Natural Language Processing
CS 6320

Lecture 13

Semantic Role Labeling

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What is Semantic Role Labeling?

Semantic Role Labeling, also called Thematic Role Labeling, or Case Role Assignment or Shallow Semantic Parsing is the task of automatically finding the thematic roles for each predicate in a sentence.

What is Automatic Semantic Role Labeling?

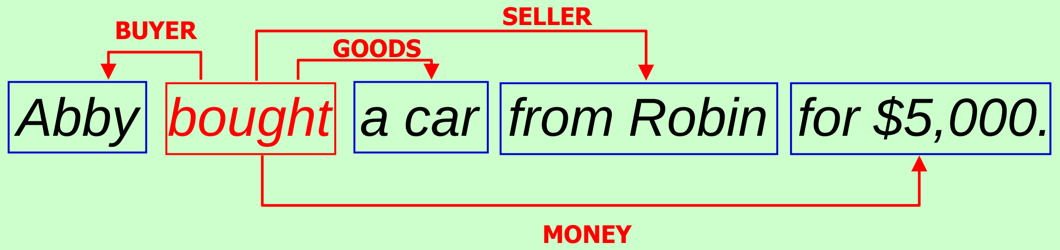
Given a sentence:

Abby bought a car from Robin for $5,000.

a) Identify predicates:

Abby bought a car from Robin for $5,000.

b) Identify and assign thematic/semantic roles for each predicate:



Why Study Semantic Role Labeling?

- Who did What to Whom, When, Where, Why, How, etc.

- Proved to be useful in:
  - Question Answering (QA)
    [Narayanan and Harabagiu, COLING'02]
  - Information Extraction (IE)
    [Surdeanu et al., ACL'03]

Using Semantic Role Labeling in QA

- Parsing Questions

***Q**: What kind of materials were stolen from the Russian navy?*

FS(Q): What [GOODS: kind of nuclear materials] were [Target-Predicate:stolen] [VICTIM: from the Russian Navy]?

- Parsing Answers

***A(Q)**: Russia's Pacific Fleet has also fallen prey to nuclear theft; in 1/96, approximately 7 kg of HEU was reportedly stolen from a naval base in Sovetskaya Gavan.*

FS(A(Q)): *[VICTIM(P1): Russia's Pacific Fleet] has also fallen prey to [Goods(P1): nuclear] [Target-Predicate(P1): theft]; in 1/96, [GOODS(P2): approximately 7 kg of HEU] was reportedly [Target-Predicate (P2): stolen] [VICTIM (P2): from a naval base] [SOURCE(P2): in Sovetskaya Gavan]*

- Result: exact answer= "*approximately 7 kg of HEU*"

Semantic Roles

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 French government has built a regulation-size baseball diamond ...*
CONTENT	The proposition or content of a propositional event. *Mona asked "You met Marry Ann at a supermarket"?*
INSTRUMENT	An instrument used in an event. *He turned to poaching catfish, stunning them with a shocking device ...*
BENEFICIARY	The beneficiary of an event. *Whenever Ann Callahan makes hotel reservation 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.*

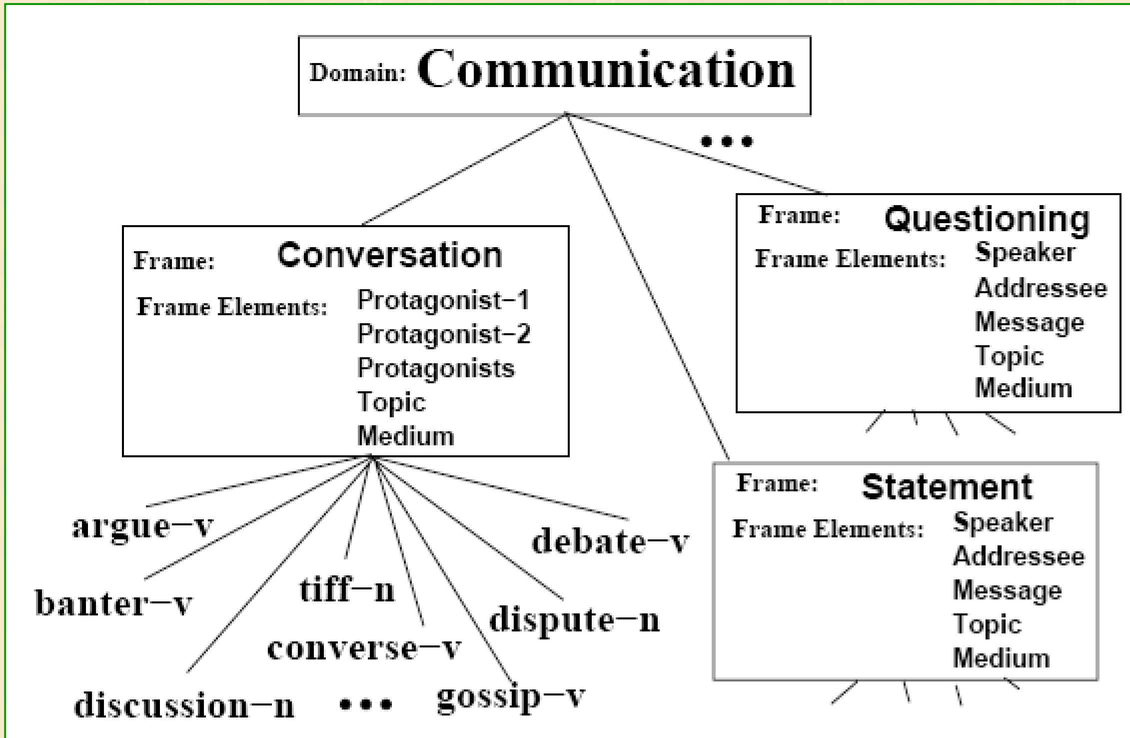
Common Realizations for Major Thematic Roles

Thematic Role	Realization
AGENT	as subject in active sentences preposition *by* in passive sentences
EXPERIENCER	as animate subject in active sentences with no agent
THEME	as object of transitive verbs as subject of non-action verbs
INSTRUMENT	as subject in active sentences with no agent preposition *with*
BENEFICIARY	as indirect object with transitive verbs preposition *for*

FrameNet

- The FrameNet Project [Baker et al.,1998], developed at ICSI Berkeley, proposes roles that are neither as general as the ten abstract thematic roles, nor as specific as the thousands of potential verb specific roles.
- FrameNet encodes a set of frames (semantic representation of situations)
- Frames are characterized by:
  - target words or lexical predicates whose meaning includes aspects of the frame;
  - frame elements (FEs) which represent the semantic roles of the frame;
  - examples of annotations performed for instances of each target word in various texts.

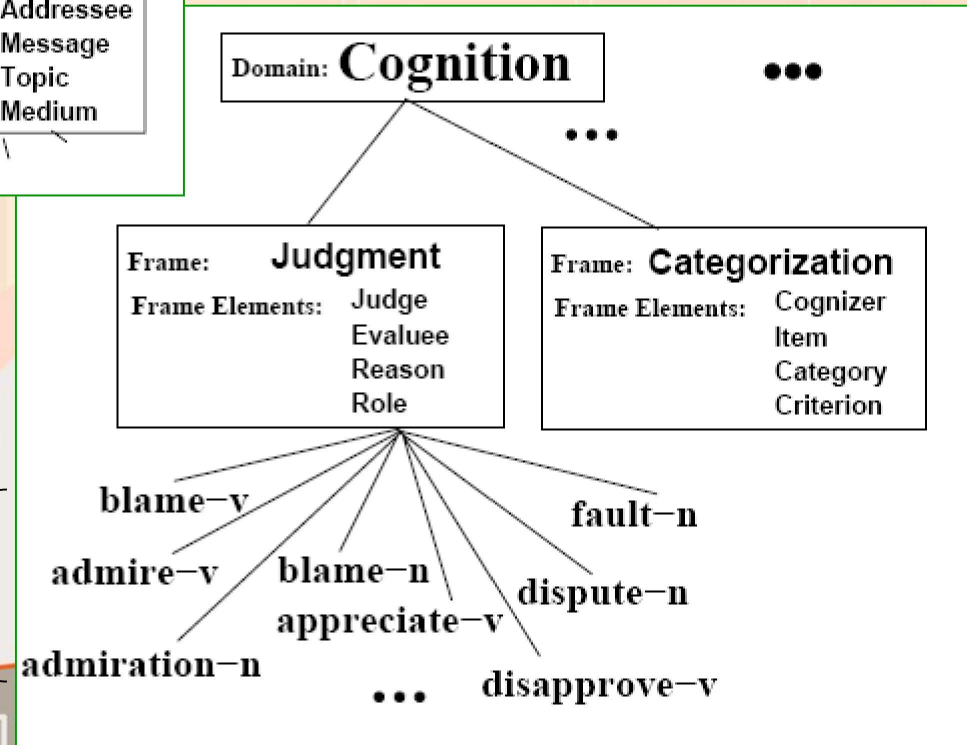
Sample Domains and Frames from FrameNet



12 domains in the preliminary version of FrameNet Project:

1.Body
2.Cognition
3.Communication
4.Emotion
5.General
6.Health
7 .Motion
8 .Perception
9 . Society
10.Space
11.Time
12.Transaction

Target words that evoke Conversation and Judgment frames



FrameNet Annotation

- The project methodology was done on a frame-by-frame basis:
  1) choose a semantic frame (e.g. Commerce_buy)
  2) define the frame and its frame elements (e.g. BUYER, GOODS, SELLER, MONEY)
  3) list the various lexical predicates (verbs, nouns and adjectives) that evoke the frame (buy.v, purchase.v, purchase.n)
  4) extract sentences for each predicate from various corpora, e.g. British National Corpus

Frame Example: Commerce_buy

Definition: These are words describing a basic commercial transaction involving a buyer and a seller exchanging money and goods, taking the perspecitive of the buyer. The words vary individually in the patterns of frame element realization they allow. For example, the typical pattern for the verb BUY: BUYER buys GOODS from SELLER for MONEY.

