Semantic Role Labeling

Chapter 18

Semantic Role Labeling

Who did *what* to *whom* at *where?*

The police officer detained the suspect at the scene of the crime

Agent Predicate Theme Location

Can we figure out that these have the same meaning?

XYZ corporation **bought** the stock.

They **sold** the stock to XYZ corporation.

The stock was **bought** by XYZ corporation.

The **purchase** of the stock by XYZ corporation...

The stock **purchase** by XYZ corporation...

3

A Shallow Semantic Representation: Semantic Roles

Predicates (bought, sold, purchase) represent an **event** and **semantic roles** express the abstract role that arguments of a predicate can take in the event

More specific ⟷ More general

buyer **agent** **proto-agent**

4

Getting to semantic roles

What roles are involved in a breaking event?

First order logic event representation for Sasha broke the window:

5

Getting to semantic roles

First order logic event representation:

Sasha broke the window	$\exists e,x,y\ Breaking(e) \wedge Breaker(e,Sasha) \wedge BrokenThing(e,y) \wedge Window(y)$
Pat opened the door	$\exists e,x,y\ Opening(e) \wedge Opener(e,Pat) \wedge OpenedThing(e,y) \wedge Door(y)$

Subjects of break and open: **Breaker** and **Opener**

Deep roles specific to each event (breaking, opening)

Hard to reason about them for NLU applications like QA

6

Thematic roles

- **Breaker** and **Opener** have something in common!
  - Volitional actors
  - Often animate
  - Direct causal responsibility for their events
- Thematic roles are a way to capture this semantic commonality between *Breakers* and *Openers*.
- They are both AGENTS.
- The *BrokenThing* and *OpenedThing*, are THEMES.
  - prototypically inanimate objects affected in some way by the action

7

Thematic roles

- One of the oldest linguistic models
  - Indian grammarian Panini between the 7th and 4th centuries BCE
- Modern formulation from Fillmore (1966,1968), Gruber (1965)
  - Fillmore influenced by Lucien Tesnière's (1959) *Éléments de Syntaxe Structurale,* the book that introduced dependency grammar
  - Fillmore first referred to roles as *actants* (Fillmore, 1966) but switched to the term *case*

8

Thematic roles

- A typical set:

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*.

9

Thematic grid, case frame

Example usages of "break"

- John broke the window
- John broke the window with a rock
- The rock broke the window
- The window broke
- The window was broken by John

10

Thematic grid, case frame

Example usages of "break"

John *broke the window.*
AGENT THEME

John *broke the window with a rock.*
AGENT THEME INSTRUMENT

The rock *broke the window.*
INSTRUMENT THEME

The window broke.
THEME

The window was broken by John.
THEME AGENT

11

Thematic grid, case frame

Example usages of "break"

John *broke the window.*
AGENT THEME

John *broke the window with a rock.*
AGENT THEME INSTRUMENT

The rock *broke the window.*
INSTRUMENT THEME

The window broke.
THEME

The window was broken by John.
THEME AGENT

thematic grid, case frame
Break:
AGENT, THEME, INSTRUMENT.

Some realizations:

AGENT/Subject, THEME/Object
AGENT/Subject, THEME/Object, INSTRUMENT/PP_{with}
INSTRUMENT/Subject, THEME/Object
THEME/Subject

12

Diathesis alternations (or verb alternation)

Doris *gave* *the book* *to Cary.*
AGENT THEME GOAL

Doris *gave* *Cary* *the book.*
AGENT GOAL THEME

Break: AGENT, INSTRUMENT, or THEME as subject

Give: THEME and GOAL in either order

Dative alternation: particular semantic classes of verbs like *give*, "verbs of future having" (*advance*, *allocate*, *offer*, *owe*), "send verbs" (*forward*, *hand*, *mail*), "verbs of throwing" (*kick*, *pass*, *throw*), etc.

13

Problems with Thematic Roles

Hard to create standard set of roles or formally define them

Often roles need to be fragmented to be defined.

Levin and Rappaport Hovav (2015): two kinds of INSTRUMENTS

intermediary instruments that can appear as subjects

The cook opened the jar with the new gadget.

The new gadget opened the jar.

enabling instruments that cannot

Shelly ate the sliced banana with a fork.

*The fork ate the sliced banana.

