"自然语言处理导论"课程讲义

# 语义角色标注

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### 大纲

□语义角色标注

□ PropBank与FrameNet

# □ 解决方案

- □句法树方法
- □序列标注方法

# □语义角色标注



□ PropBank与FrameNet

# □ 解决方案

- □句法树方法
- □序列标注方法

# 语义

□ 这些句子是否有同样的含义?

- □ Yesterday, Kristina hit Scott with a baseball
- Scott was hit by Kristina yesterday with a baseball
- Yesterday, Scott was hit with a baseball by Kristina
- With a baseball, Kristina hit Scott yesterday
- Yesterday Scott was hit by Kristina with a baseball
- □ Kristina hit Scott with a baseball yesterday

# 语义

### □ 何为语义?

- □ 哲学性问题,目前语言学领域未有定论
- □ 提出了众多的语义表示方法

### □ 代表理论: 一<mark>阶谓词逻辑</mark>[Neo-Davidsonian事件表示]

- □ 对一个事件的形式化表示(一阶谓词逻辑), 例如
  - Sasha broke the window
    - $\exists e, x, y \ Breaking(e) \land Breaker(e, Sasha) \land BrokenThing(e, y) \land Window(y)$
  - Pat opened the door
    - $\exists e, x, y \ Opening(e) \land Opener(e, Pat) \land OpenedThing(e, y) \land Door(y)$
- □ 谓词需要人工定义、且无法穷尽
- □ 这种表示很难分析得到,更难以进行有效推理

### 一阶谓词逻辑 到 语义角色标注

### □ 一阶谓词逻辑没有考虑语义的共性

- □ Breaker和Opener虽然对应了不同的事件,但有语义共同之处
  - 主动行动者(volitional actor)
  - 有生命的(animate)
  - 事件的直接原因(direct causal responsibility)

### □ 语义角色(semantic roles)

- □ 通过捕捉语义间的共性,降低分析的难度和复杂度
- □ 在上一例子中,两者可以统一:
  - Breaker和Opener都是 AGENTS (施事)
  - BrokenThing 和OpenedThing 都是 THEMES (客体)

除了施事和客体 还有很多其它 类型的语义角色!

# 语义角色标注

- □ 语义角色标注 (Semantic Role Labeling, SRL)
  - □ 一种浅层语义分析技术
  - □ 确定作为谓语变元的名词性短语所扮演的语义角色
- **回例子:** The student solved problems with a calculator in the classroom this morning
  - □ 谓语(Predicate): solved
  - □ 施事(Agent): the student
  - □ 客体(Theme): problems
  - □ 工具(Instrument): a calculator
  - □ 地点(Location): the classroom
  - □ 时间(Time): this morning

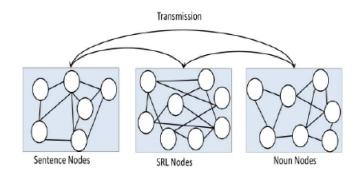
语义角色的类型 是人工确定的, 有很多不同的划 分方式

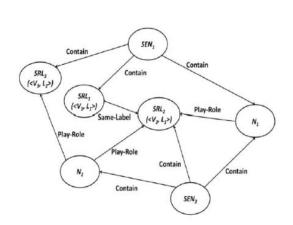
- □ 语义角色标注的应用非常广泛
- □ 问答系统
  - □ 同一类问题的答案往往对应同一种语义角色
  - Who -> agent / experiencer
  - What -> force / theme / content
  - How -> instrument
  - Where -> goal / source
  - For whom -> beneficiary

- □ 语义角色标注的应用非常广泛
- □ 问答系统
- □ 信息抽取
  - □ 同一类信息往往对应同一种语义角色
  - London gold fell \$4.70 to \$ 308.45

Slot	Filler	Semantic Role
Product	London gold	Experiencer
Price change	-\$4.70	Theme
Current price	\$308.45	Goal

- □ 语义角色标注的应用非常广泛
- □ 问答系统
- □ 信息抽取
- □ 文档摘要
  - □ 层级化摘要
  - □ 需要归纳不同文档中同一语义角色





- □ 语义角色标注的应用非常广泛
- □ **问答系统** [Hendrix et al., 1973; Shen & Lapata, 2007; Surdeanu et al., 2011]
- □ 信息抽取
- □ 文档摘要
- □ 知识获取
- □ 机器翻译 [Wilks, 1973; Liu & Gildea, 2010; Lo et al., 2013]
- □ 对话系统 [Bobrow et al., 1977]
- □ **口语理解** [Nash-Webber, 1975]
- ...