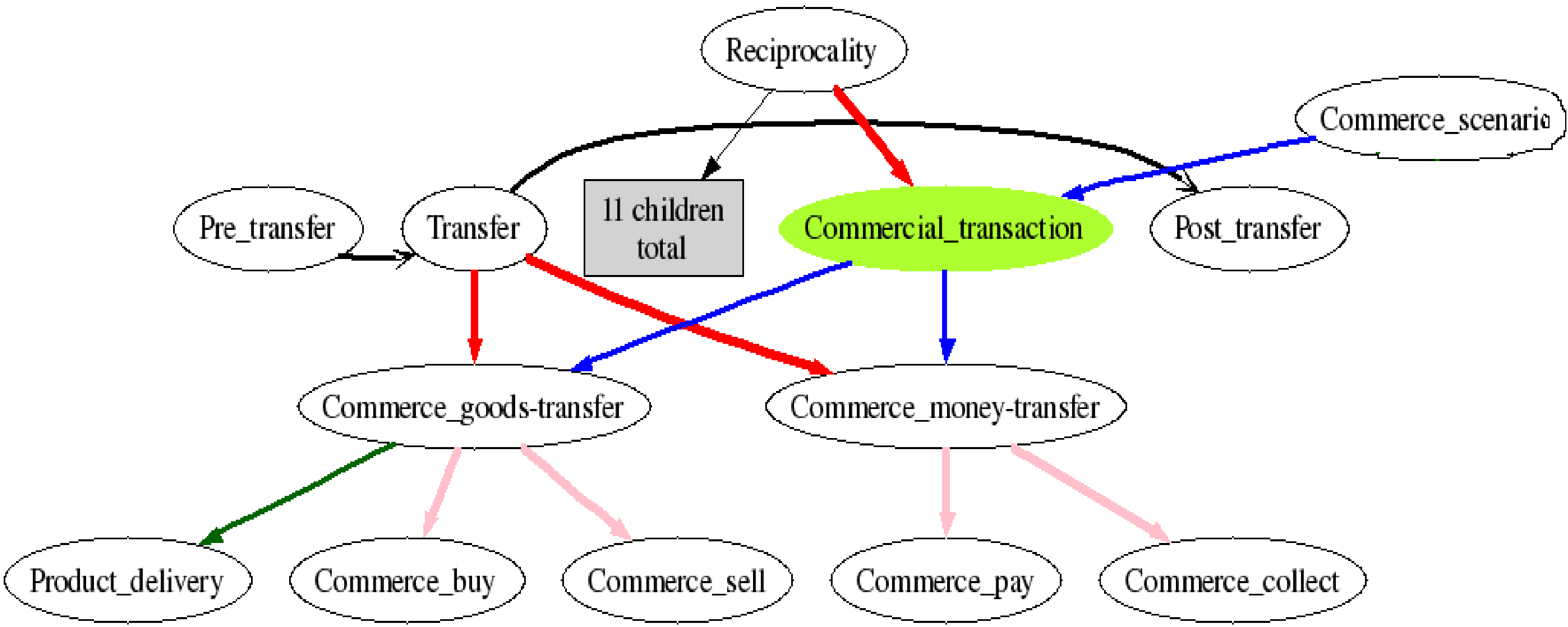
Frame Element	
Buyer	The Buyer wants the Goods and offers Money to a Seller in exchange for them. *Lee BOUGHT a textbook from Abby.*
Goods	The FE Goods is anything (including labor or time, for example) which is exchanged for Money in a transaction. *(Only one winner PURCHASED the paintings)*
Money	Money is the thing given in exchange for Goods in a transaction. *Sam BOUGHT the car for $12,000.*
Seller	The Seller has possession of the Goods and exchanges them for Money from a Buyer. *Most of my audio equipment, I PURCHASED from a department store near my apartment*
Place	Where the event takes place.

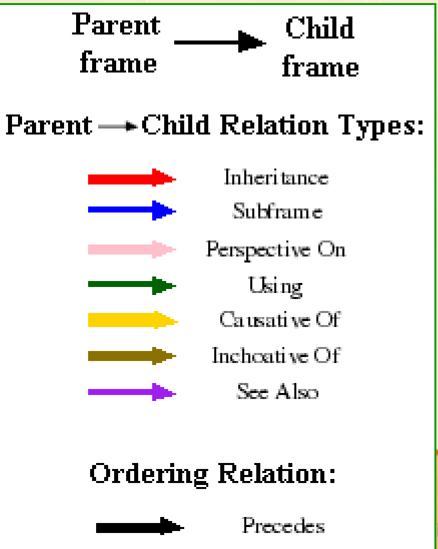
Frame-to-Frame Relations

Frame Relation – a directed relation between two frames, where one frame is called Super_Frame (less dependent, more abstract) and the other frame is called Sub_Frame (the more dependent, less abstract)

Relation	Sub	Super
Inheritance	Child	Parent
Perspective_on	Perspectivized	Neutral
Subframe	Component	Complex
Precedes	Later	Earlier
Inchoative_of	Inchoative	State
Causative_of	Causative	Inchoative/State
Using	Child	Parent
See_also	Referring Entry	Main Entry

Frame Relations for Commercial transaction

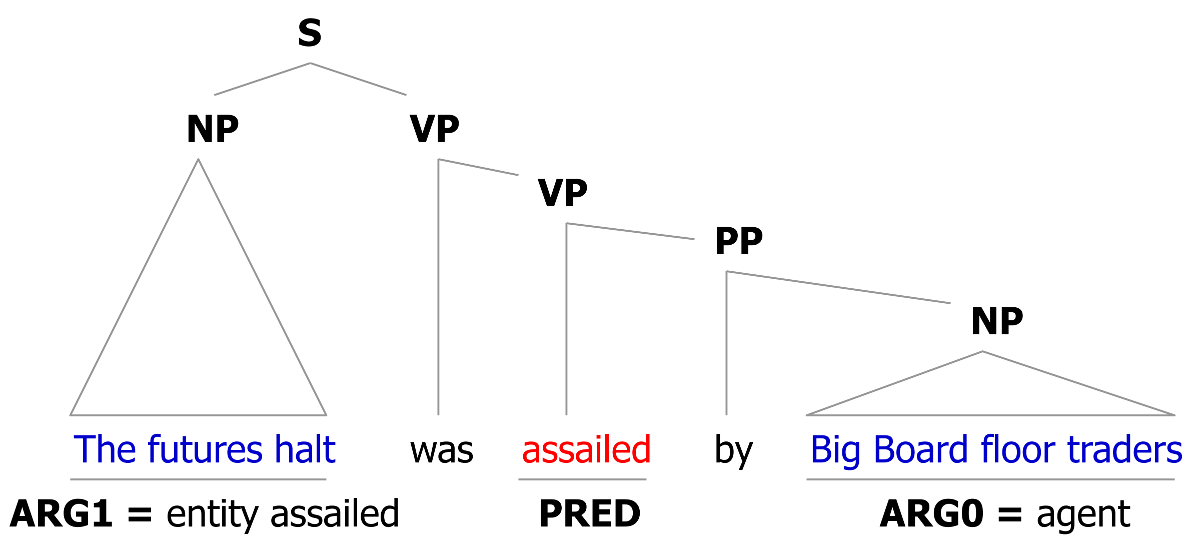




Commercial_transaction frame specifies a compex schema involving an exchange of multiple themes (Money and Goods) between the Buyer and Seller, including also two sub-frames: Commerce_goods_transfer and Commerce_money_transfer

Proposition Bank (PropBank)

- A one million word corpus annotated with predicate argument structures
- Developed at University of Pennsilvania
- Annotation is performed on the Penn TreeBank
- Predicates are lexicalized only by verbs
- Arguments numbered from 0..5
- Adjunctive arguments: Locative, Temporal, Manner, Cause, etc.



PropBank Example

[$_{A0}$ He] [$_{AM\text{-}MOD}$ would] [$_{AM\text{-}NEG}$ n't] [$_{V}$ accept] [$_{A1}$ anything of value] from [$_{A2}$ those he was writing about] .

Here, the roles for the predicate accept (that is, the *roleset* of the predicate) are defined in the PropBank Frames scheme as:

V: verb
A0: acceptor
A1: thing accepted
A2: accepted-from
A3: attribute
AM-MOD: modal
AM-NEG: negation

Using Semantic Role Labeling in QA

- Parsing Questions

Q: *What kind of materials were stolen from the Russian navy?*

PAS(Q): What [ARG1: kind of nuclear materials] were [Predicate:stolen] [ARG2: from the Russian Navy]?

- Parsing Answers

A(Q): *Russia's Pacific Fleet has also fallen prey to nuclear theft; in 1/96, approximately 7 kg of HEU was reportedly stolen from a naval base in Sovetskaya Gavan.*

PAS(A(Q)): [Arg1(P1redicate 1): Russia's Pacific Fleet] has [ArgM-Dis(Predicate 1) also] [Predicate 1: fallen] [Arg1(Predicate 1): prey to nuclear theft]; [ArgM-TMP(Predicate 2): in 1/96], [Arg1(Predicate 2): approximately 7 kg of HEU] was [ArgM-ADV(Predicate 2) reportedly] [Predicate 2: stolen] [Arg2(Predicate 2): from a naval base] [Arg3(Predicate 2): in Sovetskaya Gavan]

- Result: exact answer= "*approximately 7 kg of HEU*"

Common Realizations in Argument Numbers

- Arg0 = agent
- Arg1 = direct object / theme / patient
- Arg2 = indirect object / benefactive / instrument / attribute / end state
- Arg3 = start point / benefactive / instrument / attribute
- Arg4 = end point

Recall that FrameNet employs a large number of frame-specific frame elements as roles, while PropBank makes use of a smaller number of generic argument labels.

