CHAPTER

20 Semantic Role Labeling

Sometime between the 7th and 4th centuries BCE, the Indian grammarian Pāṇini[1] wrote a famous treatise on Sanskrit grammar, the Aṣṭādhyāyī ('8 books'), a treatise that has been called "one of the greatest monuments of human intelligence" (Bloomfield, 1933, 11). The work describes the linguistics of the Sanskrit language in the form of 3959 sutras, each very efficiently (since it had to be memorized!) expressing part of a formal rule system that brilliantly prefigured modern mechanisms of formal language theory (Penn and Kiparsky, 2012). One set of rules, relevant to our discussion in this chapter, describes the **kārakas**, semantic relationships between a verb and noun arguments, roles like *agent*, *instrument*, or *destination*. Pāṇini's work was the earliest we know of that tried to understand the linguistic realization of events and their participants. This task of understanding how participants relate to events—being able to answer the question "Who did what to whom" (and perhaps also "when and where")—is a central question of natural language understanding.

Let's move forward 2.5 millennia to the present and consider the very mundane goal of understanding text about a purchase of stock by XYZ Corporation. This purchasing event and its participants can be described by a wide variety of surface forms. The event can be described by a verb (*sold, bought*) or a noun (*purchase*), and XYZ Corp can be the syntactic subject (of *bought*), the indirect object (of *sold*), or in a genitive or noun compound relation (with the noun *purchase*) despite having notionally the same role in all of them:

- 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...

In this chapter we introduce a level of representation that captures the commonality between these sentences: there was a purchase event, the participants were XYZ Corp and some stock, and XYZ Corp was the buyer. These shallow semantic representations , **semantic roles**, express the role that arguments of a predicate take in the event, codified in databases like PropBank and FrameNet. We'll introduce **semantic role labeling**, the task of assigning roles to spans in sentences, and **selectional restrictions**, the preferences that predicates express about their arguments, such as the fact that the theme of *eat* is generally something edible.

[1] Figure shows a birch bark manuscript from Kashmir of the Rupavatra, a grammatical textbook based on the Sanskrit grammar of Panini. Image from the Wellcome Collection.

20.1 Semantic Roles

Consider how in Chapter 16 we represented the meaning of arguments for sentences like these:

(20.1) Sasha broke the window.

(20.2) Pat opened the door.

A neo-Davidsonian event representation of these two sentences would be

$$\begin{aligned}&\exists e,x,y\ Breaking(e) \wedge Breaker(e,Sasha)\\&\qquad \wedge BrokenThing(e,y) \wedge Window(y)\\&\exists e,x,y\ Opening(e) \wedge Opener(e,Pat)\\&\qquad \wedge OpenedThing(e,y) \wedge Door(y)\end{aligned}$$

In this representation, the roles of the subjects of the verbs *break* and *open* are *Breaker* and *Opener* respectively. These **deep roles** are specific to each event; *Breaking* events have *Breakers*, *Opening* events have *Openers*, and so on.

deep roles

If we are going to be able to answer questions, perform inferences, or do any further kinds of natural language understanding of these events, we'll need to know a little more about the semantics of these arguments. *Breakers* and *Openers* have something in common. They are both volitional actors, often animate, and they have direct causal responsibility for their events.

thematic roles

agents

Thematic roles are a way to capture this semantic commonality between *Breakers* and *Eaters*. We say that the subjects of both these verbs are **agents**. Thus, AGENT is the thematic role that represents an abstract idea such as volitional causation. Similarly, the direct objects of both these verbs, the *BrokenThing* and *OpenedThing*, are both prototypically inanimate objects that are affected in some way by the action. The semantic role for these participants is **theme**.

theme

Thematic Role	Definition
AGENT	The volitional causer of an event
EXPERIENCER	The experiencer of an event
FORCE	The non-volitional causer of the event
THEME	The participant most directly affected by an event
RESULT	The end product of an event
CONTENT	The proposition or content of a propositional event
INSTRUMENT	An instrument used in an event
BENEFICIARY	The beneficiary of an event
SOURCE	The origin of the object of a transfer event
GOAL	The destination of an object of a transfer event

Figure 20.1 Some commonly used thematic roles with their definitions.

