第八章 知识图谱

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从文本中抽取知识

- 命名实体识别
- **细粒度实体分类**
- 关系抽取
- 事件抽取

细粒度实体分类（Fine-grained Entity Typing, FET）

3月20日消息，微软旗下语音识别子公司Nuance今日发布一款 AI 临床笔记软件，命名为DAX Express，主要面向医护人员。

目标输出

实体提及[1]	位置	类别
3月20日	(0, 3)	/日期
微软	(8, 9)	/机构, /机构/公司, /机构/公司/科技公司
Nuance	(20, 25)	/机构, /机构/公司, /机构/公司/科技公司
DAX Express	(46, 56)	/产品, /产品/软件

- 给定一个细粒度实体类别体系，对文本中已识别出的实体进行分类
- 先用NER先识别出实体位置，再用FET对它们分类
- FET一般是多标签分类，即一个样本可以有多个类别标签

FET的应用

- 除用于知识图谱构建，还可应用于：
  - 关系抽取（relation extraction）
    - 头尾实体的类别可作为确定它们关系的辅助信息
  - 实体链接（entity linking）
    - 根据实体类别辅助确定正确的实体
  - 指代消解（coreference resolution）
    - 指代消解目标：识别文本中哪些词指代了相同的实体
    - 同实体类别的词或短语更可能指代了同一个实体
  - 等

Onoe, Yasumasa, and Greg Durrett. "Interpretable Entity Representations through Large-Scale Typing." Findings of EMNLP. 2020.

FET的难点

- 实体类别数多
  - 有些类别可能不易区分
  - 需要的训练数据多

Dataset	FIGER	OntoNotes	BBN	UltraFine	CFET
#Types	117	89	47	10K	7k

- 预测的类别应与上下文相关，或需从上下文推断出来

Rogers, the UW's leading scorer, will be a game-time decision.

/organization, /organization/sports_team

FET数据集

- 普通细粒度实体分类
  - 使用人工设计的实体类别体系，一般组织成层次结构
  - 类别例子：/person, /person/politician, /person/actor, /location/city
  - 数据集：FIGER、OntoNotes、BBN、Few-NERD等
- 极细粒度实体分类（Ultra-fine entity typing, UFET）
  - 直接使用普通的词或短语作为类别标签
  - 类别例子：person, politician, actor, city, victim, criminal, company
  - 数据集：Ultrafine、CFET等
    - 其中CFET为中文数据集

FET数据集

- 普通FET数据集统计信息

Dataset	FIGER	OntoNotes	BBN
#documents	18	76	459
#mentions	563	9,604	13,766
#types	113	89	47
type hierarchy depth	2	3	2

文档数（#documents）和样本数（#mentions）只统计人工标注的测试集

- 其中提出FIGER数据集的论文是第一个系统化地重点研究细粒度实体分类的工作，该数据集标注质量也较高，但人工标注的用于测试的样本数少
- BBN的测试集中，每个样本只标注单条类别路径的标签
  - 如/LOCATION, /LOCATION/REGION，但不会给一个样本同时标/LOCATION, /ORGANIZATION
- BBN数据集没有对/PERSON类别进行细分

FET数据集

- OntoNotes (Gillick et al, 2014) 数据集的类别体系

PERSON

- **artist**
  - actor
  - author
  - director
  - music
- **education**
  - student
  - teacher
- **athlete**
- **business**
- **coach**
- **doctor**
- **legal**
- **military**
- **political figure**
- **religious leader**
- **title**

LOCATION

- **structure**
  - airport
  - government
  - hospital
  - hotel
  - restaurant
  - sports facility
  - theatre
- **geography**
  - body of water
  - island
  - mountain
- **transit**
  - bridge
  - railway
  - road
- **celestial**
- **city**
- **country**
- **park**

ORGANIZATION

- **company**
  - broadcast
  - news
- **education**
- **government**
- **military**
- **music**
- **political party**
- **sports league**
- **sports team**
- **stock exchange**
- **transit**

OTHER

- **art**
  - broadcast
  - film
  - music
  - stage
  - writing
- **event**
  - accident
  - election
  - holiday
  - natural disaster
  - protest
  - sports event
  - violent conflict
- **health**
  - malady
  - treatment
- **award**
- **body part**
- **currency**
- **language**
  - programming language
- **living thing**
  - animal
- **product**
  - camera
  - car
  - computer
  - mobile phone
  - software
  - weapon
- **food**
- **heritage**
- **internet**
- **legal**
- **religion**
- **scientific**
- **sports & leisure**
- **supernatural**

Gillick, D., Lazic, N., Ganchev, K., Kirchner, J., & Huynh, D. (2014). Context-dependent fine-grained entity type tagging. *arXiv preprint arXiv:1412.1820*.