Adjuncts in PropBank

ArgM-DIR	directionals	walk along the road
ArgM-LOC	locatives	walk around the countryside
ArgM-MNR	manner	works well with others
ArgM-TMP	temporal	in 1987
ArgM-EXT	extent	raised prices by 15%
ArgM-REC	reciprocals	John and Mary killed each other
ArgM-PRD	predication	Mary called John an idiot
ArgM-PRP	purpose	I live to eat
ArgM-DIS	discourse	also, however
ArgM-ADV	other adverbial	generally?
ArgM-MOD	modal	possibly
ArgM-NEG	negative	did not
ArgM	bare ArgM	adjuncts not related to verb, e.g. extraposed modifier

PropBank Example

The company bought a wheel-loader from Dresser.

Arg0:	The company
rel:	bought
Arg1:	a wheel-loader
Arg2-from:	Dresser

TV stations bought "Seinfeld" reruns for record prices.

Arg0:	TV stations
rel:	bought
Arg1:	"Cosby" reruns
Arg3-for:	record prices

BUY

Arg0: buyer
Arg1: commodity
Arg2: seller
Arg3: price
Arg4: beneficiary

SELL

Arg0: seller
Arg1: commodity
Arg2: buyer
Arg3: price
Arg4: beneficiary

PAY

Arg0: buyer
Arg1: price paid
Arg2: seller
Arg3: commodity
Arg4: beneficiary

Same roleset; different order

PropBank/FrameNet Role Mappings

BUY

Arg0: buyer
Arg1: commodity
Arg2: seller
Arg3: price
Arg4: beneficiary

SELL

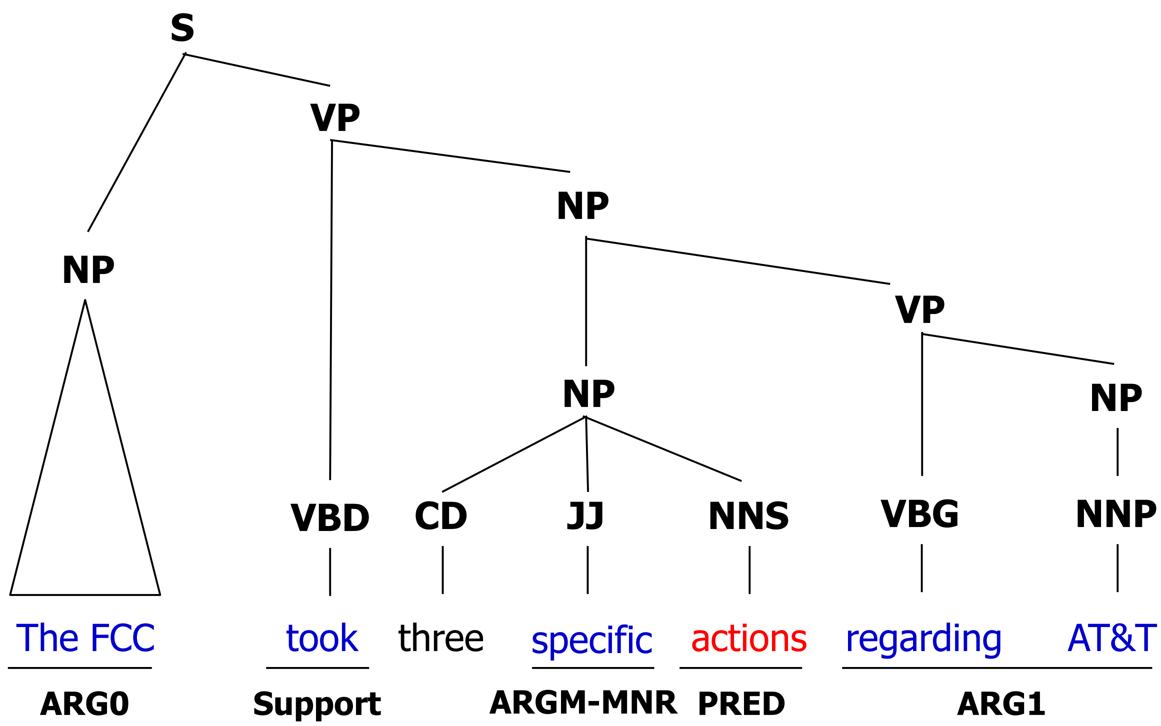
Arg0: seller
Arg1: commodity
Arg2: buyer
Arg3: price
Arg4: beneficiary

Trade, Exchange

Arg0: one party
Arg1: commodity
Arg2: other party
Arg3: price
Arg4: beneficiary

NomBank

- ❑ Provides argument structures for instances of about 5000 common nouns in the Penn Treebank II
  - ➢ Developed at New York University
    - ▪ Annotation is performed on the Penn TreeBank
      - ○ Predicates are lexicalized only by nouns
      - ○ Arguments numbered from 0..4
      - ○ Adjunctive arguments: Locative, Temporal, Manner, Cause, etc.
      - ○ SUPPORT items



A Combined PropBank/Nombank Graphical Representation

They gave the chefs a standing ovation

PropBank

REL: gave

Arg0: they

Arg1: a standing ovation

Arg2: the chefs

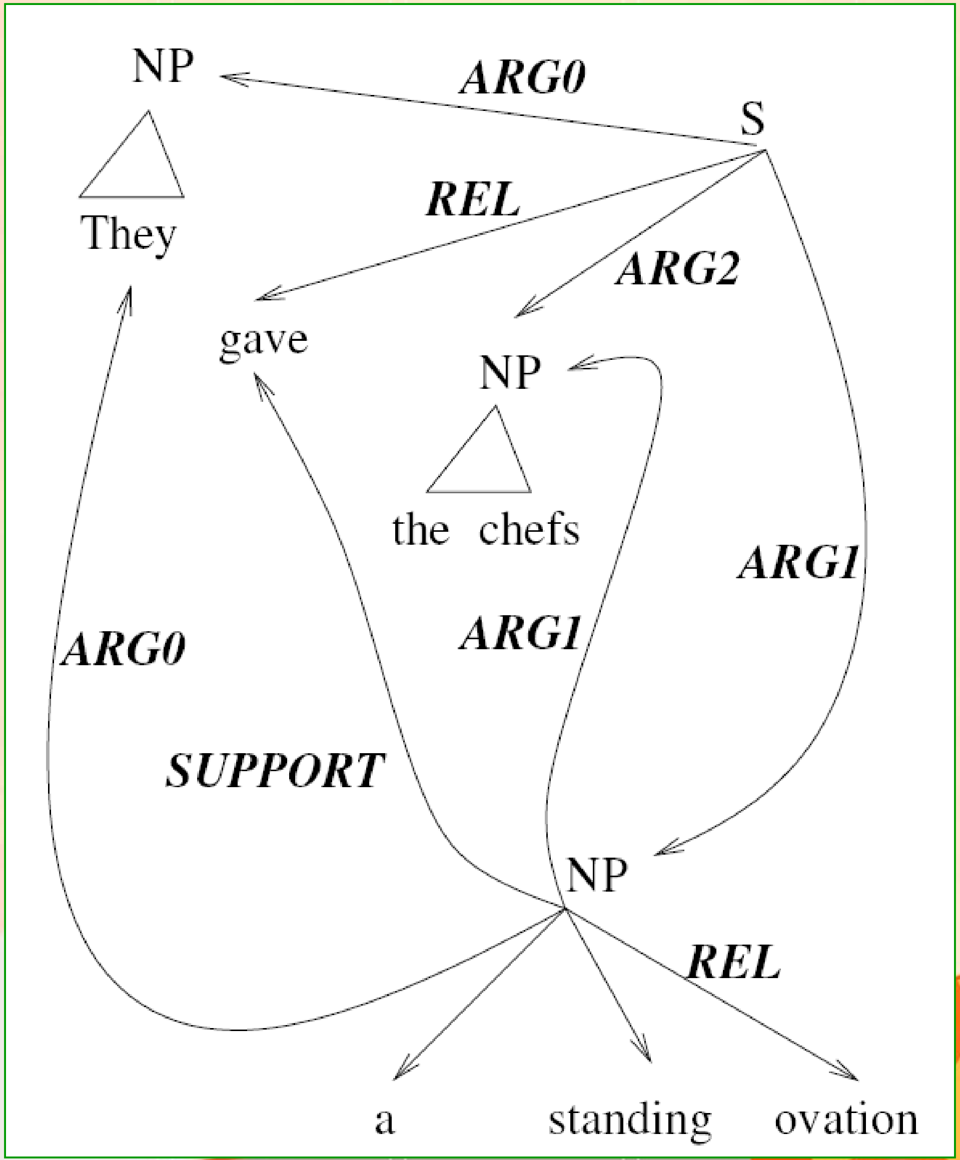
NomBank

REL: ovation

Arg0: they

Arg1: the chefs

Support: gave



Automatic Labeling of Semantic Roles

- Given a sentence:

Abby bought a car from Robin for $5,000.

a) Identify predicates:

Abby bought a car from Robin for $5,000.

b) Identify and assign thematic roles for each predicate:

[$_{\text{Buyer}}$Abby] bought [$_{\text{Goods}}$a car] [$_{\text{Seller}}$from Robin] [$_{\text{Money}}$for $5,000].