Although thematic roles are one of the oldest linguistic models, as we saw above, their modern formulation is due to Fillmore (1968) and Gruber (1965). Although there is no universally agreed-upon set of roles, Figs. 20.1 and 20.2 list some thematic roles that have been used in various computational papers, together with rough definitions and examples. Most thematic role sets have about a dozen roles, but we'll see sets with smaller numbers of roles with even more abstract meanings, and sets with very large numbers of roles that are specific to situations. We'll use the general term **semantic roles** for all sets of roles, whether small or large.

semantic roles

Thematic Role	Example
AGENT	*The waiter* spilled the soup.
EXPERIENCER	*John* has a headache.
FORCE	*The wind* blows debris from the mall into our yards.
THEME	Only after Benjamin Franklin broke *the ice*...
RESULT	The city built a *regulation-size baseball diamond*...
CONTENT	Mona asked *"You met Mary Ann at a supermarket?"*
INSTRUMENT	He poached catfish, stunning them *with a shocking device*...
BENEFICIARY	Whenever Ann Callahan makes hotel reservations *for her boss*...
SOURCE	I flew in *from Boston*.
GOAL	I drove *to Portland*.

Figure 20.2 Some prototypical examples of various thematic roles.

20.2 Diathesis Alternations

The main reason computational systems use semantic roles is to act as a shallow meaning representation that can let us make simple inferences that aren't possible from the pure surface string of words, or even from the parse tree. To extend the earlier examples, if a document says that *Company A acquired Company B*, we'd like to know that this answers the query *Was Company B acquired?* despite the fact that the two sentences have very different surface syntax. Similarly, this shallow semantics might act as a useful intermediate language in machine translation.

Semantic roles thus help generalize over different surface realizations of predicate arguments. For example, while the AGENT is often realized as the subject of the sentence, in other cases the THEME can be the subject. Consider these possible realizations of the thematic arguments of the verb *break*:

(20.3) *John* *broke the window.*
AGENT THEME

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

(20.5) *The rock* *broke the window.*
INSTRUMENT THEME

(20.6) *The window broke.*
THEME

(20.7) *The window was broken by John.*
THEME AGENT

These examples suggest that *break* has (at least) the possible arguments AGENT, THEME, and INSTRUMENT. The set of thematic role arguments taken by a verb is often called the **thematic grid**, θ-grid, or **case frame**. We can see that there are (among others) the following possibilities for the realization of these arguments of *break*:

thematic grid

case frame

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

It turns out that many verbs allow their thematic roles to be realized in various syntactic positions. For example, verbs like *give* can realize the THEME and GOAL arguments in two different ways:

(20.8) a. *Doris* *gave* *the book* *to Cary.*
AGENT THEME GOAL
b. *Doris* *gave* *Cary* *the book.*
AGENT GOAL THEME

verb alternation
dative alternation

These multiple argument structure realizations (the fact that *break* can take AGENT, INSTRUMENT, or THEME as subject, and *give* can realize its THEME and GOAL in either order) are called **verb alternations** or **diathesis alternations**. The alternation we showed above for *give*, the **dative alternation**, seems to occur with particular semantic classes of verbs, including "verbs of future having" (*advance*, *allocate*, *offer*, *owe*), "send verbs" (*forward*, *hand*, *mail*), "verbs of throwing" (*kick*, *pass*, *throw*), and so on. Levin (1993) lists for 3100 English verbs the semantic classes to which they belong (47 high-level classes, divided into 193 more specific classes) and the various alternations in which they participate. These lists of verb classes have been incorporated into the online resource VerbNet (Kipper et al., 2000), which links each verb to both WordNet and FrameNet entries.

20.3 Semantic Roles: Problems with Thematic Roles

Representing meaning at the thematic role level seems like it should be useful in dealing with complications like diathesis alternations. Yet it has proved quite difficult to come up with a standard set of roles, and equally difficult to produce a formal definition of roles like AGENT, THEME, or INSTRUMENT.

For example, researchers attempting to define role sets often find they need to fragment a role like AGENT or THEME into many specific roles. Levin and Rappaport Hovav (2005) summarize a number of such cases, such as the fact there seem to be at least two kinds of INSTRUMENTS, *intermediary* instruments that can appear as subjects and *enabling* instruments that cannot:

(20.9) a. The cook opened the jar with the new gadget.
b. The new gadget opened the jar.

(20.10) a. Shelly ate the sliced banana with a fork.
b. *The fork ate the sliced banana.

In addition to the fragmentation problem, there are cases in which we'd like to reason about and generalize across semantic roles, but the finite discrete lists of roles don't let us do this.