# 语义角色

- □ 语义角色 (Semantic Roles)的语言学定义
  - □ 一种**浅层**的语义表示
  - □ 语义由一句话描述的事件(event)表示
  - □ 事件由谓语(predicate)表示
  - □ 谓语可以携带多个论元(arguments),表示与事件相关的对象
  - □ **语义角色是论元**在**事件**中充当的**抽象角色**

□ 语义角色同样有多种粒度

更具体

更一般

Tom likes the ball. (Experiencer,感事)

原型施事是对施事的一般化:

The sky is blue. (Theme,主事)

以下均是原型施事

Tom hits the ball. (施事)

Hitter (打击者)

Agent (施事) Proto-agent (原型施事) 12

# 题旨角色 (Thematic Role)

### □ 语义角色由题旨角色发展而来

- □ 最古老的语言学模型之一
  - 印度语法学家Panini [7th to 4th BCE]

对依存句法在语义上的进一步细化!

- □ 现代阐述
  - Fillmore的格理论(case theory) [1966, 1968], Gruber [1965]
    - Fillmore受Lucien Tesnière的Éléments de Syntaxe Structurale [1959] 启 发,起初称这些角色为actant [1966]后改为case
    - 中心动词与名词短语作为句法的深层结构,之间的语义关系被称为深层格
- □示例

Thematic Role	Definition	Example
AGENT	The volitional causer of an event	The waiter spilled the soup.
EXPERIENCER	The experiencer of an event	John has a headache.
FORCE	The non-volitional causer of the event	The wind blows debris from the mall into our yards.
THEME	The participant most directly affected by an event	Only after Benjamin Franklin broke the ice
RESULT	The end product of an event	The city built a regulation-size baseball diamond
CONTENT	The proposition or content of a propositional event	Mona asked "You met Mary Ann at a supermarket?"
INSTRUMENT	An instrument used in an event	He poached catfish, stunning them with a shocking device
BENEFICIARY	The beneficiary of an event	Whenever Ann Callahan makes hotel reservations for her boss
SOURCE	The origin of the object of a transfer event	I flew in from Boston.
GOAL	The destination of an object of a transfer event	I drove to Portland.

# 题旨角色的问题

- □ 难以建立标准的角色集合或准确定义题旨角色
  - □ 粒度 与 原子性 常常冲突
  - □ 角色通常需要被分裂才能被准确定义

- □ 例如,题旨角色中的INSTRUMENTS(工具)并包含了两种类型的角色[Levin & Hovav, 2015]:
  - □ 媒介工具(intermediary instruments): 可作主语
    - The cook opened the jar with the new gadget
    - The new gadget opened the jar
  - □ 赋能工具(enabling instruments): 不可做主语
    - Shelly ate the sliced banana with a fork
    - \*The fork ate the sliced banana.

# 语义角色的粒度

□ 实际中处理的语义角色有两类

- □ 更一般化的、更少角色(一般所说的语义角色)
  - □ 基于原型施事、原型受事 [Dowty 1991]
  - □ PropBank语料库为代表(语义角色标注所用的语料)

- □ 更细粒度的、更多角色(框架语义)
  - frames [Fillmore 1968, 1977]
  - □ 根据一类谓语定义特定的角色
  - □ FrameNet语料库为代表

# 语义角色标注的特性

### □ 语义角色与句法的关系

- □ 常见情况下, 语义角色可以通过特定句法位置确定
  - Agent: subject
  - Patient: direct object
  - Instrument: object of with
  - Beneficiary: object of for
  - Source: object of from
- □ 但以上泛化规则不是绝对的,至多也只是倾向
  - The hammer hit the window (这里不是Agent, 是Instrument)
  - The ball was passed to Mary from John (这里不是Agent, 是 Patient)
  - John went to the movie with Mary (不是instrument)
  - John bought the car for \$20K. (不是受益者Beneficiary)