14

Alternatives to thematic roles

1. **Fewer roles**: generalized semantic roles, defined as prototypes (Dowty 1991)

   PROTO-AGENT

   PROTO-PATIENT

   PropBank

2. **More roles**: Define roles specific to a group of predicates

   FrameNet

15

PropBank

- Palmer, Martha, Daniel Gildea, and Paul Kingsbury. 2005. The Proposition Bank: An Annotated Corpus of Semantic Roles. *Computational Linguistics*, 31(1):71–106

16

PropBank Roles

Following Dowty 1991

Proto-Agent

- Volitional involvement in event or state
- Sentience (and/or perception)
- Causes an event or change of state in another participant
- Movement (relative to position of another participant)

Proto-Patient

- Undergoes change of state
- Causally affected by another participant
- Stationary relative to movement of another participant

17

PropBank Roles

- Following Dowty 1991
  - Role definitions determined verb by verb, with respect to the other roles
  - Semantic roles in PropBank are thus verb-sense specific.
- Each verb sense has numbered argument: Arg0, Arg1, Arg2,…

  Arg0: PROTO-AGENT

  Arg1: PROTO-PATIENT

  Arg2: usually: benefactive, instrument, attribute, or end state

  Arg3: usually: start point, benefactive, instrument, or attribute

  Arg4 the end point

  (Arg2-Arg5 are not really that consistent, causes a problem for labeling)

18

PropBank Frame Files

agree.01
Arg0: Agreer
Arg1: Proposition
Arg2: Other entity agreeing

Ex1: [$_{Arg0}$ The group] *agreed* [$_{Arg1}$ it wouldn't make an offer].
Ex2: [$_{ArgM\text{-}TMP}$ Usually] [$_{Arg0}$ John] *agrees* [$_{Arg2}$ with Mary] [$_{Arg1}$ on everything].

fall.01
Arg1: Logical subject, patient, thing falling
Arg2: Extent, amount fallen
Arg3: start point
Arg4: end point, end state of arg1
Ex1: [$_{Arg1}$ Sales] *fell* [$_{Arg4}$ to $25 million] [$_{Arg3}$ from $27 million].
19 Ex2: [$_{Arg1}$ The average junk bond] *fell* [$_{Arg2}$ by 4.2%].

Advantage of a ProbBank Labeling

` **increase.01** "go up incrementally"
Arg0: causer of increase
Arg1: thing increasing
Arg2: amount increased by, EXT, or MNR
Arg3: start point
Arg4: end point

This would allow us to see the commonalities in these 3 sentences:

[$_{Arg0}$ Big Fruit Co.] increased [$_{Arg1}$ the price of bananas].
[$_{Arg1}$ The price of bananas] was increased again [$_{Arg0}$ by Big Fruit Co.]
20 [$_{Arg1}$ The price of bananas] increased [$_{Arg2}$ 5%].

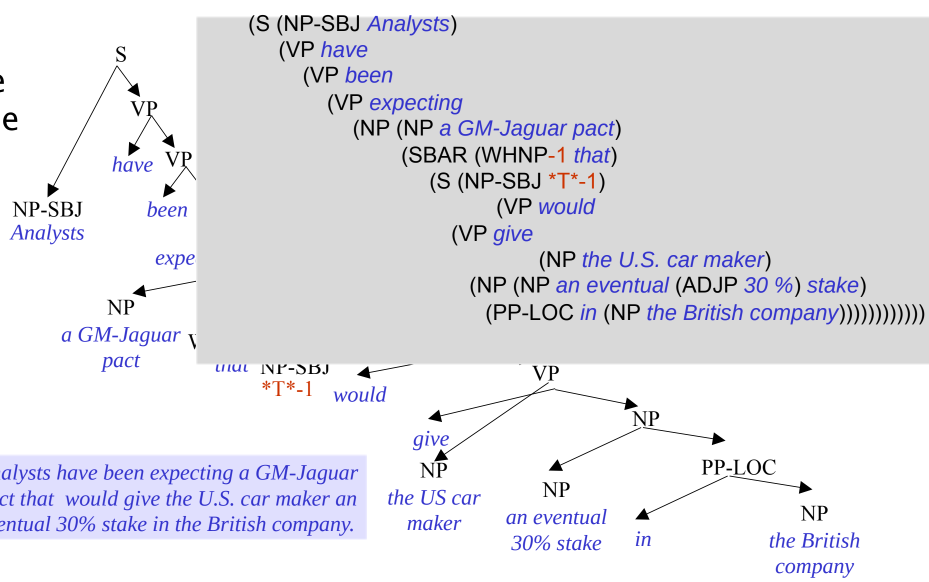
Modifiers or adjuncts of the predicate: Arg-M