Finally, it has proved difficult to formally define the thematic roles. Consider the AGENT role; most cases of AGENTS are animate, volitional, sentient, causal, but any individual noun phrase might not exhibit all of these properties.

semantic role

These problems have led to alternative **semantic role** models that use either many fewer or many more roles.

proto-agent
proto-patient

The first of these options is to define **generalized semantic roles** that abstract over the specific thematic roles. For example, PROTO-AGENT and PROTO-PATIENT are generalized roles that express roughly agent-like and roughly patient-like meanings. These roles are defined, not by necessary and sufficient conditions, but rather by a set of heuristic features that accompany more agent-like or more patient-like meanings. Thus, the more an argument displays agent-like properties (being volitionally involved in the event, causing an event or a change of state in another participant, being sentient or intentionally involved, moving) the greater the likelihood that the argument can be labeled a PROTO-AGENT. The more patient-like the properties (undergoing change of state, causally affected by another participant, stationary relative to other participants, etc.), the greater the likelihood that the argument can be labeled a PROTO-PATIENT.

The second direction is instead to define semantic roles that are specific to a particular verb or a particular group of semantically related verbs or nouns.

In the next two sections we describe two commonly used lexical resources that make use of these alternative versions of semantic roles. **PropBank** uses both proto-roles and verb-specific semantic roles. **FrameNet** uses semantic roles that are specific to a general semantic idea called a *frame*.

20.4 The Proposition Bank

PropBank

The **Proposition Bank**, generally referred to as **PropBank**, is a resource of sentences annotated with semantic roles. The English PropBank labels all the sentences in the Penn TreeBank; the Chinese PropBank labels sentences in the Penn Chinese TreeBank. Because of the difficulty of defining a universal set of thematic roles, the semantic roles in PropBank are defined with respect to an individual verb sense. Each sense of each verb thus has a specific set of roles, which are given only numbers rather than names: **Arg0**, **Arg1**, **Arg2**, and so on. In general, **Arg0** represents the PROTO-AGENT, and **Arg1**, the PROTO-PATIENT. The semantics of the other roles are less consistent, often being defined specifically for each verb. Nonetheless there are some generalization; the **Arg2** is often the benefactive, instrument, attribute, or end state, the **Arg3** the start point, benefactive, instrument, or attribute, and the **Arg4** the end point.

Here are some slightly simplified PropBank entries for one sense each of the verbs *agree* and *fall*. Such PropBank entries are called **frame files**; note that the definitions in the frame file for each role (“Other entity agreeing”, “Extent, amount fallen”) are informal glosses intended to be read by humans, rather than being formal definitions.

(20.11) **agree.01**
Arg0: Agreer
Arg1: Proposition
Arg2: Other entity agreeing

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

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

Note that there is no Arg0 role for *fall*, because the normal subject of *fall* is a PROTO-PATIENT.

The PropBank semantic roles can be useful in recovering shallow semantic information about verbal arguments. Consider the verb *increase*:

(20.13) **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

A PropBank semantic role labeling would allow us to infer the commonality in the event structures of the following three examples, that is, that in each case *Big Fruit Co.* is the AGENT and *the price of bananas* is the THEME, despite the differing surface forms.

(20.14) [$_{\text{Arg0}}$ Big Fruit Co.] increased [$_{\text{Arg1}}$ the price of bananas].
(20.15) [$_{\text{Arg1}}$ The price of bananas] was increased again [$_{\text{Arg0}}$ by Big Fruit Co.]
(20.16) [$_{\text{Arg1}}$ The price of bananas] increased [$_{\text{Arg2}}$ 5%].

PropBank also has a number of non-numbered arguments called **ArgMs**, (ArgM-TMP, ArgM-LOC, etc.) which represent modification or adjunct meanings. These are relatively stable across predicates, so aren’t listed with each frame file. Data labeled with these modifiers can be helpful in training systems to detect temporal, location, or directional modification across predicates. Some of the ArgM’s include:

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

NomBank

While PropBank focuses on verbs, a related project, **NomBank** (Meyers et al., 2004) adds annotations to noun predicates. For example the noun *agreement* in *Apple’s agreement with IBM* would be labeled with Apple as the Arg0 and IBM as the Arg2. This allows semantic role labelers to assign labels to arguments of both verbal and nominal predicates.