A Semantic Role Labeling Algorithm

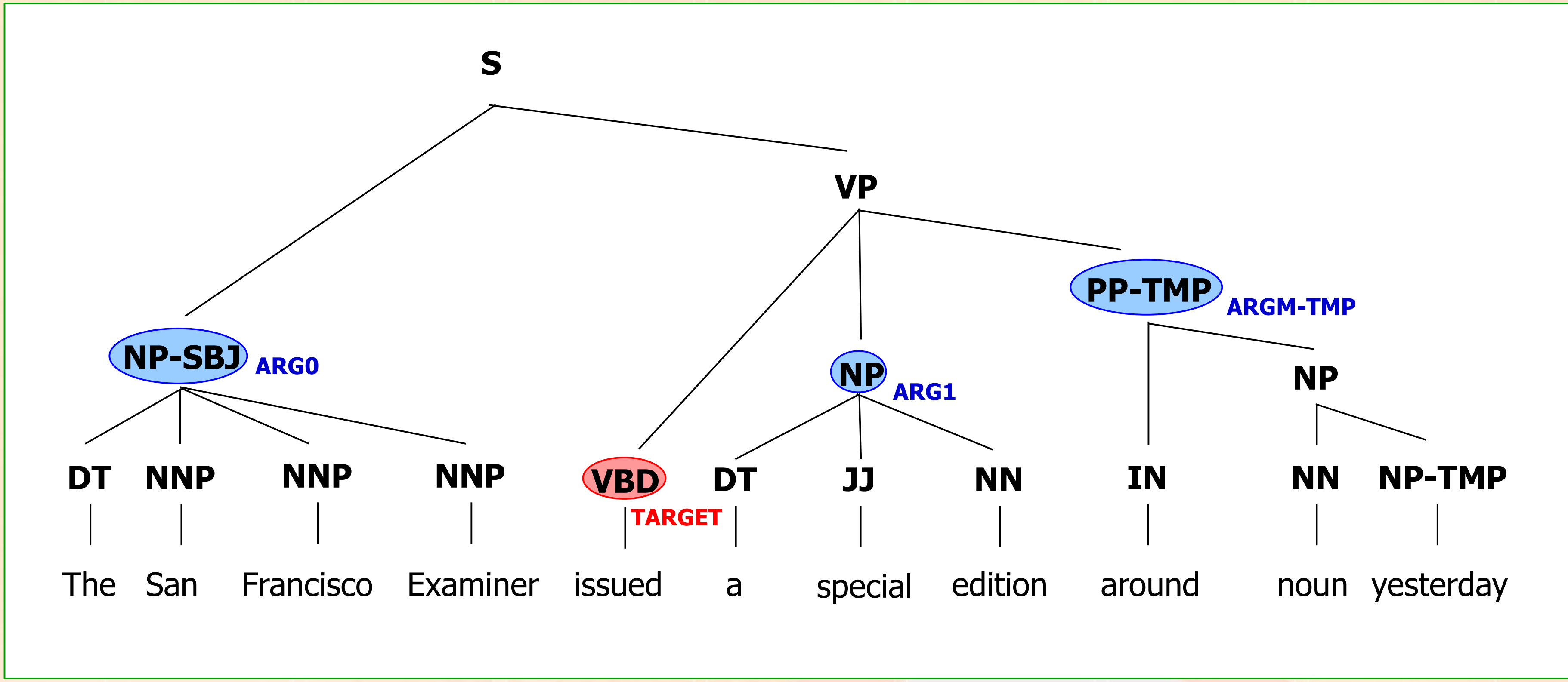
```
function SEMANTICROLELABEL(words) returns labeled tree

    parse ← PARSE(words)
    for each predicate in parse do
        for each node in parse do
            featurevector ← EXTRACTFEATURES(node, predicate, parse)
            CLASSIFYNODE(node, featurevector, parse)
```

Semantic Role Labeling Using Two Classifiers

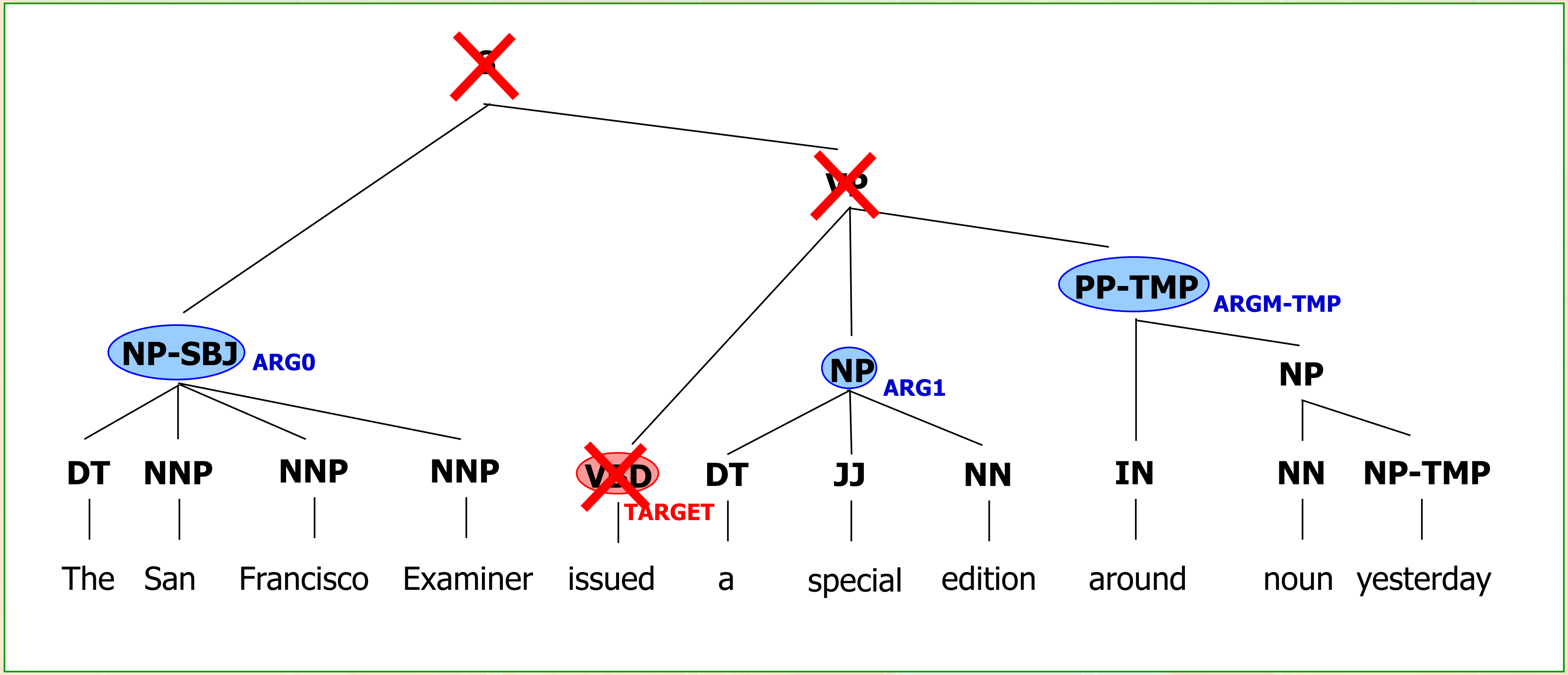
- Instead of training a single stage classifier, some role labeling algorithms do classification in multiple stages for efficiency:
  - Pruning: to speed the execution, some constituents are eliminated from consideration as possible roles, based on simple rules;
  - Identification: a binary classification of each node as an ARG (positive example) to be labeled or NONE (negative example)
  - Classification: a one-of-N classification of all the constituents that were labeled as ARG by the previous stage.

Example



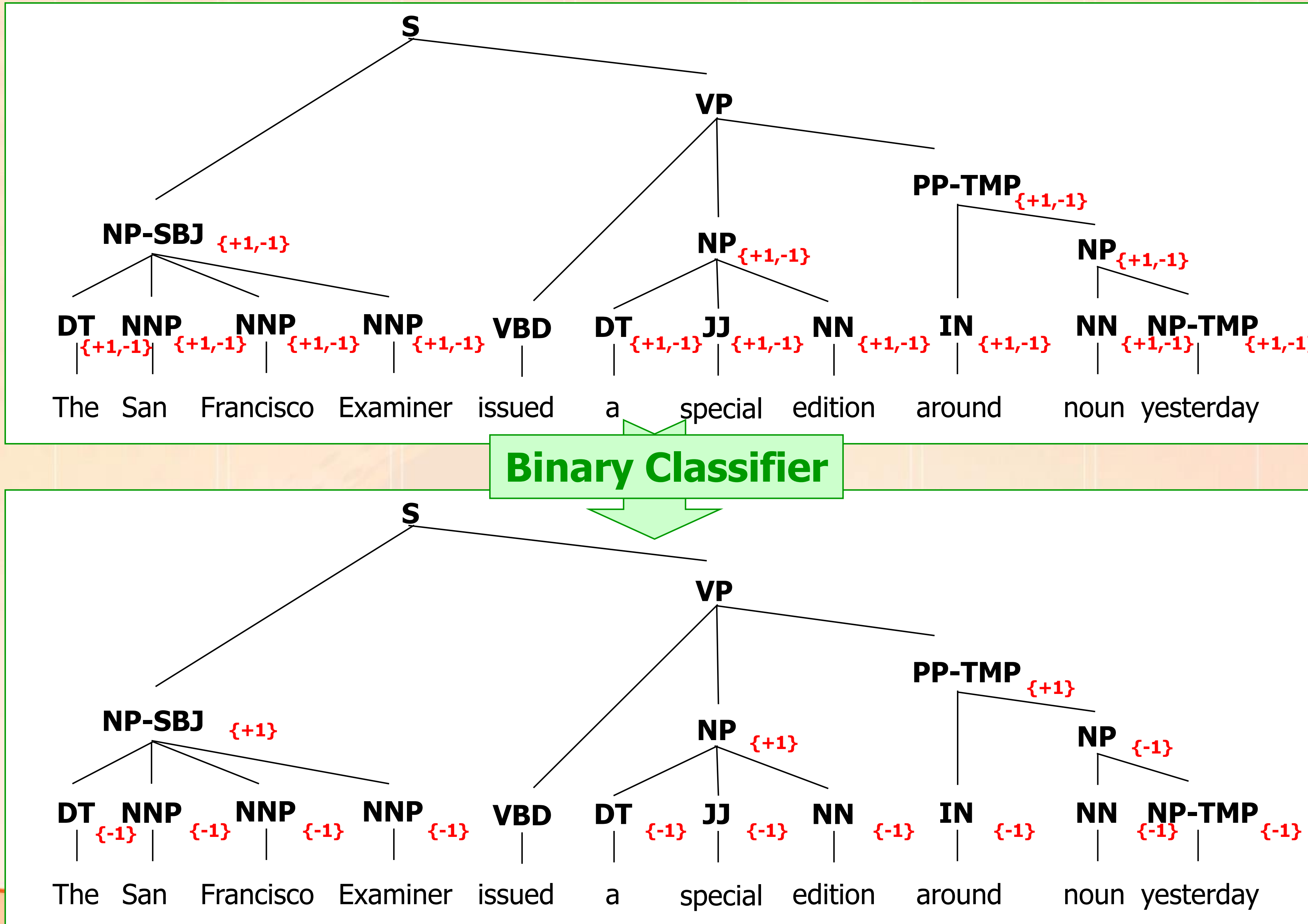
[$_{\text{ARG0}}$ The San Francisco Examiner] issued [$_{\text{ARG1}}$ a special edition] [$_{\text{ARGM-TMP}}$ around noun yesterday].

