

Intro to SRL

Semantic Role Labeling

Wz -10/04/21



In 2002, Donald Trump, in partnership with NBC television, took control of the Miss Universe Organization, which produces the Miss Universe, Miss USA and Miss Teen USA contests.

What would be the main idea?

Who did what to whom (when and where)

In 2002, ^{Who} **Donald Trump**, in partnership
with NBC television, ^{Did what} **took control of the**
^{Whom} **Miss Universe Organization**, which
produces the Miss Universe, Miss USA
and Miss Teen USA contests.

Donald Trump took control of the MUO



Who

Did what

Whom

Argument/Agent

Predicate

Argument/Patient

Semantic role (abstract)



(Argument/Agent Predicate Argument/Patient)

In practice (AllenNLP)

<https://demo.allennlp.org/semantic-role-labeling>

In 2002, **Donald Trump**, in partnership with NBC television, **took** control of the **Miss Universe Organization**, which produces the Miss Universe, Miss USA and Miss Teen USA contests.

Frames for **took** :

In 2002

ARGM-TMP

Donald Trump

ARG0

in partnership with NBC television

ARGM-MNR

took

V

control of the Miss Universe Organization , which produces the Miss Universe , Miss USA and Miss Teen USA contests

ARG1

(Argument/Agent Predicate Argument/Patient)

In practice (AllenNLP)

In 2002, Donald Trump, in partnership with NBC television, took control of the **Miss Universe Organization**, which **produces** the **Miss Universe, Miss USA and Miss Teen USA contests**.

Frames for **produces** :

In 2002 , Donald Trump , in partnership with NBC television ,
took control of

the Miss Universe Organization

ARG0

which

R-ARG0

produces

V

the Miss Universe , Miss USA and Miss Teen USA contests .

ARG1

(Argument/Agent Predicate Argument/Patient)

In practice (AllenNLP)

Frames for **took** :

In 2002
ARGM-TMP


Donald Trump ,
ARG0

in partnership with NBC television ,
ARGM-MNR

took
V

control of the Miss Universe Organization , which produces
the Miss Universe , Miss USA and Miss Teen USA contests
ARG1

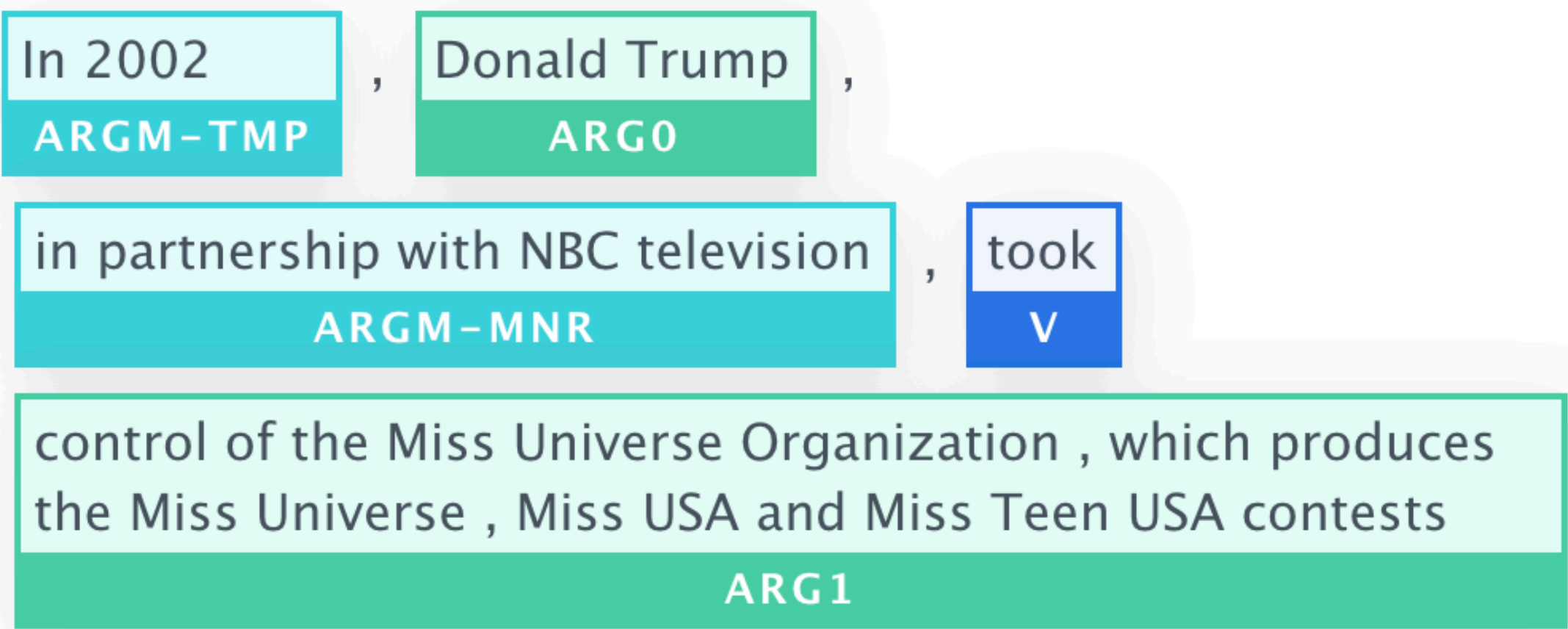
Ex1: [Arg1 Sales] *fell* [Arg4 to \$25 million] [Arg3 from \$27 million].
Ex2: [Arg1 The average junk bond] *fell* [Arg2 by 4.2%].