20.5 FrameNet

While making inferences about the semantic commonalities across different sentences with *increase* is useful, it would be even more useful if we could make such inferences in many more situations, across different verbs, and also between verbs and nouns. For example, we’d like to extract the similarity among these three sentences:

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

Note that the second example uses the different verb *rise*, and the third example uses the noun rather than the verb *rise*. We’d like a system to recognize that *the* *price of bananas* is what went up, and that *5%* is the amount it went up, no matter whether the *5%* appears as the object of the verb *increased* or as a nominal modifier of the noun *rise*.

FrameNet

The **FrameNet** project is another semantic-role-labeling project that attempts to address just these kinds of problems (Baker et al. 1998, Fillmore et al. 2003, Fillmore and Baker 2009, Ruppenhofer et al. 2016). Whereas roles in the PropBank project are specific to an individual verb, roles in the FrameNet project are specific to a **frame**.

What is a frame? Consider the following set of words:

> *reservation, flight, travel, buy, price, cost, fare, rates, meal, plane*

There are many individual lexical relations of hyponymy, synonymy, and so on between many of the words in this list. The resulting set of relations does not, however, add up to a complete account of how these words are related. They are clearly all defined with respect to a coherent chunk of common-sense background information concerning air travel.

frame **model** **script**

We call the holistic background knowledge that unites these words a **frame** (Fillmore, 1985). The idea that groups of words are defined with respect to some background information is widespread in artificial intelligence and cognitive science, where besides **frame** we see related works like a **model** (Johnson-Laird, 1983), or even **script** (Schank and Abelson, 1977).

frame elements

A frame in FrameNet is a background knowledge structure that defines a set of frame-specific semantic roles, called **frame elements**, and includes a set of predicates that use these roles. Each word evokes a frame and profiles some aspect of the frame and its elements. The FrameNet dataset includes a set of frames and frame elements, the lexical units associated with each frame, and a set of labeled example sentences. For example, the **change_position_on_a_scale** frame is defined as follows:

> 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).

core roles **non-core roles**

Some of the semantic roles (frame elements) in the frame are defined as in Fig. 20.3. Note that these are separated into **core roles**, which are frame specific, and **non-core roles**, which are more like the Arg-M arguments in PropBank, expressing more general properties of time, location, and so on.

Here are some example sentences:

(20.20) [$_{\text{ITEM}}$ Oil] *rose* [$_{\text{ATTRIBUTE}}$ in price] [$_{\text{DIFFERENCE}}$ by 2%].

(20.21) [$_{\text{ITEM}}$ It] has *increased* [$_{\text{FINAL\_STATE}}$ to having them 1 day a month].

(20.22) [$_{\text{ITEM}}$ Microsoft shares] *fell* [$_{\text{FINAL\_VALUE}}$ to 7 5/8].

(20.23) [$_{\text{ITEM}}$ Colon cancer incidence] *fell* [$_{\text{DIFFERENCE}}$ by 50%] [$_{\text{GROUP}}$ among men].

(20.24) a steady *increase* [$_{\text{INITIAL\_VALUE}}$ from 9.5] [$_{\text{FINAL\_VALUE}}$ to 14.3] [$_{\text{ITEM}}$ in dividends]

(20.25) a [$_{\text{DIFFERENCE}}$ 5%] [$_{\text{ITEM}}$ dividend] *increase...*

Note from these example sentences that the frame includes target words like *rise*, *fall*, and *increase*. In fact, the complete frame consists of the following words:

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.

Figure 20.3 The frame elements in the **change_position_on_a_scale** frame from the FrameNet Labelers Guide (Ruppenhofer et al., 2016).

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	

FrameNet also codes relationships between frames, allowing frames to inherit from each other, or representing relations between frames like causation (and generalizations among frame elements in different frames can be representing by inheritance as well). Thus, there is a **Cause_change_of_position_on_a_scale** frame that is linked to the **Change_of_position_on_a_scale** frame by the **cause** relation, but that adds an AGENT role and is used for causative examples such as the following:

(20.26) [$_{\text{AGENT}}$ They] *raised* [$_{\text{ITEM}}$ the price of their soda] [$_{\text{DIFFERENCE}}$ by 2%].

Together, these two frames would allow an understanding system to extract the common event semantics of all the verbal and nominal causative and non-causative usages.

FrameNets have also been developed for many other languages including Spanish, German, Japanese, Portuguese, Italian, and Chinese.