ArgM-TMP	when?	yesterday evening, now
LOC	where?	at the museum, in San Francisco
DIR	where to/from?	down, to Bangkok
MNR	how?	clearly, with much enthusiasm
PRP/CAU	why?	because ... , in response to the ruling
REC		themselves, each other
ADV	miscellaneous	
PRD	secondary predication	...ate the meat raw

PropBanking a Sentence

Martha Palmer 2013

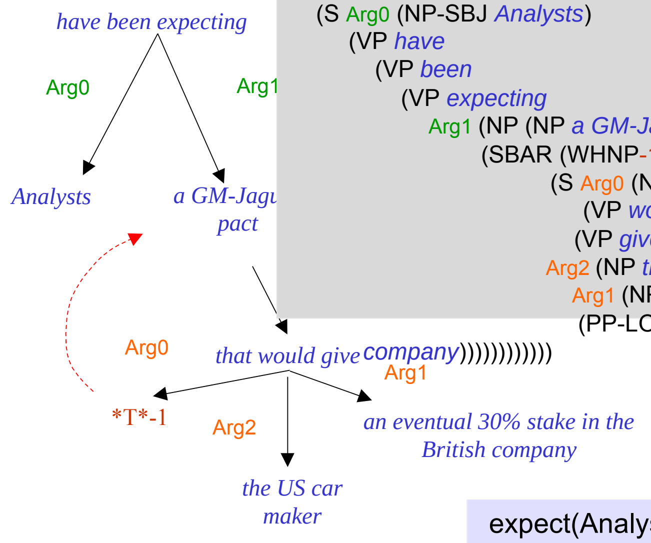
A sample parse tree



Analysts have been expecting a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.

The same parse tree PropBanked

Martha Palmer 2013




```
(S Arg0 (NP-SBJ Analysts)
    (VP have
       (VP been
          (VP expecting
              Arg1 (NP (NP a GM-Jaguar pact)
                  (SBAR (WHNP-1 that)
                      (S Arg0 (NP-SBJ *T*-1)
                          (VP would
                          (VP give
                          Arg2 (NP the U.S. car maker)
                          Arg1 (NP (NP an eventual (ADJP 30 %) stake)
                           (PP-LOC in (NP the British
company))))))))))))
```

expect(Analysts, GM-J pact)
give(GM-J pact, US car maker, 30% stake)

23

Annotated PropBank Data

- Penn English TreeBank, OntoNotes 5.0.
  - Total ~2 million words
- Penn Chinese TreeBank
- Hindi/Urdu PropBank
- Arabic PropBank

2013 Verb Frames Coverage
Count of word sense (lexical units)

Language	*Final Count*
English	**10,615***
Chinese	**24, 642**
Arabic	**7,015**

From Martha Palmer 2013 Tutorial

24

Capturing descriptions of the same event by different nouns/verbs

[$_{\text{Arg1}}$ The price of bananas] increased [$_{\text{Arg2}}$ 5%].
[$_{\text{Arg1}}$ The price of bananas] rose [$_{\text{Arg2}}$ 5%].
There has been a [$_{\text{Arg2}}$ 5%] rise [$_{\text{Arg1}}$ in the price of bananas].

25

FrameNet

- Baker et al. 1998, Fillmore et al. 2003, Fillmore and Baker 2009, Ruppenhofer et al. 2006
- Roles in PropBank are specific to a verb
- Role in FrameNet are specific to a **frame: a** background knowledge structure that defines a set of frame-specific semantic roles, called **frame elements**,
  - includes a set of predicates that use these roles
  - each word evokes a frame and profiles some aspect of the frame

26

The “Change position on a scale” Frame

This frame consists of words that indicate the change of an ITEM’s position on a scale (the ATTRIBUTE) from a starting point (INITIAL VALUE) to an end point (FINAL VALUE)

[ITEM Oil] *rose* [ATTRIBUTE in price] [DIFFERENCE by 2%].

[ITEM It] has *increased* [FINAL_STATE to having them 1 day a month].

[ITEM Microsoft shares] *fell* [FINAL_VALUE to 7 5/8].

[ITEM Colon cancer incidence] *fell* [DIFFERENCE by 50%] [GROUP among men].

a steady *increase* [INITIAL_VALUE from 9.5] [FINAL_VALUE to 14.3] [ITEM in dividends]

a [DIFFERENCE 5%] [ITEM dividend] *increase*...