- Adopted from **PropBank**
- Arg0 : Agent
- Arg1 : Patient 
- Arg2 : Benefactive, instrument, attribute or end state
- Arg3 : start point, benefactive, instrument, or attribute
- Arg4 : the end point

(Argument/Agent Predicate Argument/Patient)

In practice (AllenNLP)

Frames for **took** :



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

- Ex1: [Arg1 Sales] *fell* [Arg4 to \$25 million] [Arg3 from \$27 million].
- Ex2: [Arg1 The average junk bond] *fell* [Arg2 by 4.2%].

Labeled datasets,
including PropBank, FrameNet,
or CoNLL05/09/11/12

Supervised Learning



Sentence1
Sentence2
Sentence3
Sentences
Sentences
Sentences
Sentences
Sentences
Sentences
Sentences
Sentences
Sentences
Sentences
Sentences
Sentences

Input

Sentence

Input

(Arg, v, Arg)
(Arg, v, Arg)
(Arg, v, Arg)
(Arg, v, Arg)
(Arg, v, Arg)
(Arg, v, Arg)
(Arg, v, Arg)
(Arg, v, Arg)
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(Arg, v, Arg)

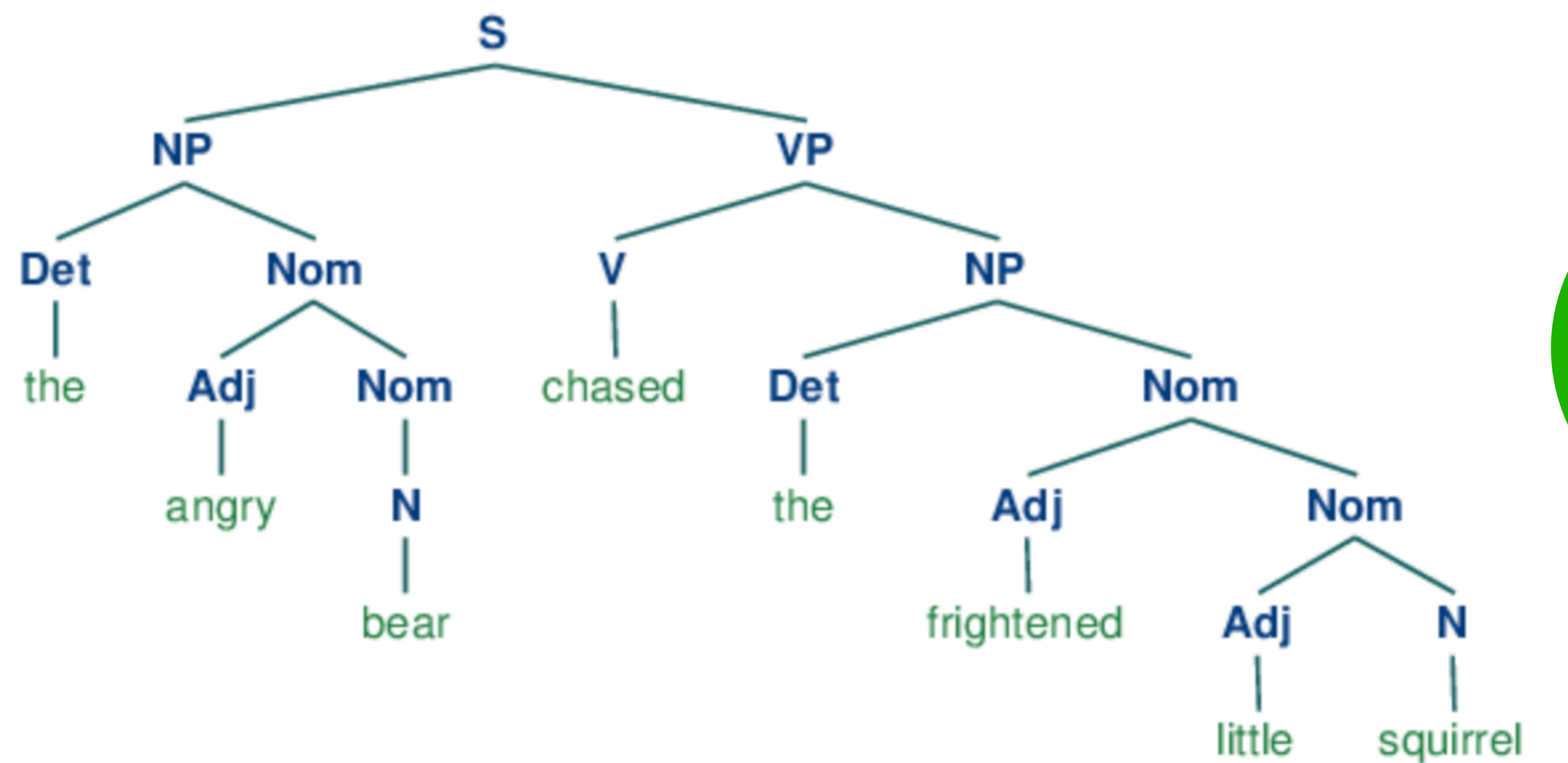
Applications

Question-answer system,
Information retrieval,
Machine translation,
Computational reasoning

....

Semantic role labeling

Parsing vs SRL



(Arg, v, Arg)

**The
angry
bear**

Chased

**The
frightened
little squirrel**

Semantic Role Labeling as Syntactic Dependency Parsing

By Tianze Shi, Igor Malioutov and Ozan Iroy

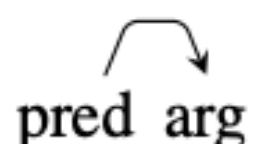
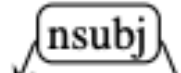