### 语义角色标注的特性

### □ 语义角色与选择限制(Selectional Restrictions)的关系

- □ 选择限制: 比如一个动词只能跟有限的名词搭配, 比如 "吃手机"不太可能出现
- □ 语义角色标注可以帮助解决选择限制的问题

### □ 例子: I want to eat *someplace nearby*.

- Two interpretations
  - a) sensible: eat is intransitive and someplace nearby is a location adjunct
  - B) speaker is Godzilla: eat is transitive and someplace nearby is a direct object
- □ 通过语义角色标注: a > b

### 选择限制 与 选择倾向

- □ 选择限制(selectional restrictions)或选择倾向 (selectional preferences)?
- □ 早期,选择限制是严格约束[Katz and Fodor, 1963]
- □ 很快,人们明白选择限制其实只是倾向[Wilks, 1975]
  - □ 目前的语义分析还难以解决

### □ 例子

- But it fell apart in 1931, perhaps because people realized you can' t eat gold for lunch if you' re hungry.
- In his two championship trials, Mr. Kulkarni ate glass on an empty stomach, accompanied only by water and tea.

□语义角色标注

□ PropBank与FrameNet ←



# □ 解决方案

- □句法树方法
- □序列标注方法

### □ The Proposition Bank (PropBank) [Palmer et al. 2005]

- □ 采用粗粒度的角色定义[Dowty 1991]
- □ 使用原型施事(proto-agent)和原型受事(proto-patient)

### □ PropBank中根据动词的词义标注以下几类论元

- ARG0: PROTO-AGENT
- ARG1: PROTO-PATIENT
- ARG2: benefactive, instrument, attribute, end state
- ARG3: start point, benefactive, instrument or attribute
- ARG4: end point
- ARGM: modifiers or adjuncts of the predicate
  - TMP, LOC, DIR, MNR, ADV, ...

### □ 标注示例

- □ 根据动词确定每个Arg的具体含义
  - Predicate accept<sub>1</sub> "take willingly"
    - Arg0: acceptor
    - Arg1: thing accepted
    - Arg2: accepted-from
    - ► Arg3: attribute
  - ►  $[A_{rg0}He]$   $[A_{rgM-mod}would]$   $[A_{rgM-neg}n't]$  accept  $[A_{rg1}anything]$  of value  $[A_{rg2}from those he was writing about]$ .
  - Predicate kick<sub>1</sub> "drive or impel with the foot"
    - Arg0: kicker
    - Arg1: thing kicked
    - Arg2: instrument (defaults to foot)
  - ▶  $[A_{rg0}$ John] tried  $[A_{rg0}$ \*trace\*] to kick  $[A_{rg1}$ the football].

### □ PropBank的标注可以很好的表示语义上的共性

- □ 0, 1规律比较明显, 2之后根据具体词有变化
- □ ☑ dicate increase 1 "go up incrementally"
  - > Arg0: causer of increase
  - > Arg1: thing increasing
  - > Arg2: amount increased by, EXT or MNR
  - ➤ Arg3: start point (升高的起点)
  - ➤ Arg4: end point (升高的终点)
  - ► [Arg0 Big Fruit Co.] increased [Arg1 the price of bananas].
  - ► [Arg1 The price of bananas] was increased again [Arg0 by Big Fruit Co.]

### □ PropBank 中也包含一些名词和轻动词(light verb)

□ 如decision和make a decision中的make

Example Noun: Decision

▶ Roleset: Arg0: decider, Arg1: decision...

对比make a decision 和make a toy: 是否是实际的制作?

```
"...[your<sub>ARG0</sub>] [decision<sub>REL</sub>]
[to say look I don't want to go through this anymore<sub>ARG1</sub>]"
```

Example within an LVC: Make a decision

```
"...[the President<sub>ARG0</sub>] [made<sub>REL-LVB</sub>]
the [fundamentally correct<sub>ARGM-ADJ</sub>]
[decision<sub>REL</sub>] [to get on offense<sub>ARGI</sub>]"
```