27

The “Change position on a scale” Frame

VERBS:	dwindle	move	soar	escalation	shift
advance	edge	mushroom	swell	explosion	tumble
climb	explode	plummet	swing	fall	
decline	fall	reach	triple	fluctuation	**ADVERBS:**
decrease	fluctuate	rise	tumble	gain	increasingly
diminish	gain	rocket		growth	
dip	grow	shift	**NOUNS:**	hike	
double	increase	skyrocket	decline	increase	
drop	jump	slide	decrease	rise	

28

The "Change position on a scale" Frame

Core Roles	
ATTRIBUTE	The ATTRIBUTE is a scalar property that the ITEM possesses.
DIFFERENCE	The distance by which an ITEM changes its position on the scale.
FINAL_STATE	A description that presents the ITEM's state after the change in the ATTRIBUTE's value as an independent predication.
FINAL_VALUE	The position on the scale where the ITEM ends up.
INITIAL_STATE	A description that presents the ITEM's state before the change in the ATTRIBUTE's value as an independent predication.
INITIAL_VALUE	The initial position on the scale from which the ITEM moves away.
ITEM	The entity that has a position on the scale.
VALUE_RANGE	A portion of the scale, typically identified by its end points, along which the values of the ATTRIBUTE fluctuate.
Some Non-Core Roles	
DURATION	The length of time over which the change takes place.
SPEED	The rate of change of the VALUE.
GROUP	The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.

29

Relation between frames

Inherits from:
Is Inherited by:
Perspective on:
Is Perspectivized in:
Uses:
Is Used by:
Subframe of:
Has Subframe(s):
Precedes:
Is Preceded by:
Is Inchoative of:
Is Causative of:

30

Relation between frames

"cause change position on a scale"

Is Causative of: Change_position_on_a_scale

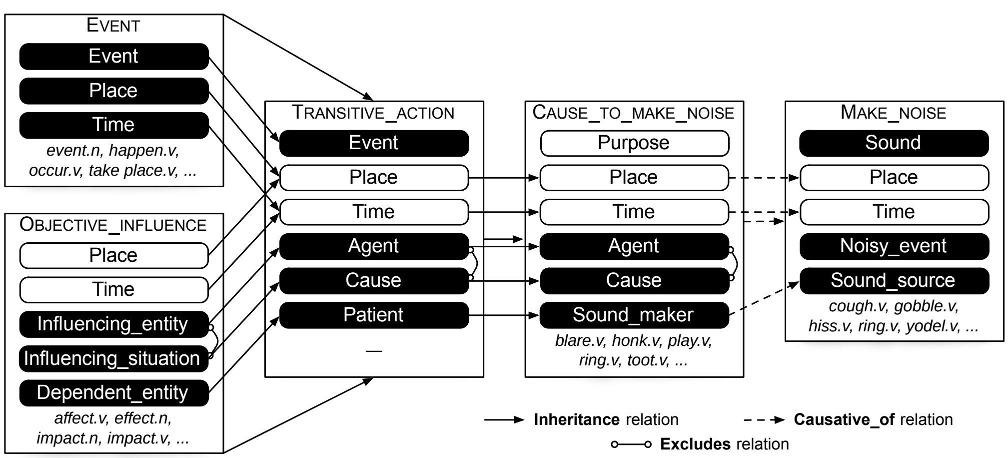
Adds an agent Role

[AGENT They] *raised* [ITEM the price of their soda] [DIFFERENCE by 2%].

- *add.v, crank.v, curtail.v, cut.n, cut.v, decrease.v, development.n, diminish.v, double.v, drop.v, enhance.v, growth.n, increase.v, knock down.v, lower.v, move.v, promote.v, push.n, push.v, raise.v, reduce.v, reduction.n, slash.v, step up.v, swell.v*