Example: Pruning

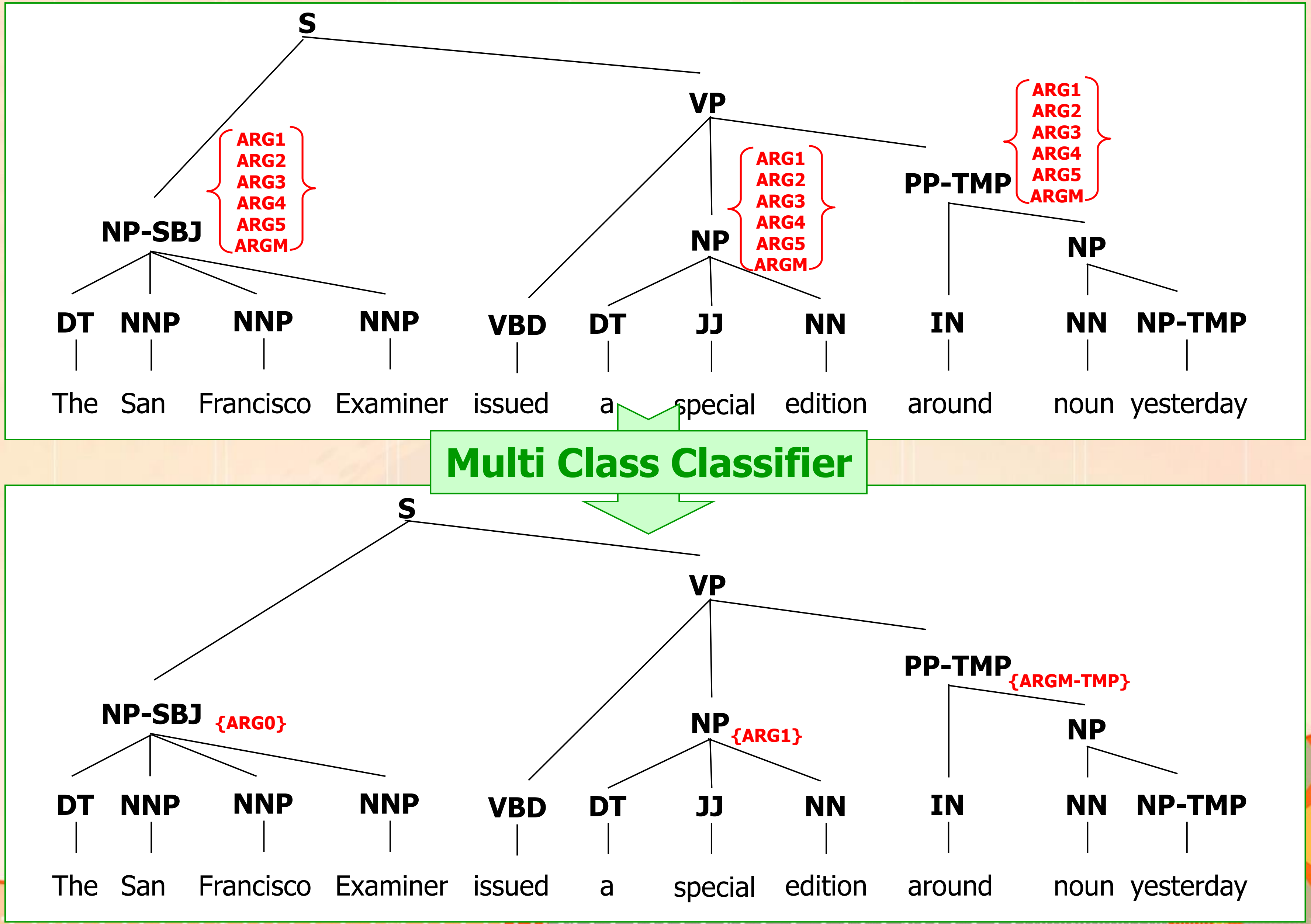


Also, all the leafs of the parse trees can be ignored

Example: Argument Identification



Example: Argument Classification



Extracting Features

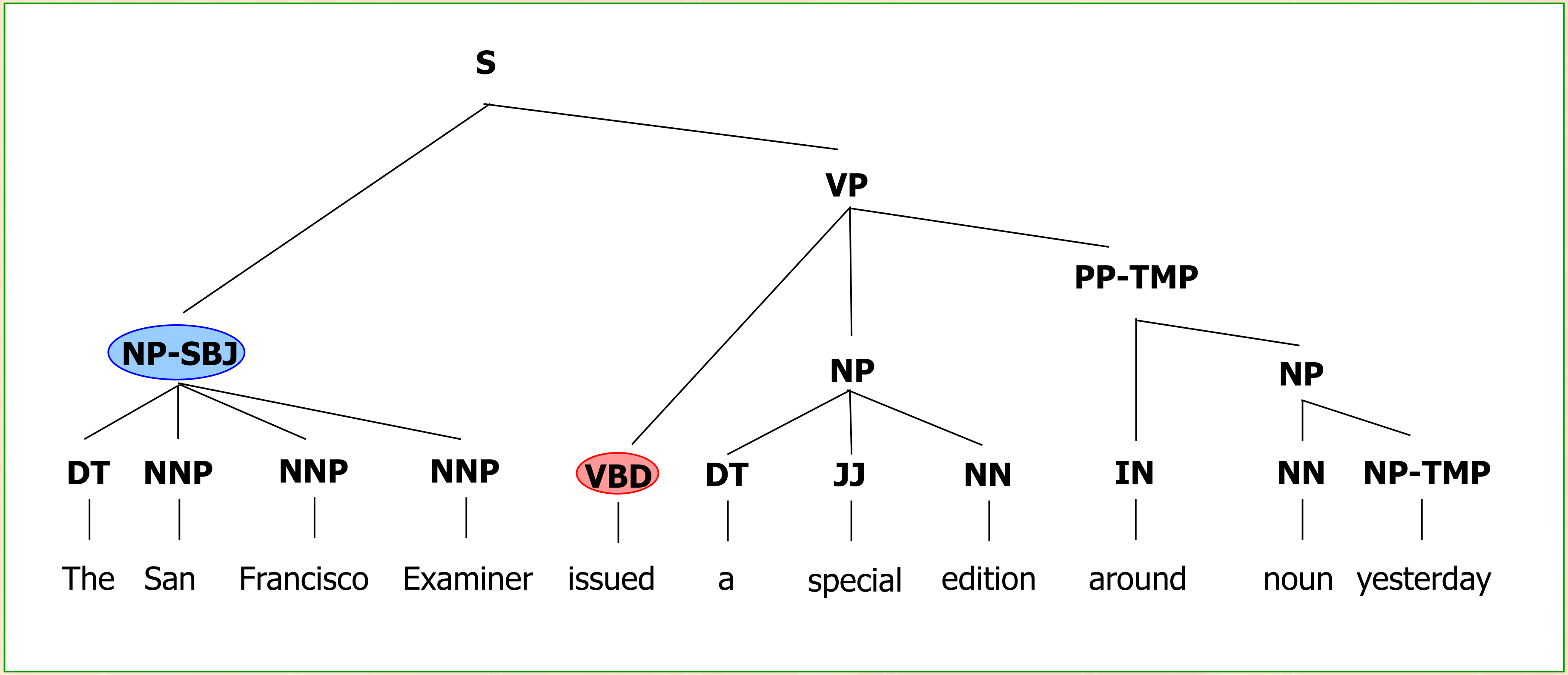
function SEMANTICROLELABEL(*words*) **returns** labeled tree

```
parse ← PARSE(words)
for each predicate in parse do
    for each node in parse do
        featurevector ← EXTRACTFEATURES(node, predicate, parse)
        CLASSIFYNODE(node, featurevector, parse)
```

The syntactic parse tree is traversed for each predicate;

- In traversing the tree for a predicate each constituent is analyzed in order to determine whether it plays any role with respect to that predicate
- The judgment is made by first characterizing the constituent as a set of features with respect to the predicate
- A classifier trained on an appropriate training set is then passed this feature set and makes the appropriate assignment.