FET数据集

- 普通FET数据样例

Mention Example	Dataset	Labels
... **Edward McClain** has been sitting at his spot outside the grocery store for years ...	FIGER (GOLD)	/person
Silicon Valley heaved a sigh of relief yesterday.	BBN	/LOCATION/REGION /LOCATION
The new **beer**, introduced this week at a liquor industry convention, is imported ...	BBN	/SUBSTANCE/FOOD /SUBSTANCE
... modestly compares its "hydraulic active suspension" to a **cheetah** ...	BBN	/ANIMAL
... but **Valley Federal** had said it expected to post a modest pretax gain and to ...	OntoNotes	/organization/company /organization
... but Valley Federal had said **it** expected to post a modest pretax gain and to ...	OntoNotes	/organization/company /organization
... and **at least 500 civilians hiding inside** were killed, more than half of whom ...	OntoNotes	/person
... and to promote **development** in other areas of the two countries.	OntoNotes	/other

极细粒度实体分类

- 不人工设计类别体系，直接使用词或短语作为类别标签
  - 类别例子：person, politician, actor, city, victim, patient, company
- 相比普通FET，类别更丰富，覆盖更广
  - Ultrafine和CFET分别含约10k和7k实体类别

FET数据集

- UFET数据样例

数据集	样本	标签
Ultrafine	In 1988 , **Pitt** had his first starring role, in Dark Side Of The Sun, where he played a young American taken by his family to the ...	performer, adult, man, male, entertainer, professional, person, actor
Ultrafine	... states that Paul of Tarsus, imprisoned and on trial claimed his right as a Roman citizen to be tried before Caesar, and the judicial process had to be suspended until **he** was brought to Rome.	citizen, criminal, person
CFET	高尔基大街（现易名为**特维尔大街**）是莫斯科一条最主要的大街	街道, 旅游景点, 路, 大街, 街, 道路
CFET	我在**西堤**牛排上海虹口龙之梦店：同学小聚 哈哈	品牌, 地方, 餐馆, 位置

Ultrafine和CFET分别含约6000和4800个人工标注的样本，等分为train/dev/test

极细粒度实体分类

- 缺点：增加了应用的难度
  - 分类预测的效果变差，甚至人工标注数据时也可能标不全
    - 类别多，每个样本对应的正确类别标签也多
  - 基于分类结果执行某些操作的难度增加
  - 类别定义不清晰，有些类别词可能有歧义

自动构建训练数据

- FET类别数多，标注难度大，人工标注训练数据成本高
  - 应对方法：自动生成训练数据
  - 学术界对细粒度实体分类的研究目前大多基于自动生成的训练数据

- 三种主要的自动构建训练数据方法
  - 基于知识图谱的构建方法
  - 基于head word的方法
  - 基于预训练模型的方法

自动构建训练数据

- 基于知识图谱的构建方法
  1. 获得实体提及
     - 使用Wikipedia的内部超链接（anchor links），或使用NER工具标注
  2. 得到实体提及在知识图谱中的对应实体
     - 基于Wikipedia内部超链接的链接目标，或使用实体链接
  3. 基于知识图谱中实体的类别得到标签
     - 将知识图谱中的实体类别映射到所使用的标签体系

基于知识图谱的训练数据获取 – 例

A piece of text from Wikipedia

increase. On November 17, Gov. Schwarzenegger signed Executive Order S-1-03, rescinding the vehicle license fee retroactive to October 1, 2003 when the fee increase went into effect. Analysts

mention

Wikipedia page of Arnold Schwarzenegger

Arnold Schwarzenegger

From Wikipedia, the free encyclopedia

Arnold Alois Schwarzenegger (/ˈʃvɑːrtsnɛɡər/;[1][a] German: [ˈaɐ̯nɔlt ˈʃvaɐ̯tsn̩ˌʔɛɡɐ]; born July 30, 1947) is an Austrian-American actor, filmmaker, businessman, author, philanthropist, activist, politician, and former professional bodybuilder and powerlifter.[2] He served as the 38th Governor of California from 2003 to 2011.

Obtain Freebase types

Freebase Types:
people.person; film.actor; sports.pro_athlete; government.politician; book.author; …

Map to target types

Target Types:
/person; /person/actor; /person/athlete; /person/politician; /person/author

weak labels for the mention

这种训练数据也被叫做**远程监督**

基于知识图谱的训练数据获取

- 存在的问题：
  - 使用Wikipedia内部超链接或实体链接得到所指代的实体都可能出错
    - 从而根据实体从知识库中获得的类别标签也是错的
  - 得到的标签与上下文无关
  - 应用到UFET时召回率低
    - 在Ultrafine数据集上，该方法平均为每个样本获取的标签数少于2个，但人工标注的样本平均每个有5.4个标签

自动构建FET训练数据

- 基于head word生成
  - Head word: the central element in a phrase

如：

phrase	head word
the 44th president of the United States	president
Nanjing University of Aeronautics and Astronautics	university
the man with her	man
a group of students	group

用于极细粒度实体分类：如果head word是一个目标类别，则直接使用head word作为标签
用于普通细粒度实体分类：将head word映射到类别体系中的标签

基于head word生成类别标签

- 存在的问题：
  - 对很多实体提及不适用，如“Bob Dylan”、 “Microsoft”
  - 应用到UFET时召回率低

自动构建训练数据

- 基于预训练语言模型的方法

An unlabeled mention in a sentence:

Highway 61 Revisited is the sixth studio album by Bob Dylan.