31

Relations between frames



32

Figure from Das et al 2010

Schematic of Frame Semantics

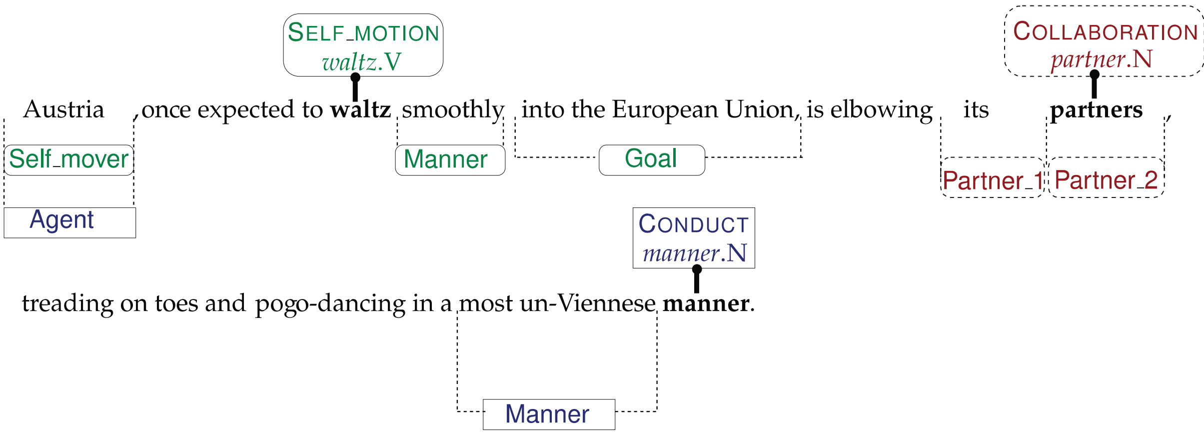
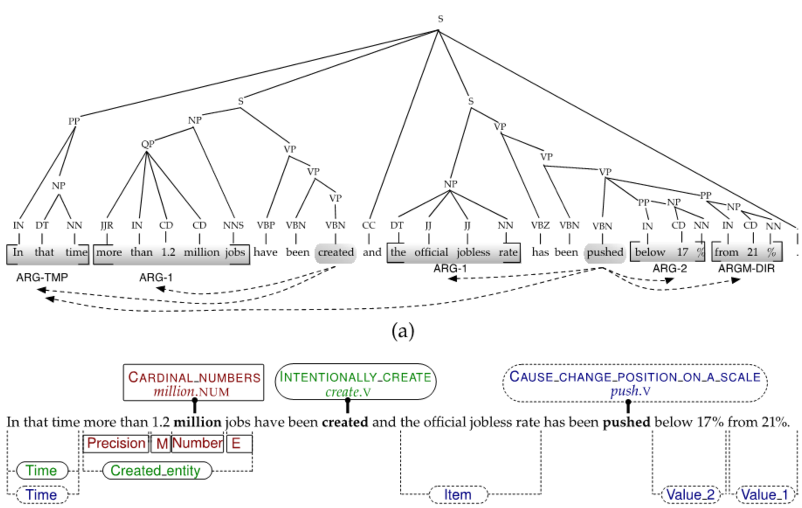


Figure from Das et al (2014)

33

FrameNet and PropBank representations



34

Semantic role labeling (SRL) algorithms

- The task of finding the semantic roles of each argument of each predicate in a sentence.
- FrameNet versus 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]
ARG0	TARGET	ARG1	ARGM-TMP

35

History

- Semantic roles as a intermediate semantics, used early in
  - machine translation (Wilks, 1973)
  - question-answering (Hendrix et al., 1973)
  - spoken-language understanding (Nash-Webber, 1975)
  - dialogue systems (Bobrow et al., 1977)
- Early SRL systems

  Simmons 1973, Marcus 1980:
  - parser followed by hand-written rules for each verb
  - dictionaries with verb-specific case frames (Levin 1977)

36

Why Semantic Role Labeling

- A useful shallow semantic representation
- Improves downstream NLP tasks like
  - question answering
  - machine translation

37

A simple modern algorithm

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*)

