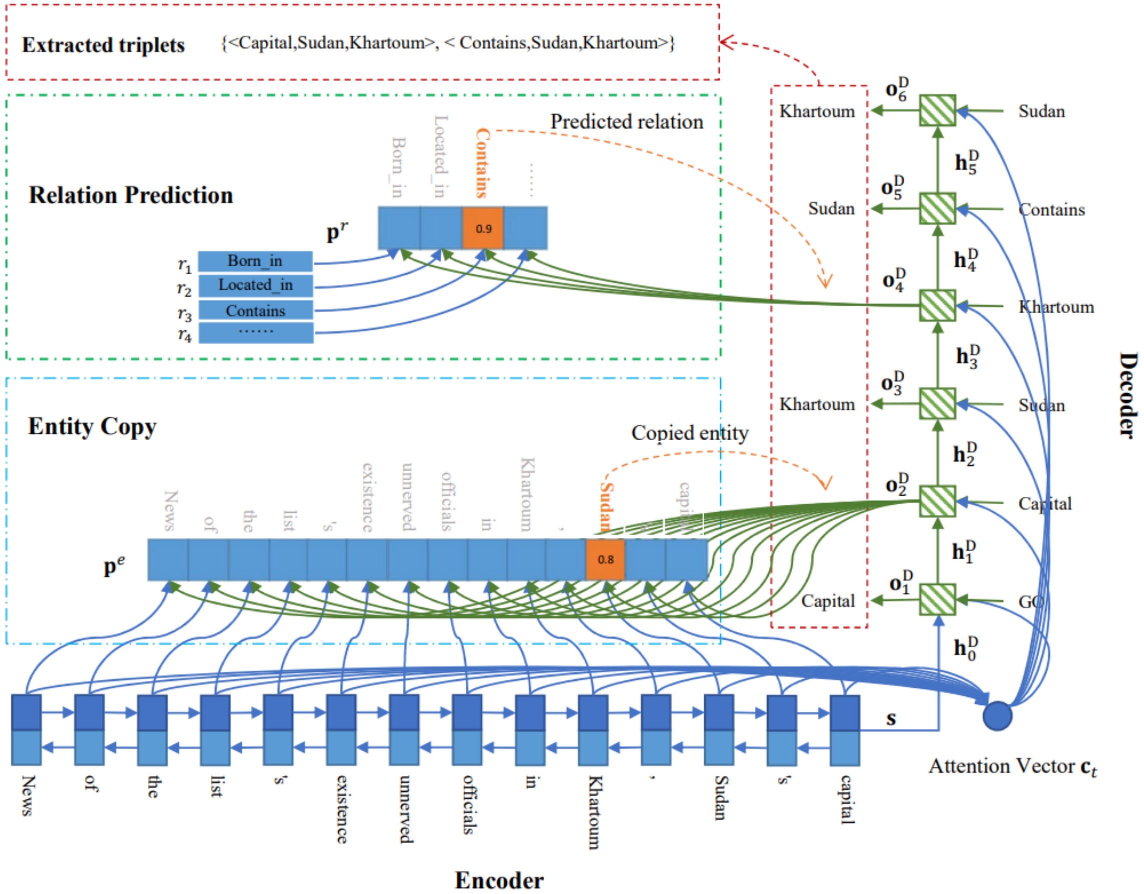
News of the list’s existence unnerved
officials in Khartoum, Sudan’s capital..
->
[<Capital, Sudan, Khartoum>,
< Contains, Sudan, Khartoum>}



Seq2Seq

- Sequence in, Sequence out -> CopyRE (Zeng X et al.,2018)

- Cons:
  - Fixed order of the triplets (EMNLP19)
  - Incomplete Entities (AAAI20)
  - Fixed number of the triplets
  - Decreasing F1 with increasing outputs
    - Problem: Exposure bias
    - Solution: Multi-head decoding?



Results

Model	NYT			WebNLG		
	Precision	Recall	F1	Precision	Recall	F1
NovelTagging (2017)	64.2	31.7	42.0	52.5	19.3	28.3
CopyRE-Mul (2018)	61.0	56.6	58.7	37.7	36.4	37.1
GraphRel (2019)	63.9	60.0	61.9	44.7	41.1	42.9
CopyMTL-One (2019)	72.7	69.2	70.9	57.8	60.1	58.9
BERT-MHATT (2019)	77.7	82.1	79.8	69.0	74.5	71.6
HBT (2019)	89.7	85.4	87.5	89.5	88.0	88.8

1. BERT-MHATT and CopyMT-One are my work submitted to AAAI20
2. HBT is the newest model in arxiv (Sep, 2019)
3. BERT-MHATT and HBT can both be seen as Table Filling

Discussion

- Table Filling
  - Pros: high performance
  - Cons:
    - Computational expensive
    - Class imbalance

  Think about paragraph level!

- Tagging
  - Cons:
    - Overlapping relations
    - Degrade to Table Filling

- Seq2Seq
  - Pros: Simple
  - Cons:
    - Low performance with multiple triplets
    - Triplet order
    - Triplet number

Future

- Incremental learning | catastrophic Forgetting Problem
  - KG are never complete. Just keep learning.
  - I want my KG learn COVID-19 and Remdesivirr automatically while not forgetting what they learn before.
- Longtail Problem
  - COVID-19 is majority while black plague is minority.
- Is JERE a KGC?
  - Knowledge graph completion: given head and relation, predict tail.
  - Sentences are different, but the train set and the test set share same triplets.
    - CONLL03: 20% overlap
    - NYT: 70% overlap
- Possible application: Academic KG from paper

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