Highway 61 Revisited is the sixth studio album by [MASK] such as Bob Dylan.

Feed to BERT MLM

Most probable words for “[MASK]”: artists, musicians, musician, songwriters, performers

artist, *musician*, *songwriter*, *performer* 作为标签

Dai, Hongliang, Yangqiu Song, and Haixun Wang. "Ultra-Fine Entity Typing with Weak Supervision from a Masked Language Model." Proceedings of ACL. 2021.

自动构建训练数据

- 基于预训练语言模型的方法

Input	Top Words for [MASK]
In late 2015, [MASK] such as Leonardo DiCaprio starred in The Revenant.	actors, stars, actor, directors, filmmakers
At some clinics, they and some other [MASK] are told the doctors don't know how to deal with AIDS, and to go someplace else.	patients, people, doctors, kids, children
Finkelstein says he expects the company to “benefit from some of the disruption faced by our competitors and any other [MASK].”	company, business, companies, group, investors

- 该方法为不同形式的实体提及（专有名词、代词、普通名词）都可生成类别标签
- 可以生成像patient这样的依赖于上下文的标签

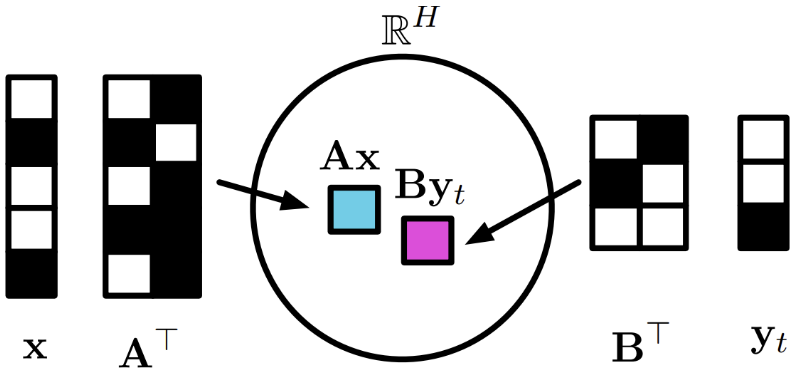
基于预训练模型的训练数据生成方法

- 优点
  - 可以得到与上下文相关的标签，且对实体提及的形式要求低
  - 可以补充基于知识图谱和基于head word的方法，提高生成标签的召回率
- 存在的问题
  - 得到的标签正确性相比基于知识图谱和head word的方法更低
  - 生成标签数目不易确定

Pattern	F1
M and any other H	25.3
M and some other H	24.8
H such as M	20.7
such H as M	18.1
H including M	17.4
H especially M	11.5

细粒度实体分类方法

- 基于手工设计特征的方法
- (Yogatama et al., 2015)的方法
  - 将mention和类别嵌入到同一向量空间后求点积，得到mention是否属于该类别的分数



$$s(\mathbf{x}, \mathbf{y}_t; \mathbf{A}, \mathbf{B}) = f(\mathbf{x}, \mathbf{A}) \cdot g(\mathbf{y}_t, \mathbf{B}) = \mathbf{Ax} \cdot \mathbf{By}_t$$

其中 $\boldsymbol{x}$：mention的特征向量；$\boldsymbol{y}_t$：类别标签t的one-hot encode向量
A和**B**：可训练参数矩阵

预测时，认为使分数s大于一个预设阈值的标签为正确标签

Yogatama, Dani, Dan Gillick, and Nevena Lazic. "Embedding methods for fine grained entity type classification." *Proceedings of ACL-IJCNLP*. 2015.

细粒度实体分类方法

- 基于手工设计特征的方法
- (Yogatama et al., 2015)使用的特征

Feature	Description	Example
Head	The syntactic head of the mention phrase	"Obama"
Non-head	Each non-head word in the mention phrase	"Barack", "H."
Cluster	Word cluster id for the head word	"59"
Characters	Each character trigram in the mention head	":ob", "oba", "bam", "ama", "ma:"
Shape	The word shape of the words in the mention phrase	"Aa A. Aa"
Role	Dependency label on the mention head	"subj"
Context	Words before and after the mention phrase	"B:who", "A:first"
Parent	The head's lexical parent in the dependency tree	"picked"
Topic	The most likely topic label for the document	"politics"