### ■ NomBank

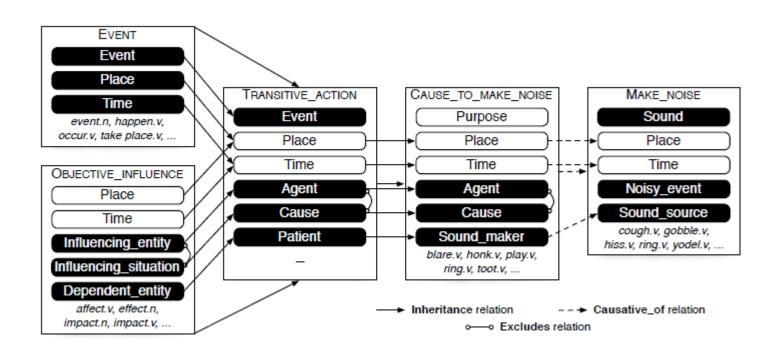
- PropBank以动词为主
- □ 在PropBank的基础上进一步扩充了名词和形容词

### FrameNet

- Baker et al. 1998, Fillmore et al. 2003, Fillmore and Baker 2009, Ruppenhofer et al. 2006
- □ PropBank中的角色根据**动词**定义
- □ FrameNet中的角色根据**框架**定义
- □ 框架的定义
  - □ 可以理解成,把同一类动词进行了聚类,这个类就是一个框架(比如"拿"、"取"可以属于一个框架;而且还确定了框架间的层级关系,比如"继承"、"原因"
  - □ 框架元素: A background knowledge structure that defines a set of frame-specific semantic roles, called frame elements (就是后一页的加黑部分,黑框部分是必须的元素,白框部分是可选元素)
  - □ 谓语(一般是动词,但也可以是名词):Includes **a set of predicates** that use these roles (就是后一页的最底下的那些词)
  - □ 实际分析过程中,每个词都要找到其对应的框架,然后获取部分框架元素

### □ 为何是Frame Net

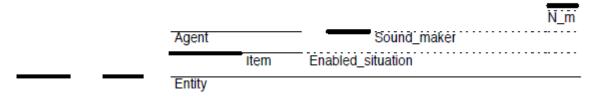
- □ 框架通过关系相连构成网络 (框架上的箭头)
- □ 框架元素之间同样由关系相连构成网络 (加黑部分的箭头)
- □ 箭头来自父类,指向子类;比如"继承"是出现最多的一个类型,代表"语义的细化"



### □ 与PropBank相比,FrameNet的复杂度更高

- □ 下例,粗黑线代表单词触发了一个语义框架,一行是一个语义框架
- □ 比如对于ring,左边的是agent,右边的是sound maker

But there still are n't enough ringers to ring more than six of the eight bells .



Noise\_makers bell.n

Cause\_to\_make\_noise ring.v

Sufficiency enough.a

Existence there be.v

### □ Frame示例

- 框架里面除了结构化的元素和谓词,还有非结构化的自然语言解释,以下是非结构化的解释举例
- apply heat: situation involving a cook, food and a heating instrument evoked by bake, blanch, boil, broil, brown, simmer, etc.
- change position on a scale: situation involving the change of an items's position on a scale (the attribute) from a starting point (initial value) to an end point (final value) evoked by decline, decrease, gain, rise, etc.
- damaging: situation involving an agent that affects a patient in such a way that the patient (or some sub-region of the patient) ends up in a non-canonical state evoked by damage, sabotage, scratch, tear, vandalise, etc.