20.6 Semantic Role Labeling

semantic role labeling

Semantic role labeling (sometimes shortened as **SRL**) is the task of automatically finding the **semantic roles** of each argument of each predicate in a sentence. Current approaches to semantic role labeling are based on supervised machine learning, often using the FrameNet and PropBank resources to specify what counts as a predicate, define the set of roles used in the task, and provide training and test sets.

Recall that the difference between these two models of semantic roles is that FrameNet (20.27) employs many frame-specific frame elements as roles, while PropBank (20.28) uses a smaller number of numbered argument labels that can be interpreted as verb-specific labels, along with the more general ARGM labels. Some examples:

(20.27)	[You]	can't	[blame]	[the program]	[for being unable to identify it]
	COGNIZER		TARGET	EVALUEE	REASON

(20.28)	[The San Francisco Examiner]	issued	[a special edition]	[yesterday]
	ARG0	TARGET	ARG1	ARGM-TMP

20.6.1 A Feature-based Algorithm for Semantic Role Labeling

A simplified feature-based semantic role labeling algorithm is sketched in Fig. 20.4. Feature-based algorithms—from the very earliest systems like (Simmons, 1973)—begin by parsing, using broad-coverage parsers to assign a parse to the input string. Figure 20.5 shows a parse of (20.28) above. The parse is then traversed to find all words that are predicates.

For each of these predicates, the algorithm examines each node in the parse tree and uses supervised classification to decide the semantic role (if any) it plays for this predicate. Given a labeled training set such as PropBank or FrameNet, a feature vector is extracted for each node, using feature templates described in the next subsection. A 1-of-N classifier is then trained to predict a semantic role for each constituent given these features, where N is the number of potential semantic roles plus an extra NONE role for non-role constituents. Any standard classification algorithms can be used. Finally, for each test sentence to be labeled, the classifier is run on each relevant constituent.

```
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)
```

Figure 20.4 A generic semantic-role-labeling algorithm. CLASSIFYNODE is a 1-of-*N* classifier that assigns a semantic role (or NONE for non-role constituents), trained on labeled data such as FrameNet or PropBank.

Instead of training a single-stage classifier as in Fig. 20.5, the node-level classification task can be broken down into multiple steps:

1. **Pruning:** Since only a small number of the constituents in a sentence are arguments of any given predicate, many systems 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

The separation of identification and classification may lead to better use of features (different features may be useful for the two tasks) or to computational efficiency.

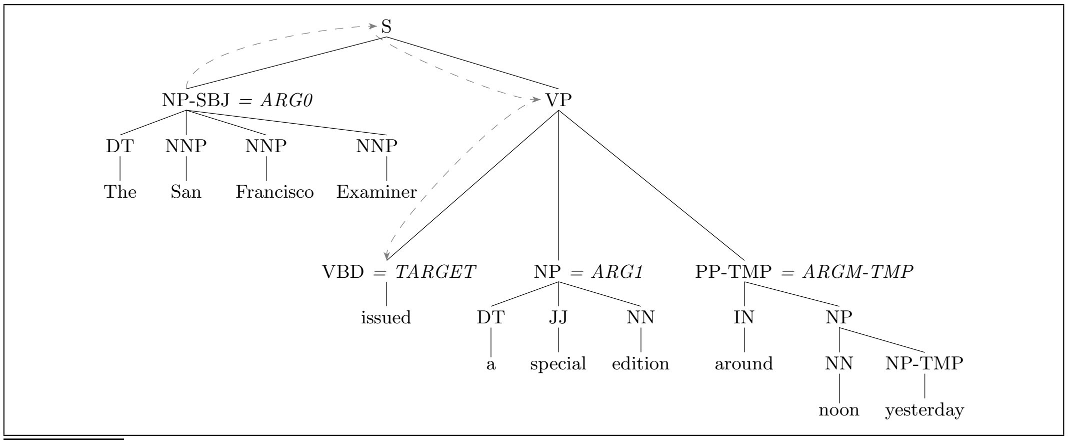

Figure 20.5 Parse tree for a PropBank sentence, showing the PropBank argument labels. The dotted line shows the **path** feature NP↑S↓VP↓VBD for ARG0, the NP-SBJ constituent *The San Francisco Examiner.*

Global Optimization

The classification algorithm of Fig. 20.5 classifies each argument separately ('locally'), making the simplifying assumption that each argument of a predicate can be labeled independently. This assumption is false; there are interactions between arguments that require a more 'global' assignment of labels to constituents. For example, constituents in FrameNet and PropBank are required to be non-overlapping. More significantly, the semantic roles of constituents are not independent. For example PropBank does not allow multiple identical arguments; two constituents of the same verb cannot both be labeled ARG0 .