细粒度实体分类方法

- 模型训练的loss函数（margin-based）

$$l(m_i, Y_i, \bar{Y}_i) = \sum_{y \in Y_i} \sum_{\bar{y} \in \bar{Y}_i} \max\left(0, \gamma - s(m_i, y) + s(m_i, \bar{y})\right)$$

m_i：第i个mention
Y_i：第i个mention的正确标签集合
$\bar{Y}_i$：第i个mention的不正确标签集合
$s(m_i, y)$：模型输出的m_i属于类别y的分数

细粒度实体分类方法

- 基于手工设计特征的方法
- (Yogatama et al., 2015)的实验效果

Method	P	R	F1
Ling and Weld (2012)	–	–	69.30
WSABIE	81.85	63.75	71.68
K-WSABIE	**82.23**	**64.55**	**72.35**

FIGER 数据集上的效果（Micro-average Precision, Recall, F1）

- 指标计算：

$$P = \frac{\sum_{m \in M} |y_m \cap \hat{y}_m|}{\sum_{m \in M} |\hat{y}_m|} \qquad R = \frac{\sum_{m \in M} |y_m \cap \hat{y}_m|}{\sum_{m \in M} |y_m|}$$

$$F1 = 2 * P * R/(P + R)$$

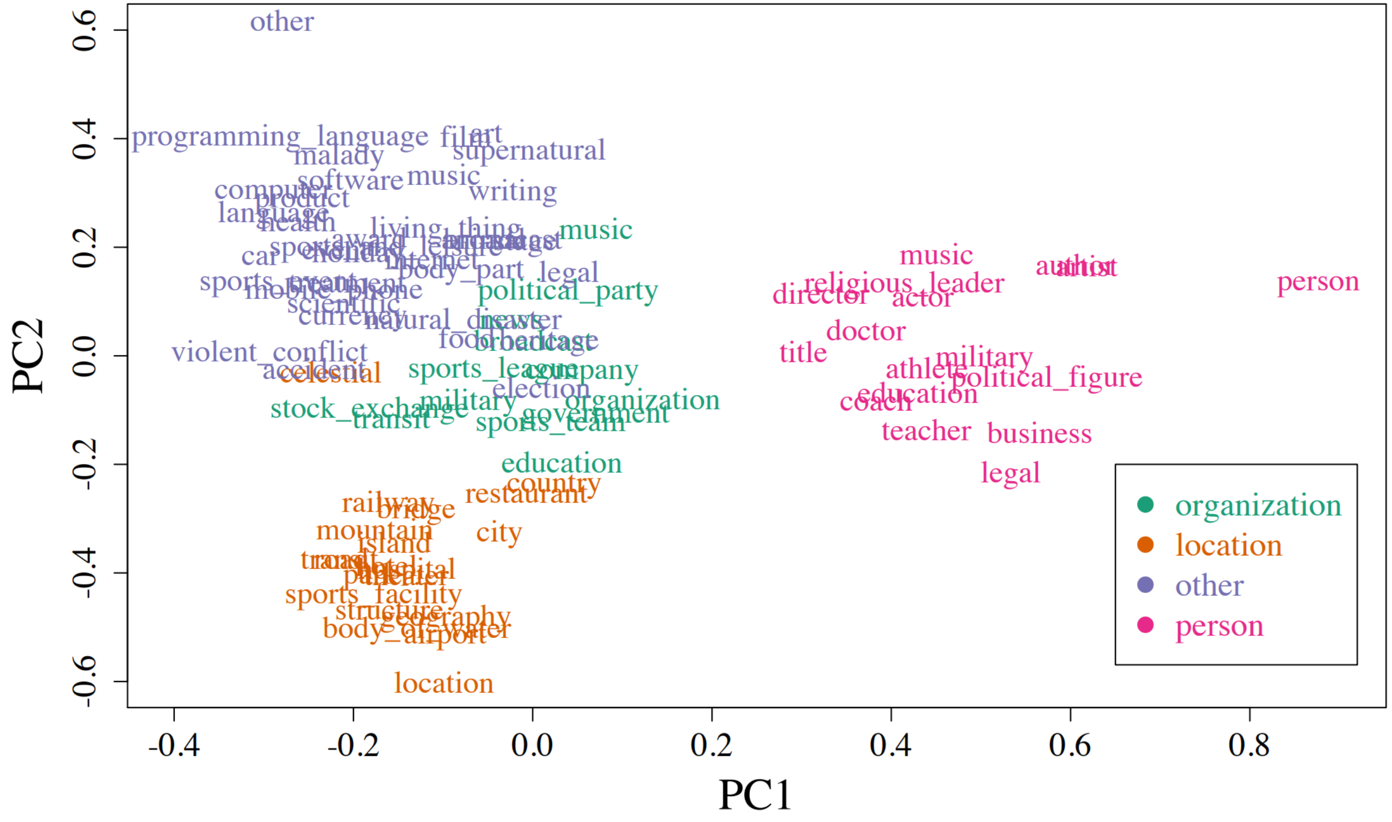
其中M为测试集需预测类别的实体提及集合，y_m和$\hat{y}_m$分别为实体提及m的正确标签集合和预测标签集合