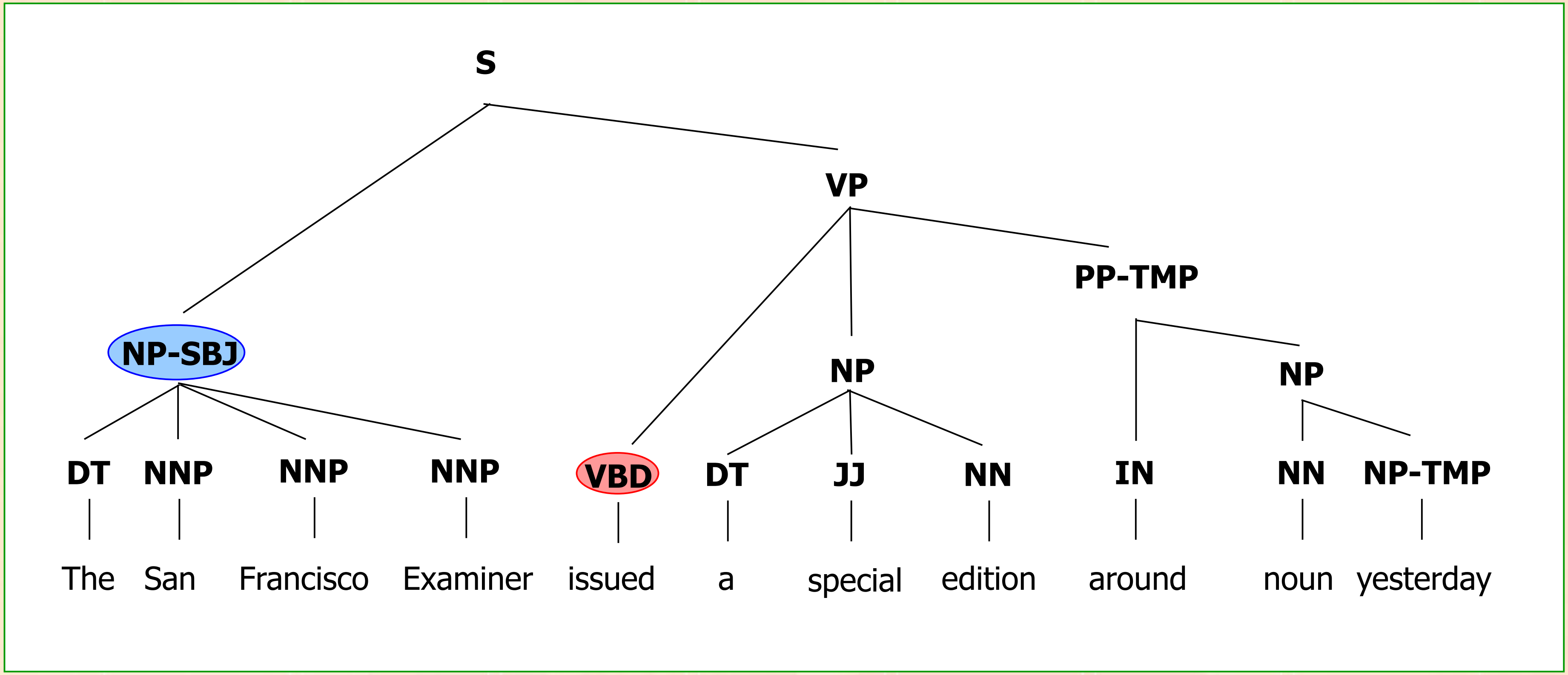
Features: Governing Predicate



In our example, the verb issued

- For PropBank the predicates are always verbs; FrameNet also has noun and adjective predicates.
- The predicate is a crucial feature since both PropBank and FrameNet labels are defined only with respect to a particular predicate
- Derived feature: predicate lemma

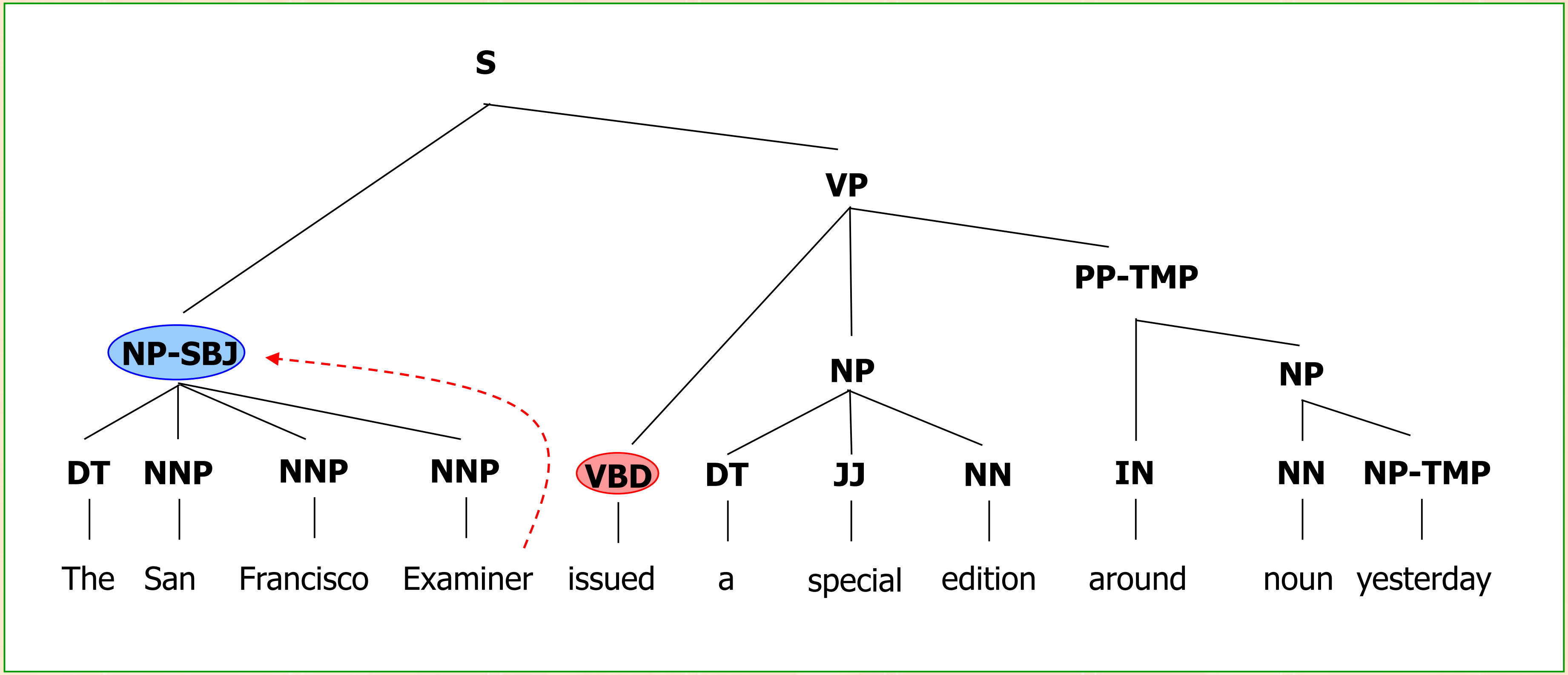
Features: Phrase Type



In our example, the phrase type of the constituent is NP (or NP-SBJ)

- It is the name of the parse node which dominates this constituent in the parse tree
- Different roles tend to be realized by different syntactic categories. Some semantic roles tend to appear as NPs, others as S or PP, etc.