### □ 标注示例

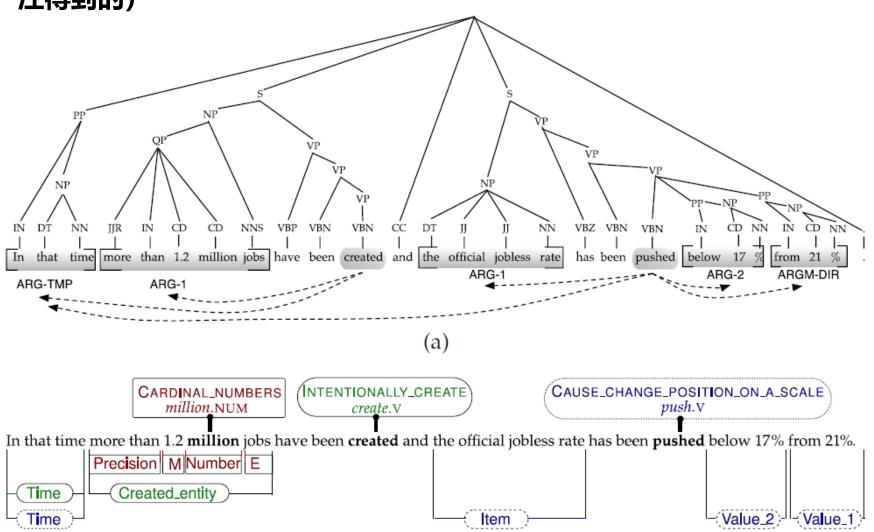
- □ frameNet除了标注了之前说的结构化知识库,还标注了非结构化的 训练语料(就像propBank的训练语料一样),以下为样例
- □ 但是语料还是偏少,几万句,这是frameNet准确度还是偏低的原因 之一
- Verbs:
  - [Cook Matilde] fried [Food the catfish] [HeatingInstrument in an iron skillet]
  - ► [Item Colgate's stocks] rose [Difference \$3.64] to [FinalValue \$49.94]
- Nouns:
  - ... the **reduction** of [ $_{Item}$ debt levels] to [ $_{Value2}$ \$25] from [ $_{Value1}$ \$2066]
- Adjectives:
  - [Sleeper They] were asleep [Duration for hours]

### □ FrameNet可以更好的表示同一类事件之间的共性

- □ PropBank针对同一动词之间的共性
- □ 比如以下几个句子,用了不同的动词,但是item和agent都能成功分析出
- ► [Agent Big Fruit Co.] increased [Item the price of bananas].
- [Item The price of bananas] rose [Agent by Big Fruit Co.]
- ➤ There has been a [Difference 5%] rise in [Item the price of bananas].

# FrameNet与PropBank

□ FrameNet vs. PropBank (上图是propBank,它是由句法树细化标 注得到的)



□语义角色标注

□ PropBank与FrameNet

# □ 解决方案

□句法树方法(



□序列标注方法

### 语义角色标注方法

# □ 目标: 寻找句子中每个谓语的每个论元的语义角色(因为是以动词为中心)

- □ 识别谓语
- □ 识别论元
- □ 标定论元角色
- □ 对象: FrameNet vs. PropBank (上面是frameNet, 下面是propBank)

```
[You] can't [blame] [the program] [for being unable to identify it]

COGNIZER TARGET EVALUEE REASON

[The San Francisco Examiner] issued [a special edition] [yesterday]

ARGO TARGET ARG1 ARGM-TMP
```

### □ 两大类方法

- □ 序列标注方法
- □ 句法树方法

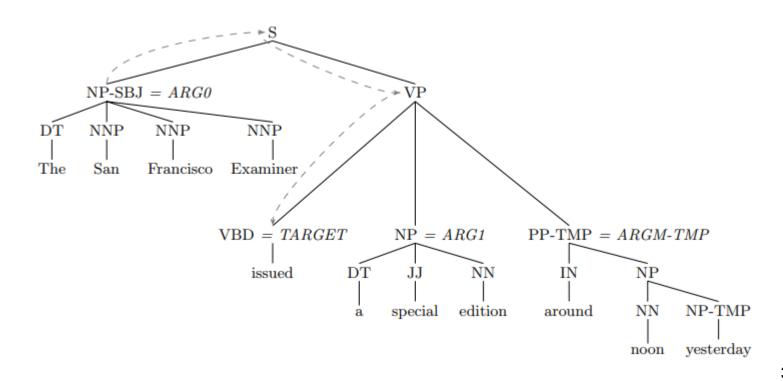
### 序列标注方法

- □ 语义角色标注视为Segmenting类的序列标注任务
- □ 标签含有两个属性
  - □ 边界属性: BIO, BIO2, BIOSE
  - □ 角色属性: Arg0, Arg1, ...
- □ 可以使用任意序列标注模型
- □ 有效的特征包括:中心词、窗口词、词性等