细粒度实体分类方法

- 基于手工设计特征的方法
- (Yogatama et al., 2015)的实验效果

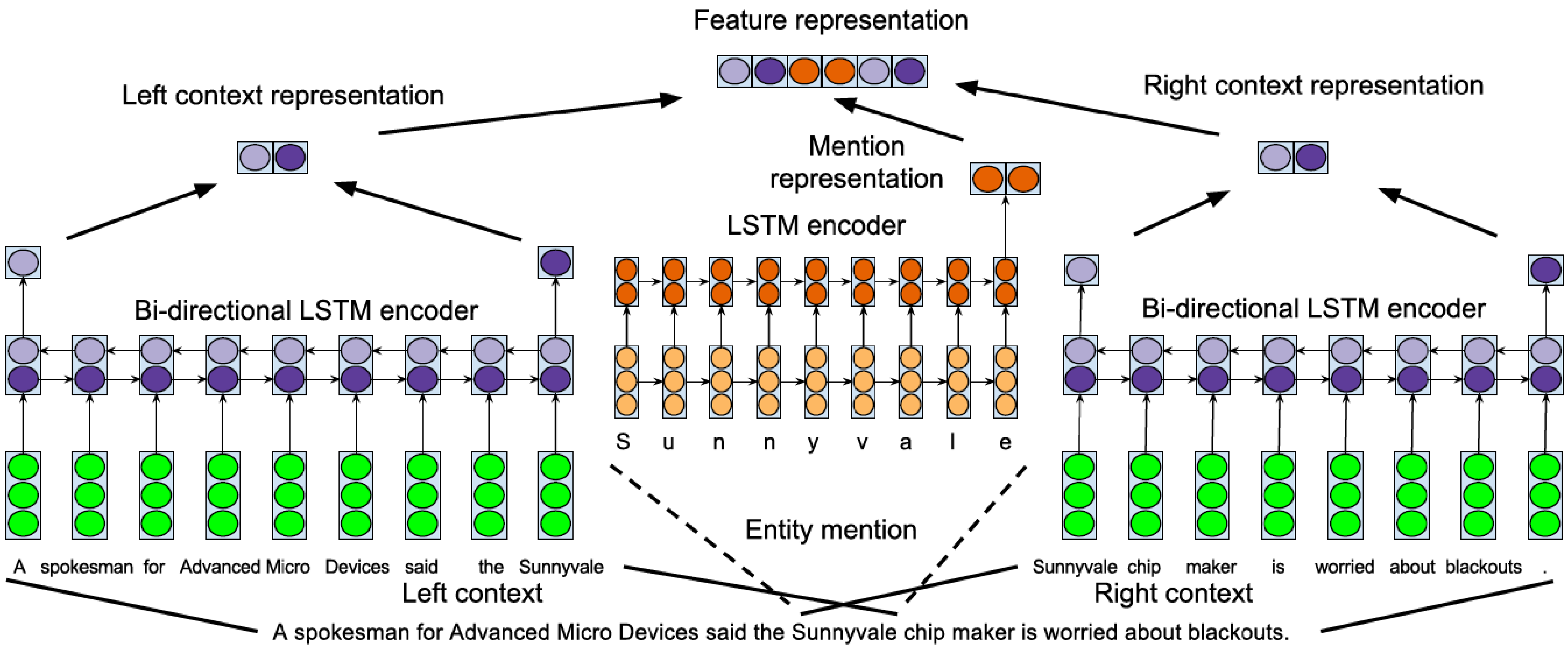
将学习到的类别标签向量映射到2维空间：

属于同一大类的类别在向量空间中距离较近



基于神经网络的细粒度实体分类

- (Abhishek et al., 2017)的方法



Abhishek, A., Anand, A., & Awekar, A. (2017). Fine-Grained Entity Type Classification by Jointly Learning Representations and Label Embeddings. In *Proceedings of EACL* (Vol. 1, pp. 797-807).

基于神经网络的细粒度实体分类

- (Abhishek et al., 2017)的方法

训练loss:

对标签属于同一类别路径的 (clean):

$$l(m_i, Y_i, \bar{Y}_i) = \sum_{y \in Y_i} \max\big(0, 1 - s(m_i, y)\big) + \sum_{y \in \bar{Y}_i} \max\big(0, 1 + s(m_i, y)\big)$$

对标签属于不同类别路径的 (noisy):

$$l(m_i, Y_i, \bar{Y}_i) = \max\big(0, 1 - s(m_i, y^*)\big) + \sum_{y \in \bar{Y}_i} \max\big(0, 1 + s(m_i, y)\big)$$