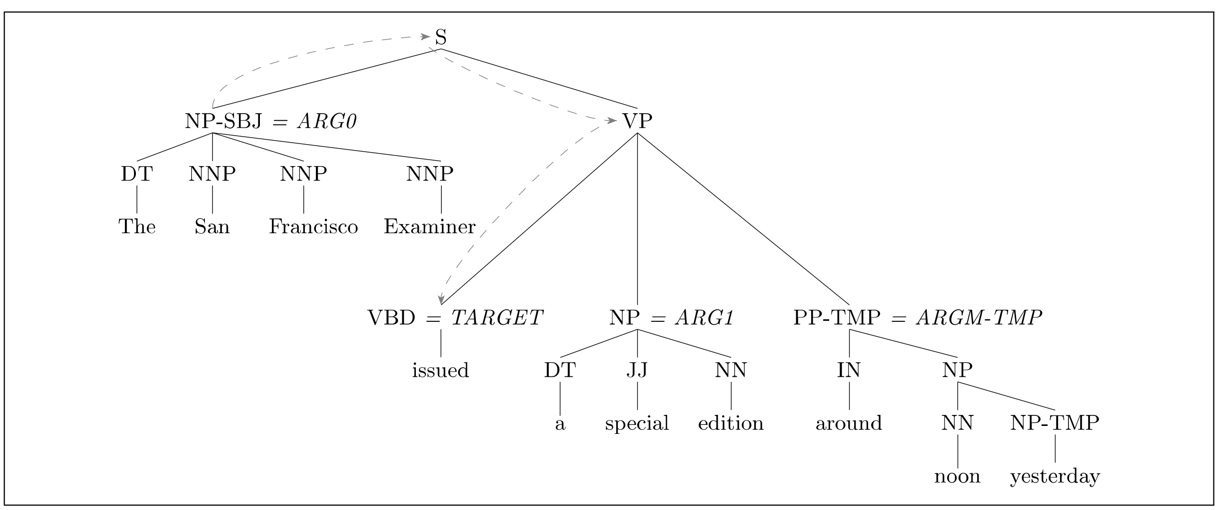
38

How do we decide what is a predicate

- If we’re just doing PropBank verbs
  - Choose all verbs
- If we’re doing FrameNet (verbs, nouns, adjectives)
  - Choose every word that was labeled as a target in training data

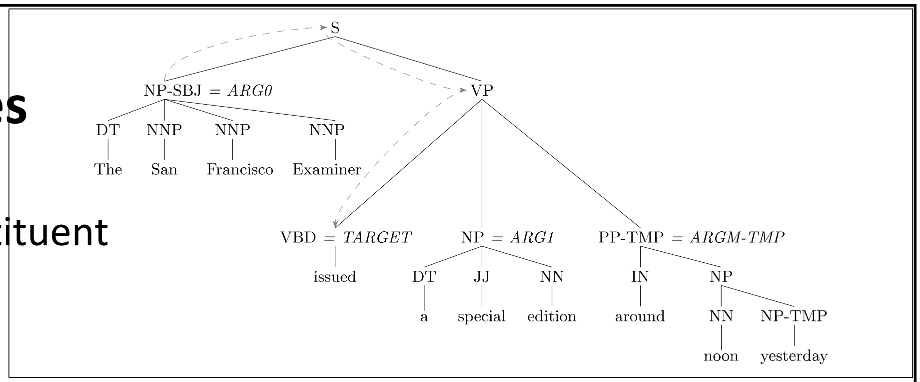
39

Semantic Role Labeling



40

Features



Headword of constituent

Examiner

Headword POS

NNP

Voice of the clause

Active

Subcategorization of pred

VP -> VBD NP PP

Named Entity type of constit

ORGANIZATION

First and last words of constit

The, Examiner

Linear position,clause re: predicate

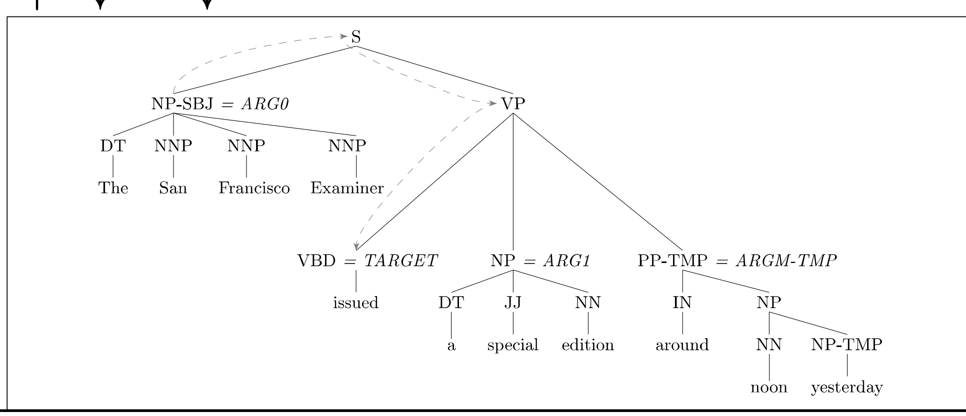
before

41

Path Features

Path in the parse tree from the constituent to the predicate

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



42

Frequent path features

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	

43

From Palmer, Gildea, Xue 2010

Final feature vector

- For "The San Francisco Examiner",
- Arg0, [issued, NP, Examiner, NNP, active, before, VP→NP PP, ORG, The, Examiner, NP↑S↓VP↓VBD]
- Other features could be used as well
  - sets of n-grams inside the constituent
  - other path features
    - the upward or downward halves
    - whether particular nodes occur in the path

44

3-step version of SRL algorithm

1. **Pruning**: use simple heuristics to prune unlikely constituents.
2. **Identification**: a binary classification of each node as an argument to be labeled or a NONE.
3. **Classification**: a 1-of-*N* classification of all the constituents that were labeled as arguments by the previous stage