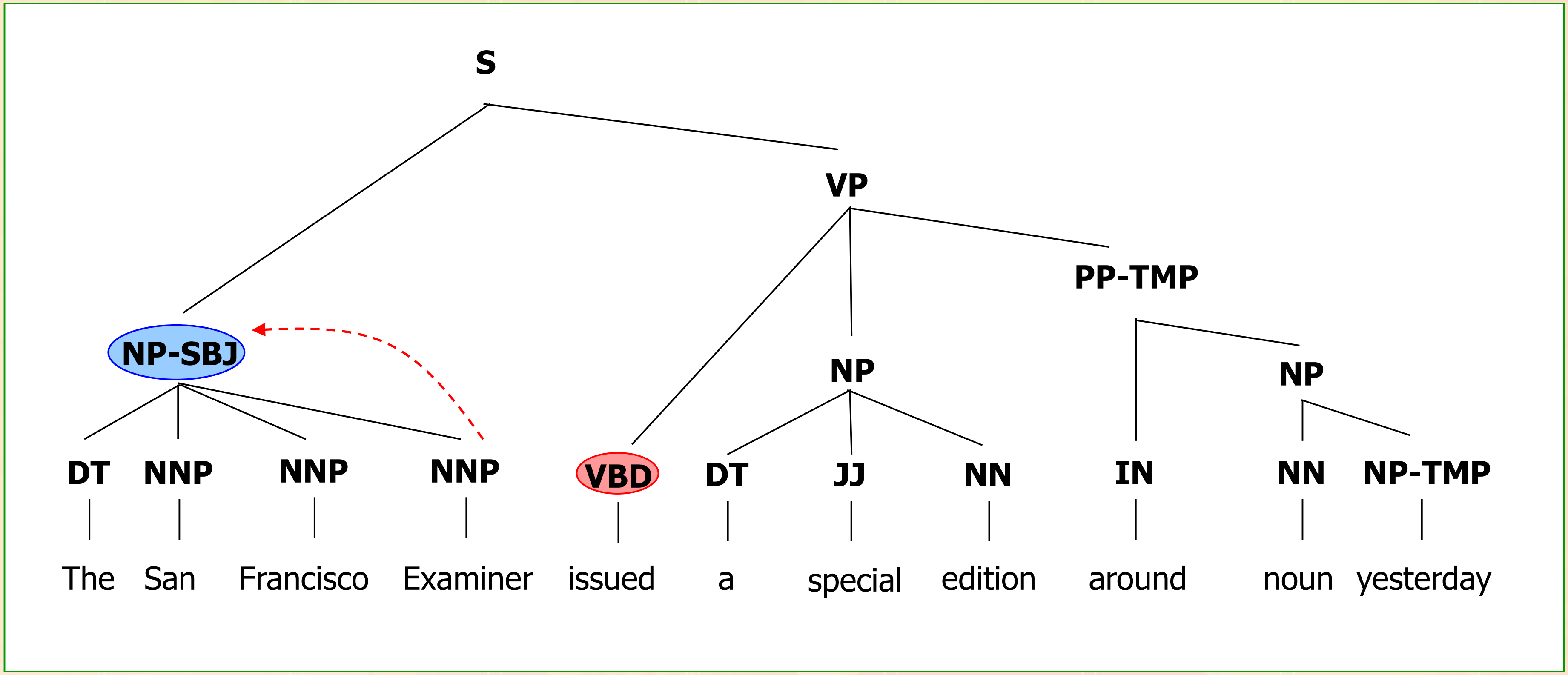
Features: Head Word



In our example, the head word of the constituent is Examiner

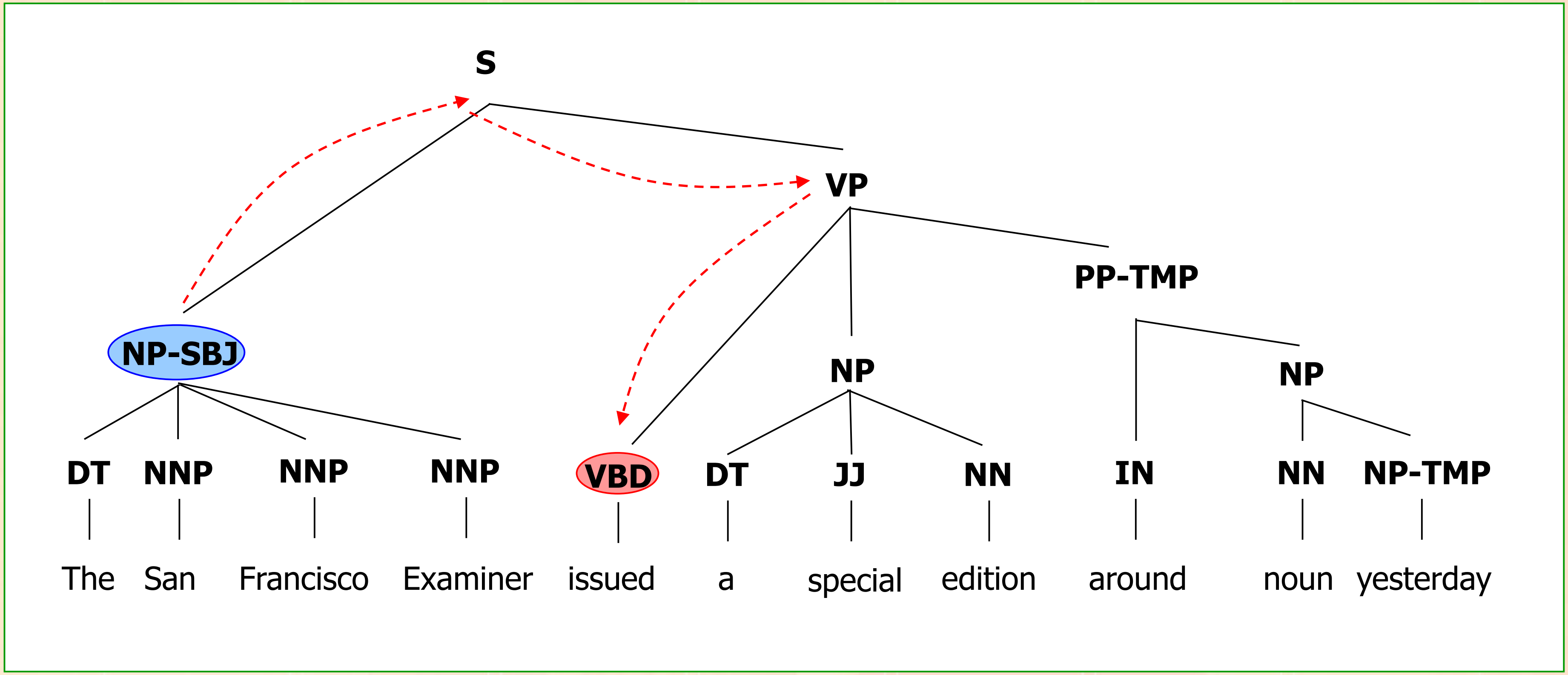
- Each head word if a constituent can be computed using standard head rules.
- Certain head words (e.g. pronouns) place strong constraints on the possible semantic roles they are likely to fill.

Features: Head Word Part of Speech



- In our example, NNP

Features: Parse Tree Path



- ➢ Is the path in the parse tree from constituent to the predicate
- ❑ It describes the syntactic relation between the constituent in the question and the target

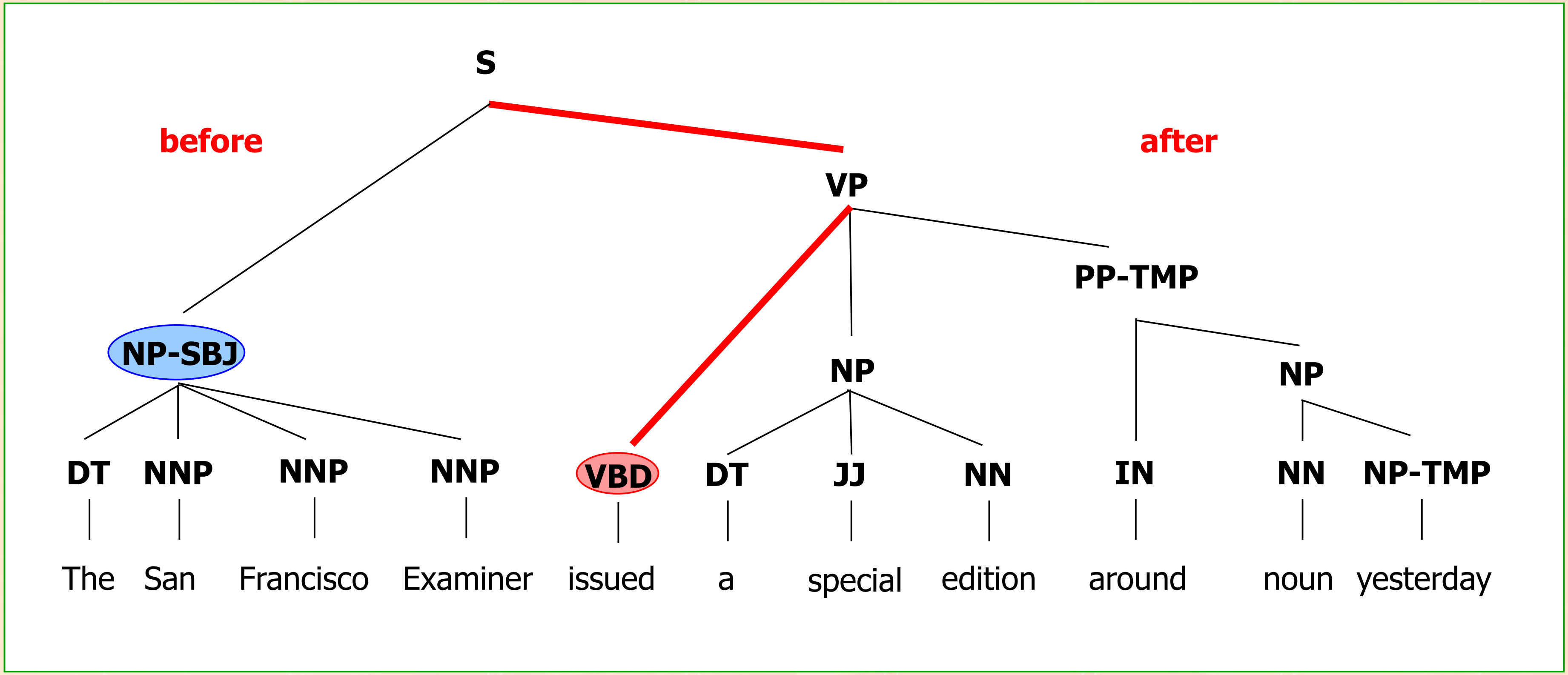
In our example, it is marked by the red dotted line

- Simple linear representation: NP↑S↓VP ↓VBD where ↑ and ↓ represent upward and downward movement in the tree respectively