其中 $y^* = argmax_{y \in Y_i}\, s(m_i, y)$

对正标签，因为其中有些可能与上下文无关，只用其中得分最高的那个计算loss

细粒度实体分类方法

- (Abhishek et al., 2017)的实验效果

Typing methods	Wiki/FIGER(GOLD)			OntoNotes			BBN		
	Acc.	Ma-F1	Mi-F1	Acc.	Ma-F1	Mi-F1	Acc.	Ma-F1	Mi-F1
FIGER* (Ling and Weld, 2012)	0.474	0.692	0.655	0.369	0.578	0.516	0.467	0.672	0.612
HYENA* (Yosef et al., 2012)	0.288	0.528	0.506	0.249	0.497	0.446	0.523	0.576	0.587
AFET-NoCo* (Ren et al., 2016)	0.526	0.693	0.654	0.486	0.652	0.594	0.655	0.711	0.716
AFET-CoH* (Ren et al., 2016)	0.433	0.583	0.551	0.521	0.680	0.609	0.657	0.703	0.712
AFET* (Ren et al., 2016)	0.533	0.693	0.664	0.551	0.711	0.647	0.670	0.727	0.735
AFET†‡ (Ren et al., 2016)	0.509	0.689	0.653	**0.553**	**0.712**	**0.646**	0.683	0.744	0.747
Attentive† (Shimaoka et al., 2016)	0.581	0.780	0.744	0.473	0.655	0.586	0.484	0.732	0.724
our-AllC†	**0.662**	0.805	0.770	0.514	0.672	0.626	0.655	0.736	0.752
our-NoM†	0.646	0.808	0.768	0.521	0.683	0.626	0.615	0.742	0.755
our†	0.658	**0.812**	**0.774**	0.522	0.685	0.633	0.604	0.741	0.757
model level transfer-learning†	-	-	-	0.531	0.684	0.637	0.645	0.784	**0.795**
feature level transfer-learning†	-	-	-	0.471	0.689	0.635	**0.733**	**0.791**	0.792

Our-AllC:直接用未改进的loss
Our-NoM: 不用mention representation

Acc: 预测对的实体提及数/总实体提及数

Ma-F1计算:

$$P = \frac{1}{|M|}\sum_{m\in M}\frac{|y_m \cap \hat{y}_m|}{|\hat{y}_m|} \quad R = \frac{1}{|M|}\sum_{m\in M}\frac{|y_m \cap \hat{y}_m|}{|y_m|}$$

$$F1 = 2 * P * R/(P + R)$$

Mi-F1计算:

$$P = \frac{\sum_{m\in M}|y_m \cap \hat{y}_m|}{\sum_{m\in M}|\hat{y}_m|} \quad R = \frac{\sum_{m\in M}|y_m \cap \hat{y}_m|}{\sum_{m\in M}|y_m|}$$

$$F1 = 2 * P * R/(P + R)$$

细粒度实体分类方法

- (Abhishek et al., 2017)的实验效果

Typing methods	Wiki/FIGER(GOLD)			OntoNotes			BBN		
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our-NoM†	0.646	0.808	0.768	0.521	0.683	0.626	0.615	0.742	0.755
our†	0.658	**0.812**	**0.774**	0.522	0.685	0.633	0.604	0.741	0.757
model level transfer-learning†	-	-	-	0.531	0.684	0.637	0.645	0.784	**0.795**
feature level transfer-learning†	-	-	-	0.471	0.689	0.635	**0.733**	**0.791**	0.792

Our-AllC: 直接用未改进的loss
Our-NoM: 不用mention representation

Model level transfer-learning: 将模型先在Wiki训练数据上训练，把得到的参数用于在其他数据集上训练前的模型初始化

Feature level transfer-learning: 将模型得到的feature representation用于另一个方法

应对弱监督训练数据

- 自动生成的训练数据标签不一定准确
- 许多缓解不准确标签不利影响的方法被提出，如
  - 改进训练loss
    - (Ren et al., 2016), (Abhishek et al., 2017)等
  - 对样本自动重标
    - (Onoe and Durrett, 2019)
  - 基于聚类的方法
    - (Chen et al., 2019)
  - 基于对抗学习的方法
    - (Shi et al., 2020)