45

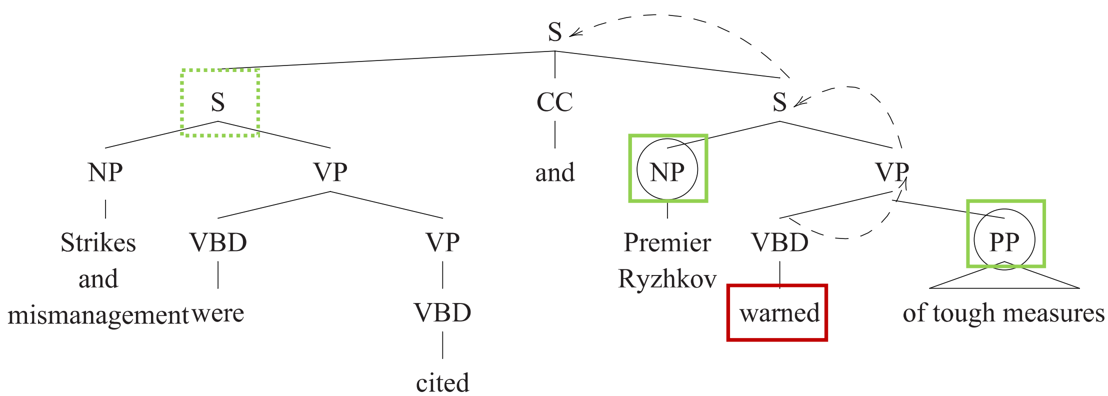
Why add Pruning and Identification steps?

- Algorithm is looking at one predicate at a time
- Very few of the nodes in the tree could be possible arguments of that one predicate
- Imbalance between
  - positive samples (constituents that are arguments of predicate)
  - negative samples (constituents that are not arguments of predicate)
- Imbalanced data can be hard for many classifiers
- So we prune the **very** unlikely constituents first, and then use a classifier to get rid of the rest.

46

Pruning heuristics – Xue and Palmer (2004)

- Add sisters of the predicate, then aunts, then great-aunts, etc
  - But ignoring anything in a coordination structure



47

A common final stage: joint inference

- The algorithm so far classifies everything **locally –** each decision about a constituent is made independently of all others
- But this can’t be right: Lots of **global** or **joint** interactions between arguments
  - Constituents in FrameNet and PropBank must be non-overlapping.
    - A local system may incorrectly label two overlapping constituents as arguments
    - PropBank does not allow multiple identical arguments
      - labeling one constituent ARG0
      - Thus should increase the probability of another being ARG1

48

How to do joint inference

- Reranking
  - The first stage SRL system produces multiple possible labels for each constituent
  - The second stage classifier the best **global** label for all constituents
  - Often a classifier that takes all the inputs along with other features (sequences of labels)

49

More complications: FrameNet

We need an extra step to find the frame

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*)

function SemanticRoleLabel(*words*) **returns** labeled tree
  parse ← Parse(*words*)
  for each *predicate* **in** *parse* **do**
    Predicatevector ← ExtractFrameFeatures(predicate,parse)
    Frame ← ClassifyFrame(predicate,predicatevector)
    for each *node* **in** *parse* **do**
      featurevector ← ExtractFeatures(*node*, *predicate*, *parse*)
      ClassifyNode(*node*, *featurevector*, *parse* , Frame)

50

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[21] 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_ℓ
the lemmatized sequence of words in the prototype
the lemmatized sequence of words in the prototype and their part-of-speech tags π_ℓ
WordNet relation[22] ρ holds between ℓ and t_i
WordNet relation[22] ρ holds between ℓ and t_i, and the prototype is ℓ
WordNet relation[22] ρ holds between ℓ and t_i, the POS tag sequence of ℓ is π_ℓ, and the POS tag sequence of t_i is π_t

51

SRL Summary

- A level of shallow semantics for representing events and their participants
  - Intermediate between parses and full semantics
- Two common architectures, for various languages
  - FrameNet: frame-specific roles
  - PropBank: Proto-roles
- Current systems extract by
  - parsing sentence
  - Finding predicates in the sentence
    - For each one, classify each parse tree constituent

52

Selectional Restrictions

Consider :

I want to eat someplace nearby.

53

Selectional Restrictions

Consider the two interpretations of:

I want to eat someplace nearby.

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

How do we know speaker didn't mean b) ?