Role labeling systems thus often add a fourth step to deal with global consistency across the labels in a sentence. For example, the local classifiers can return a list of possible labels associated with probabilities for each constituent, and a second-pass Viterbi decoding or re-ranking approach can be used to choose the best consensus label. Integer linear programming (ILP) is another common way to choose a solution that conforms best to multiple constraints.

Features for Semantic Role Labeling

Most systems use some generalization of the core set of features introduced by Gildea and Jurafsky (2000). Common basic features templates (demonstrated on the *NP-SBJ* constituent *The San Francisco Examiner* in Fig. 20.5) include:

- The governing **predicate**, in this case the verb *issued*. The predicate is a crucial feature since labels are defined only with respect to a particular predicate.
- The **phrase type** of the constituent, in this case, *NP* (or *NP-SBJ*). Some semantic roles tend to appear as *NP*s, others as *S* or *PP*, and so on.
- The **headword** of the constituent, *Examiner*. The headword of a constituent can be computed with standard head rules, such as those given in Chapter 12 in Fig. **??**. Certain headwords (e.g., pronouns) place strong constraints on the possible semantic roles they are likely to fill.
- The **headword part of speech** of the constituent, *NNP*.
- The **path** in the parse tree from the constituent to the predicate. This path is marked by the dotted line in Fig. 20.5. Following Gildea and Jurafsky (2000), we can use a simple linear representation of the path, NP↑S↓VP↓VBD. ↑ and ↓ represent upward and downward movement in the tree, respectively. The

path is very useful as a compact representation of many kinds of grammatical function relationships between the constituent and the predicate.

- The **voice** of the clause in which the constituent appears, in this case, **active** (as contrasted with **passive**). Passive sentences tend to have strongly different linkings of semantic roles to surface form than do active ones.
- The binary **linear position** of the constituent with respect to the predicate, either **before** or **after**.
- The **subcategorization** of the predicate, the set of expected arguments that appear in the verb phrase. We can extract this information by using the phrase-structure rule that expands the immediate parent of the predicate; VP $\rightarrow$ VBD NP PP for the predicate in Fig. 20.5.
- The named entity type of the constituent.
- The first words and the last word of the constituent.

The following feature vector thus represents the first NP in our example (recall that most observations will have the value NONE rather than, for example, ARG0, since most constituents in the parse tree will not bear a semantic role):

> ARG0: [issued, NP, Examiner, NNP, NP↑S↓VP↓VBD, active, before, VP $\rightarrow$ NP PP, ORG, The, Examiner]

Other features are often used in addition, such as sets of n-grams inside the constituent, or more complex versions of the path features (the upward or downward halves, or whether particular nodes occur in the path).

It's also possible to use dependency parses instead of constituency parses as the basis of features, for example using dependency parse paths instead of constituency paths.

20.6.2 A Neural Algorithm for Semantic Role Labeling

The standard neural algorithm for semantic role labeling is based on the bi-LSTM IOB tagger introduced in Chapter 9, which we've seen applied to part-of-speech tagging and named entity tagging, among other tasks. Recall that with IOB tagging, we have a begin and end tag for each possible role (B-ARG0, I-ARG0; B-ARG1, I-ARG1, and so on), plus an outside tag O.

As with all the taggers, the goal is to compute the highest probability tag sequence $\hat{y}$, given the input sequence of words w:

$$\hat{y} = \underset{y \in T}{\operatorname{argmax}} P(\mathbf{y}|\mathbf{w})$$

In algorithms like He et al. (2017), each input word is mapped to pre-trained embeddings, and also associated with an embedding for a flag (0/1) variable indicating whether that input word is the predicate. These concatenated embeddings are passed through multiple layers of bi-directional LSTM. State-of-the-art algorithms tend to be deeper than for POS or NER tagging, using 3 to 4 layers (6 to 8 total LSTMs). Highway layers can be used to connect these layers as well.

Output from the last bi-LSTM can then be turned into an IOB sequence as for POS or NER tagging. Tags can be locally optimized by taking the bi-LSTM output, passing it through a single layer into a softmax for each word that creates a probability distribution over all SRL tags and the most likely tag for word x_i is chosen as t_i, computing for each word essentially:

$$\hat{y}_i = \underset{t \in tags}{\operatorname{argmax}} P(t|w_i)$$