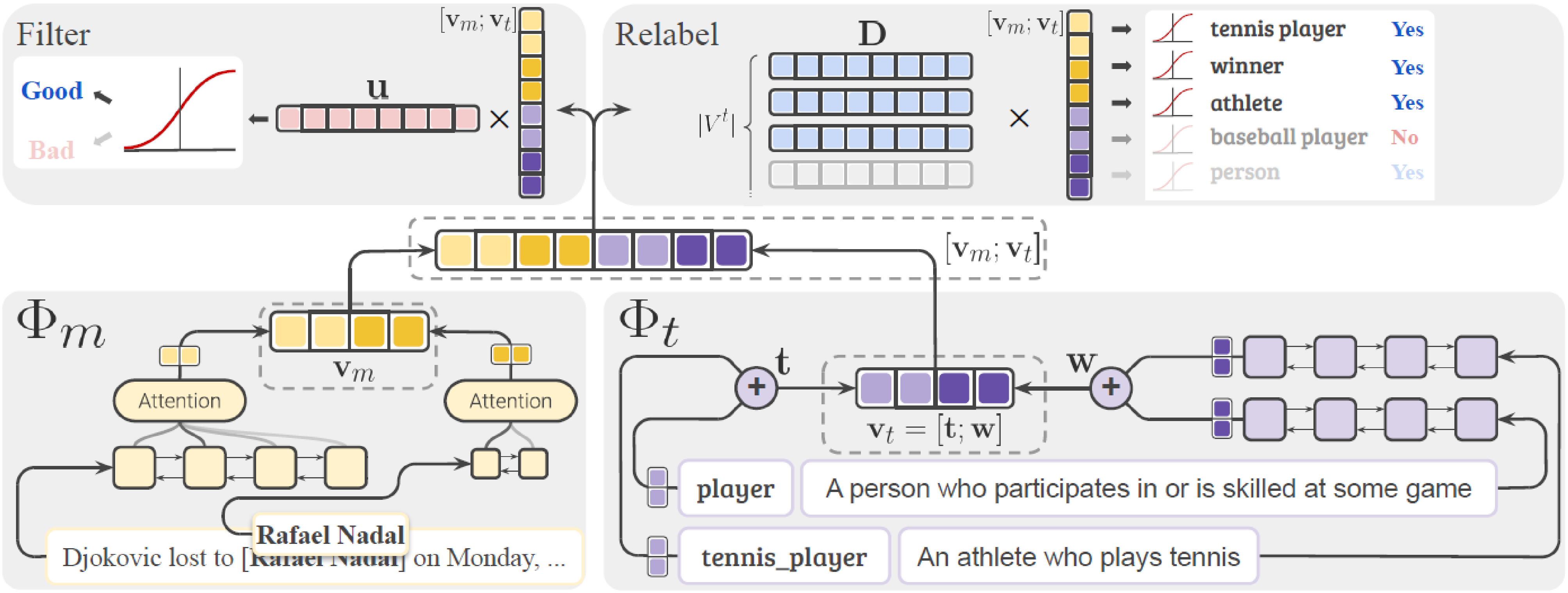
应对弱监督训练数据

- 自动重标训练样本 (Onoe and Durrett, 2019)

- 设计一个可以自动重标训练样本的模型
  - 输入自动生成的样本（包括样本的标签也作为输入）
  - 模型目标是更正可能有错的标签，输出更准确的标签
- 用重标后的样本训练细粒度实体分类模型

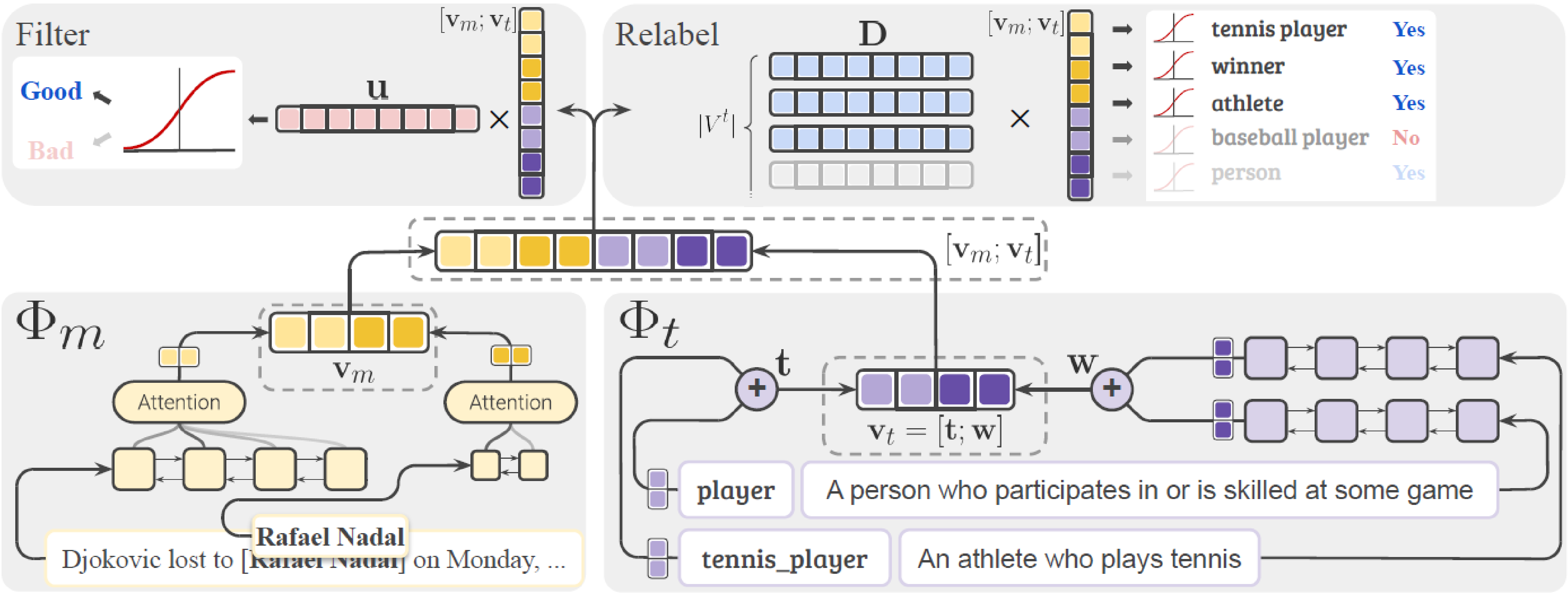
Onoe, Y., & Durrett, G. (2019, June). Learning to Denoise Distantly-Labeled Data for Entity Typing. In *Proceedings of NAACL-HLT* (pp. 2407-2417).