Because the THEME of eating tends to be something *edible*

54

Selectional restrictions are associated with senses

- The restaurant serves **green-lipped mussels.**
  - THEME is some kind of food
- Which airlines serve **Denver**?
  - THEME is an appropriate location

55

Selectional restrictions vary in specificity

I often ask the musicians to *imagine* a tennis game.

To *diagonalize* a matrix is to find its eigenvalues.

Radon is an *odorless* gas that can't be detected by human senses.

56

Representing selectional restrictions

Instead of representing "eat" as:

$$\exists e,x,y\ Eating(e) \wedge Agent(e,x) \wedge Theme(e,y)$$

Just add:

$$\exists e,x,y\ Eating(e) \wedge Agent(e,x) \wedge Theme(e,y) \wedge EdibleThing(y)$$

And "eat a hamburger" becomes

$$\exists e,x,y\ Eating(e) \wedge Eater(e,x) \wedge Theme(e,y) \wedge EdibleThing(y) \wedge Hamburger(y)$$

But this assumes we have a large knowledge base of facts about edible things and hamburgers and whatnot.

57

Let's use WordNet synsets to specify selectional restrictions

- The THEME of eat must be WordNet synset {food, nutrient}
  "any substance that can be metabolized by an animal to give energy and build tissue"
- Similarly
  THEME of imagine: synset {entity}
  THEME of lift: synset {physical entity}
  THEME of diagonalize: synset {matrix}
- *This allows*
  imagine a hamburger and *lift a hamburger*,
- Correctly rules out
  diagonalize a hamburger.

58

Selectional Preferences

- In early implementations, selectional restrictions were strict constraints
  - Eat [+FOOD]
- But it was quickly realized selectional constraints are really **preferences**
  - 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.

59

Selectional Association (Resnik 1993)

- **Selectional preference strength:** amount of information that a predicate tells us about the semantic class of its arguments.
  - *eat* tells us a lot about the semantic class of its direct objects
  - *be* doesn't tell us much
- The selectional preference strength
  - difference in information between two distributions:

    P(c) the distribution of expected semantic classes for any direct object

    P(c|v) the distribution of expected semantic classes for this verb
  - The greater the difference, the more the verb is constraining its object

60

Selectional preference strength

- Relative entropy, or the Kullback-Leibler divergence is the difference between two distributions

$$D(P||Q) = \sum_x P(x) \log \frac{P(x)}{Q(x)}$$

- Selectional preference: How much information (in bits) the verb expresses about the semantic class of its argument

$$\begin{aligned} S_R(v) &= D(P(c|v)||P(c)) \\ &= \sum_c P(c|v) \log \frac{P(c|v)}{P(c)} \end{aligned}$$

- Selectional Association of a verb with a class: The relative contribution of the class to the general preference of the verb

61

$$A_R(v,c) = \frac{1}{S_R(v)} P(c|v) \log \frac{P(c|v)}{P(c)}$$

Computing Selectional Association

- A probabilistic measure of the strength of association between a predicate and a semantic class of its argument
  - Parse a corpus
  - Count all the times each predicate appears with each argument word
  - Assume each word is a partial observation of all the WordNet concepts associated with that word
  - Some high and low associations:

Verb	Direct Object Semantic Class	Assoc	Direct Object Semantic Class	Assoc
read	WRITING	6.80	ACTIVITY	-.20
write	WRITING	7.26	COMMERCE	0
see	ENTITY	5.79	METHOD	-0.01

62

Instead of using classes, a simpler model of selectional association

- Model just the association of predicate *v* with a noun *n*

  (one noun, as opposed to the whole semantic class in WordNet)

  - Parse a huge corpus
  - Count how often a noun n occurs in relation r with verb v:

    log count(n,v,r)
  - Or the probability:

$$P(n|v,r) = \begin{cases} \frac{C(n,v,r)}{C(v,r)} & \text{if } C(n,v,r) > 0 \\ 0 & \text{otherwise} \end{cases}$$

63

Evaluation from Bergsma, Lin, Goebel

Verb	Plaus./Implaus.
see	friend/method
read	article/fashion
find	label/fever
hear	story/issue
write	letter/market
urge	daughter/contrast
warn	driver/engine
judge	contest/climate
teach	language/distance
show	sample/travel
expect	visit/mouth
answer	request/tragedy
recognize	author/pocket
repeat	comment/journal
understand	concept/session
remember	reply/smoke

64

Summary: Selectional Restrictions

- Two classes of models of the semantic type constraint that a predicate places on its argument:
  - Represent the constraint between predicate and WordNet class
  - Represent the constraint between predicate and a word

65