- □ 在没有神经网络的时代,效果极差
- 在深度学习时代,主要用LSTM进行序列标注,效果跟句法 树方法相当,大概是80-85%左右

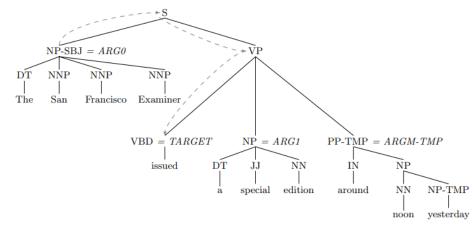
### □ 借助句法树完成分类任务

- □ 句法树提供了大量的语义线索
- □ 下例是CFG句法分析,在句法树结构上识别arg0, arg1等



### □ 一个简单的算法框架

□ 遍历一棵树,在每个节点上提 取特征,做分类



### **function** SEMANTICROLELABEL(words) **returns** labeled tree

parse ← PARSE(words)

for each predicate in parse do

for each node in parse do

featurevector ← FXTRACTEE

featurevector ← EXTRACTFEATURES(node, predicate, parse)
CLASSIFYNODE(node, featurevector, parse)

- □ 第一步: What is a predicate?
- PropBank verbs
  - □ 选定所有动词
  - □ 可以排除light verbs (表)
- □ FrameNet verbs/nouns/adjectives
  - □ 选定训练数据中所有标为中心词的词

function SEMANTICROLELABEL(words) returns labeled tree

parse ← PARSE(words)

for each predicate in parse do

for each node in parse do

featurevector ← EXTRACTFEATURES(node, predicate, parse)

CLASSIFYNODE(node, featurevector, parse)

□ 基本型Features

- Headword
  - □ (通过规则确定,如Examiner
- Headword POS
- □ 单词的主动、被动形态

function SEMANTICROLELABEL(words) returns labeled tree

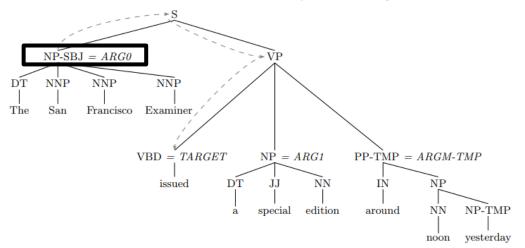
 $parse \leftarrow PARSE(words)$ 

for each predicate in parse do

for each node in parse do

 $feature vector \leftarrow \text{EXTRACTFEATURES}(node, predicate, parse)$ 

CLASSIFYNODE(node, featurevector, parse)



- Subcategorization of predicate
- Named Entity type of constituent
- First and last words of constituent
- Linear position, clause w.r.t. predicate

□ 特殊型Features

### Path

从当前节点到谓语词在句法树上的路径

function SEMANTICROLELABEL(words) returns labeled tree

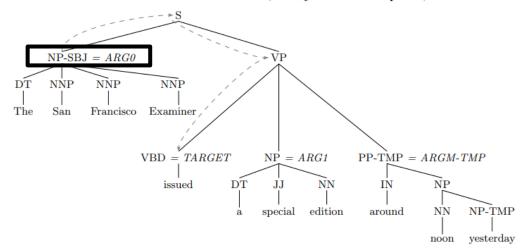
 $parse \leftarrow PARSE(words)$ 

for each predicate in parse do

for each node in parse do

 $feature vector \leftarrow \text{EXTRACTFEATURES}(node, predicate, parse)$ 

CLASSIFYNODE(node, featurevector, parse)



# $NP\uparrow S\downarrow VP\downarrow VBD$

Frequency	Path	Description
14.2%	VB↑VP↓PP	PP argument/adjunct
11.8	VB↑VP↑S↓NP	subject
10.1	VB↑VP↓NP	object
7.9	VB↑VP↑VP↑S↓NP	subject (embedded VP)
4.1	VB↑VP↓ADVP	adverbial adjunct
3.0	NN↑NP↑NP↓PP	prepositional complement of noun
1.7	VB↑VP↓PRT	adverbial particle
1.6	VB↑VP↑VP↑VP↑S↓NP	subject (embedded VP)
14.2		no matching parse constituent
31.4	Other	38

function SEMANTICROLELABEL(words) returns labeled tree

□ 分类的实现: 3-step version

parse ← PARSE(words)

for each predicate in parse do

for each node in parse do

featurevector ← EXTRACTFEATURES(node, predicate, parse)