自动重标训练样本



- 输入：一个弱监督样本，具体包含mention、上下文、弱监督标签、标签的定义
- Filter部分决定是否保留该样本（二分类）
- Relabel部分尝试对标签进行重标（多标签分类）

自动重标训练样本



模型训练：基于Ultrafine人工标注的2k个样本生成该模型的训练数据
如：对一个样本，人工标注了标签[person, athlete, player, tennis_player]，将标签改错为[person, tennis_player, actor]就变成了一个弱监督样本

自动重标训练样本

- (Onoe and Durrett, 2019)的实验效果

Model	P	R	F1
Ours + GloVe w/o augmentation	47.6	23.3	31.3
Ours + ELMo w/o augmentation	**55.8**	27.7	37.0
Ours + ELMo w augmentation	55.5	26.3	35.7
Ours + ELMo w augmentation + filter & relabel	51.5	**33.0**	**40.2**
BERT-Base, Uncased	51.6	**33.0**	**40.2**
Choi et al. (2018) w augmentation	47.1	24.2	32.0
LabelGCN (Xiong et al., 2019)	50.3	29.2	36.9

Ultrafine数据集上的效果（Macro-F1）

Model	Acc.	Ma-F1	Mi-F1
Ours + ELMo w/o augmentation	42.7	72.7	66.7
Ours + ELMo w augmentation	59.3	76.5	70.7
Ours + ELMo w augmentation + filter & relabel	63.9	**84.5**	78.9
Ours + ELMo w augmentation by Choi et al. (2018)	**64.9**	**84.5**	**79.2**
BERT-Base, Uncased	51.8	76.6	69.1
Shimaoka et al. (2017)	51.7	70.9	64.9
AFET (Ren et al., 2016a)	55.1	71.1	64.7
PLE (Ren et al., 2016b)	57.2	71.5	66.1
Choi et al. (2018)	59.5	76.8	71.8
LabelGCN (Xiong et al., 2019)	59.6	77.8	72.2

OntoNotes数据集上的效果

细粒度实体分类方法

- 基于预训练模型的方法

构建BERT输入：

[CLS] sentence [SEP] mention string [SEP]

输入BERT后得到[CLS]对应的向量表示，记为$\boldsymbol{u} \in R^d$，基于$\boldsymbol{u}$得到每个类别对应分数：

$$\boldsymbol{s} = \boldsymbol{W}\boldsymbol{u}$$

其中$W \in R^{K \times d}$，K为类别数，$\boldsymbol{s}$中的每个元素对应一个类别

损失函数： margin-based loss或binary cross entropy loss

实验结果：

Ultrafine数据集：Precision 51.0 Recall 33.8 F1 40.7

OntoNotes数据集：Acc 63.25, Ma-F1 80.84, Mi-F1 75.90

Dai, Hongliang, Yangqiu Song, and Haixun Wang. "Ultra-Fine Entity Typing with Weak Supervision from a Masked Language Model." Proceedings of ACL. 2021.

基于大模型的方法

HL

You

Given a sentence and an entity mention, output the fine-grained types of the entity mention in format ["type1", "type2", ...]

Sentence: FedEx is a major player in the package delivery market.
Entity Mention: FedEx

ChatGPT

In this context, "FedEx" is primarily an organization. The fine-grained types could include its industry or sector. Here's a potential output:

json Copy code

```json
["Organization", "Courier", "Delivery"]
```

其他细粒度实体分类方法

- 其他细粒度实体分类方法思路
  - 考虑类别体系中类别间的层次关系信息
  - 显示地利用上下文表示的语义关系
    - 如，文本中出现"*M* and other *t*"，则意味着*t* 可能是*M*的上位词
      - "… Microsoft and other companies …"
  - 微调UFET模型为普通FET任务的模型
  - 等

Dai, Hongliang, and Ziqian Zeng. "From Ultra-Fine to Fine: Fine-tuning Ultra-Fine Entity Typing Models to Fine-grained." Proceedings of ACL. 2023.
Dai, Hongliang, Yangqiu Song, and Xin Li. "Exploiting semantic relations for fine-grained entity typing." AKBC. 2020.