Most Frequent Values of the Parse Tree Path Feature

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	

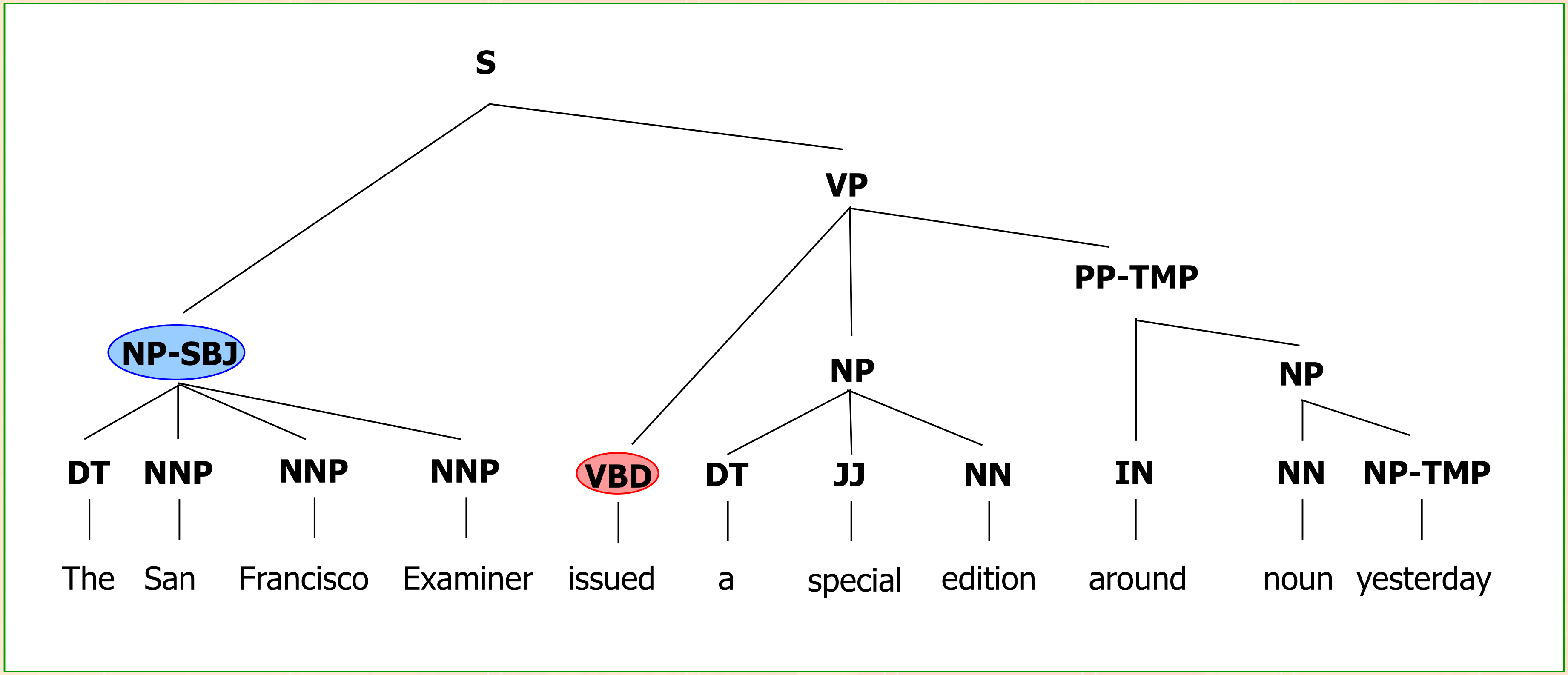
Features: Position



- Binary linear position of the constituent with respect to the predicate

In our case, the value is before

Features: Voice

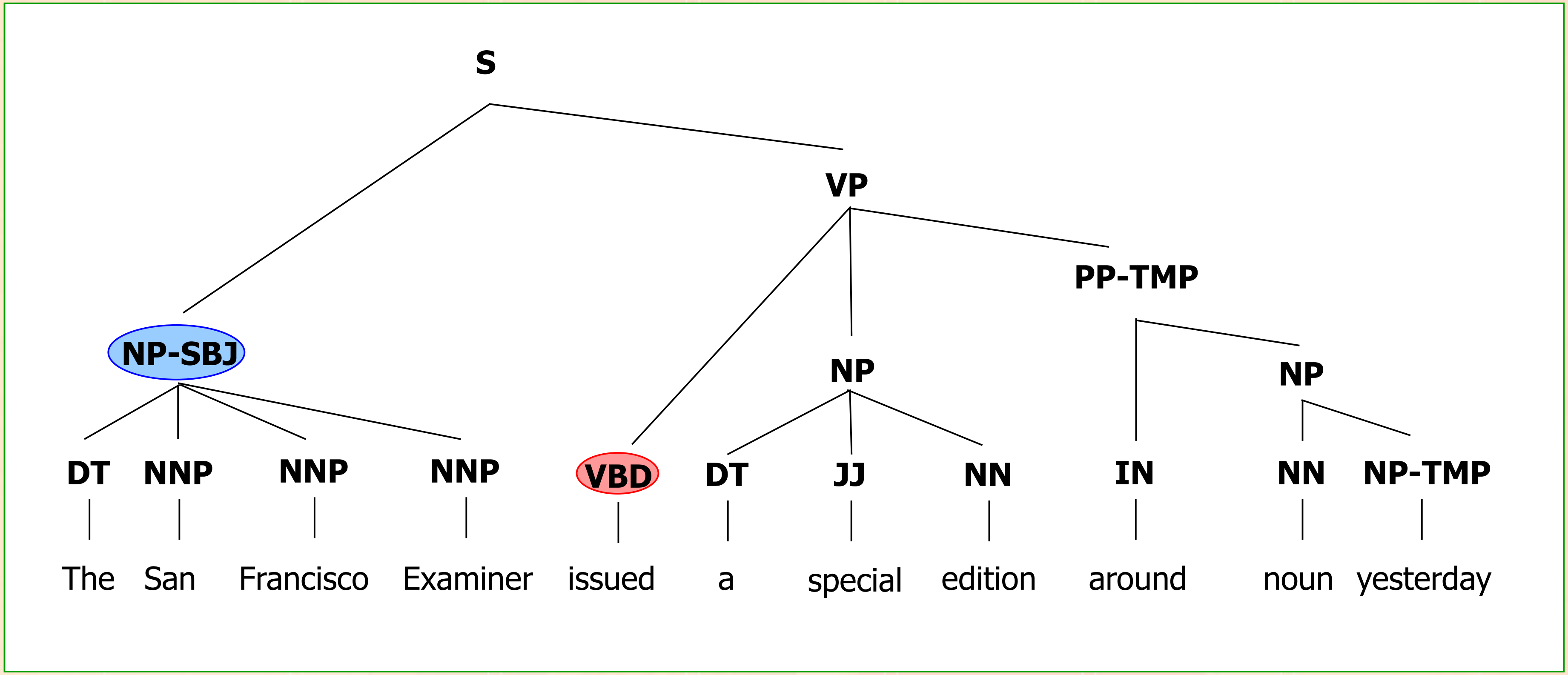


- ❑ Binary feature indicating whether the voice of the clause in which the constituent appears is active or passive.

In our case, the value is active

- ➢ Direct objects of active verbs often correspond in semantic role to subjects of passive verbs

Features: Sub-Categorization



- ❑ The set of expected arguments that appear in the verb phrase

In our case, the value is VP → NP PP

- Can be extracted by using the phrase structure rule that expands the immediate parent of the predicate

Extended Feature Set

- CONTENT WORD (cw): lexicalized feature that selects an informative word from the constituent, other than the head.
- PART OF SPEECH OF CONTENT WORD (cPos): part of speech tag of the content word.
- PART OF SPEECH OF HEAD WORD (hPos): part of speech tag of the head word.
- NAMED ENTITY CLASS OF CONTENT WORD (cNE): the class of the named entity that includes the content word.
- BOOLEAN NAMED ENTITY FLAGS: set of features that indicate if a named entity is included at any position in the phrase:
  - neOrganization: set to true if an organization name is recognized in the phrase.
  - neLocation: set to true if a location name is recognized in the phrase.
  - nePerson: set to true if a person name is recognized in the phrase.
  - neMoney: set to true if a currency expression is recognized in the phrase.
  - nePercent: set to true if a percentage expression is recognized in the phrase.
  - neTime: set to true if a time of day expression is recognized in the phrase.
  - neDate: set to true if a date temporal expression is recognized in the phrase.

Extended Feature Set - 2

- PARSE TREE PATH WITH UNIQUE DELIMITER: remove the direction in the PATH
- PARTIAL PATH: uses only the path from the constituent to the lowest common ancestor of the predicate and the constituent
- FIRST WORD: first word covered by constituent
- FIRST POS: POS of first word covered by constituent
- LAST WORD: last word covered by constituent
- LAST POS: POS of last word covered by constituent
- LEFT CONSTITUENT: left sibling constituent label
- LEFT HEAD: left sibling head
- LEFT POS HEAD: left sibling POS of head word
- RIGHT CONSTITUENT: right sibling constituent label
- RIGHT HEAD: right sibling head
- RIGHT POS HEAD: right sibling POS of head word
- PP PREP: if constituent is labeled PP get first word in PP
- DISTANCE: distance in the parse tree from constituent to the target word

Semantic Role Labeling Methods

- Various Stochastic Models
- Supervised Machine Learning
  - Training set:
    - FrameNet
    - PropBank
    - NomBank
  - Algorithms: SVM, HMM, CRF, MaxEnt, etc.
- State of the art:
  - F-Score of about 85% in discovering and classifying semantic roles.

Resources

- FrameNet
  - http://framenet.icsi.berkeley.edu/
- PropBank
  - http://www.cs.rochester.edu/~gildea/PropBank/Sort/
  - http://verbs.colorado.edu/framesets/
- NomBank
  - http://nlp.cs.nyu.edu/meyers/NomBank.html

A Neural Algorithm for Semantic Role Labeling

- *A bi-LSTM approach to semantic role labeling. Most actual networks are much deeper than shown in this figure: 3 to 4 bi-LSTM layers (6 to 8 total LSTMs) are common. He et al. (2017)*
- *The input is a concatenation of an embedding for the input word and an embedding of a binary variable which is 1 for the predicate to 0 for all other words.*