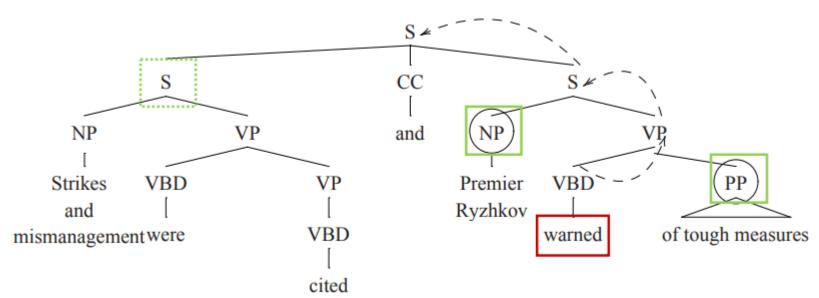
CLASSIFYNODE(node, featurevector, parse)

□ 1, 过滤: Pruning

- Simple heuristics to prune unlikely constituents
- □ 2, 识别是否跟谓词有关系: Identification
  - 是否问题: Binary classification of each node as an argument to be labeled or a NONE
- □ 3, 具体是属于哪种关系: Classification
  - 多分类问题: 1-of-N classification of all the constituents that were labeled as arguments

- □ 过滤的重要性: Why Pruning?
- □ 大量的词都跟谓词无关: One predicate at a time, Imbalance data
  - Very few of the nodes in the tree could possible be arguments of that one predicate
  - Positive samples vs negative samples
- Prune the very unlikely first, and then use a classifier to get rid of the rest

- □ 过滤的重要性: Pruning heuristics [Xue and Palmer, 2004]
- □ 比如下例,and代表了并列关系,如果找warned的论元,则先找兄弟节点,再找叔父节点,再找祖父节点,然后把左边的分支全部裁掉



- □ 怎么分类: 先局部分类, 然后re-ranking
- □ 局部分类: The algorithm classifies everything locally
- But lots of global or joint interactions
  - Non-overlapping
  - No Multiple identical arguments
- □ 重排序: 通过Reranking捕捉全局的信息
  - Possible labels -> classifier -> best global label
  - Takes all the input along with other features

- □ FrameNet更复杂一些:还需要判断是那个框架,因为不是 arg0, arg1的分类问题了,还需要判定是具体的那个框架
  - We need an extra step to find the frame
  - Features for frame identification [Das et al, 2014]

the POS of the parent of the head word of  $t_i$  the set of syntactic dependencies of the head word<sup>21</sup> of  $t_i$  if the head word of  $t_i$  is a verb, then the set of dependency labels of its children the dependency label on the edge connecting the head of  $t_i$  and its parent the sequence of words in the prototype,  $w_\ell$  the lemmatized sequence of words in the prototype the lemmatized sequence of words in the prototype and their part-of-speech tags  $\pi_\ell$  WordNet relation<sup>22</sup>  $\rho$  holds between  $\ell$  and  $t_i$  wordNet relation<sup>22</sup>  $\rho$  holds between  $\ell$  and  $t_i$ , and the prototype is  $\ell$  WordNet relation<sup>22</sup>  $\rho$  holds between  $\ell$  and  $t_i$ , the POS tag sequence of  $\ell$  is  $\pi_\ell$ , and the POS tag sequence of  $t_i$  is  $\pi_\ell$ 

### 总结: 语义角色标注

- □ 任务: who does what to whom when where how
- □ 对象: thematic roles -> Frame or Proto-A/P (propBank)
- □ 资源: PropBank, FrameNet, CoNLL shared tasks
- □ 特性: 句法线索syntactic, 选择限制selection
- □方法
  - Sequence labelling: very bad before DL
  - Syntactic: very good before DL
  - □ DL: Bi-LSTM作序列标注反而效果好

### 深度学习方法

- □ 扩展阅读:
- End-to-end Learning of Semantic Role Labelling Using Recurrent Neural Networks (E2E)
  - ACL 2015
  - Jie Zhou and Wei Xu, Baidu Research
- Deep Semantic Role Labelling: What Works and What's Next (Deep)
  - ACL 2017
  - Luheng He, Kenton Lee, Univ. of Washington
  - Mike Lewis, FAIR
  - Luke Zettlemoyer, Allen Institute for Al

# THANKS!