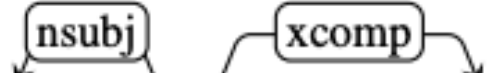
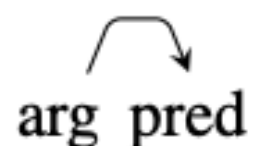
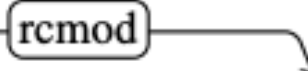
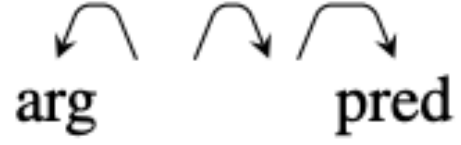
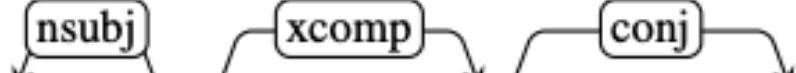
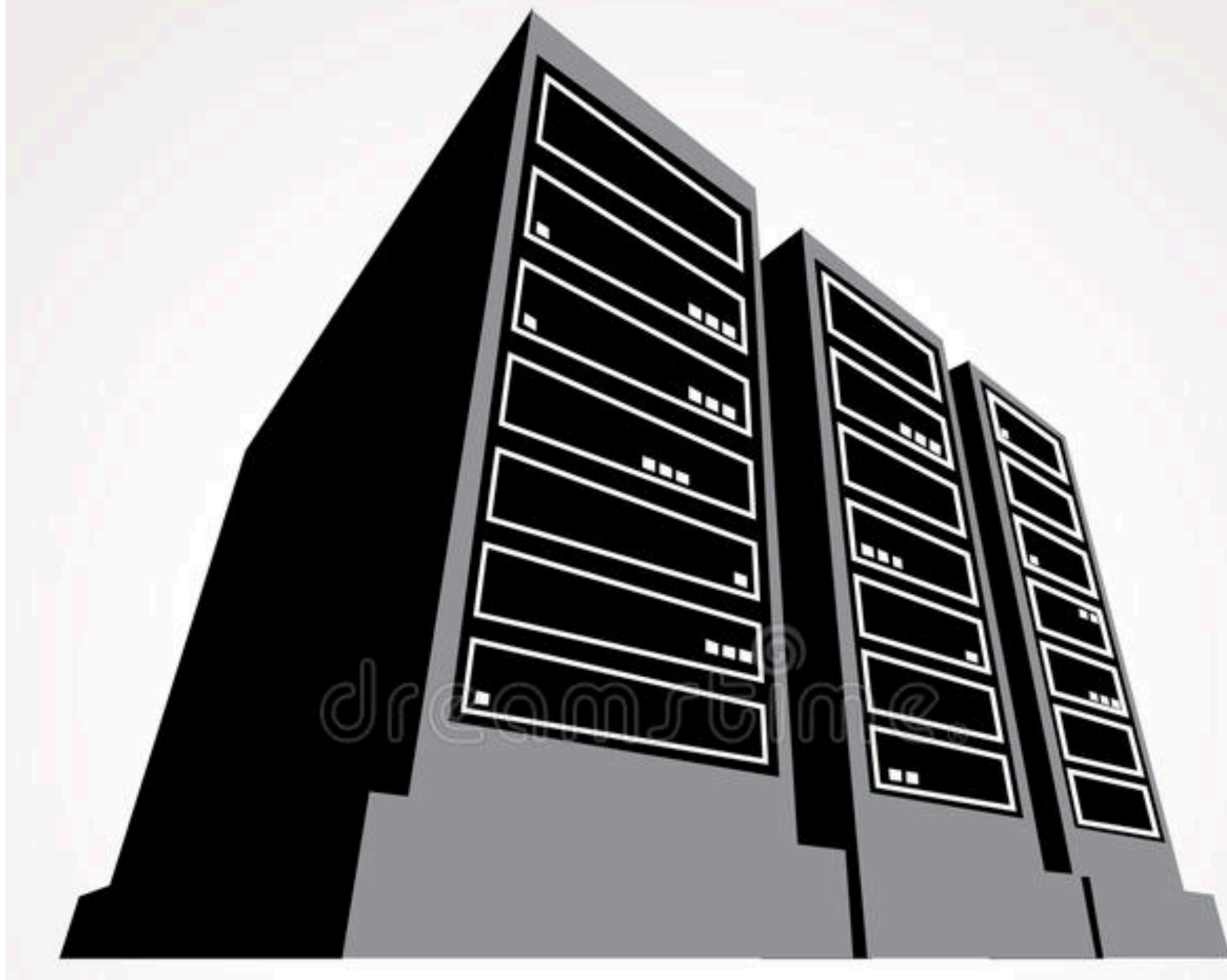
Pattern	Example	Percentage	
		English	Chinese
(D) 	 <i>She</i> <i>designed</i> the bridge ...	87.5%	82.7%
(C) 	 <i>She</i> wanted to <i>design</i> the bridge ...	6.1%	10.4%
(R) 	 The <i>bridge</i> , which is <i>designed</i> by her, ...	4.7%	5.7%
	 <i>She</i> wanted to design and <i>build</i> the bridge ...	1.1%	1.0%
Others		0.5%	0.2%

Table 1: The most common structural relations in the training data between the *predicates* (pred) and the *arguments* (arg). Appendix §C and §D include more examples as well as Chinese data.

Supervised Learning



1. Feature-based

2. Neural Algorithm

Feature-based

Standard structure - based on parsing

- 1. **Pruning**: 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 all the constituents that were labeled as arguments by the previous stage

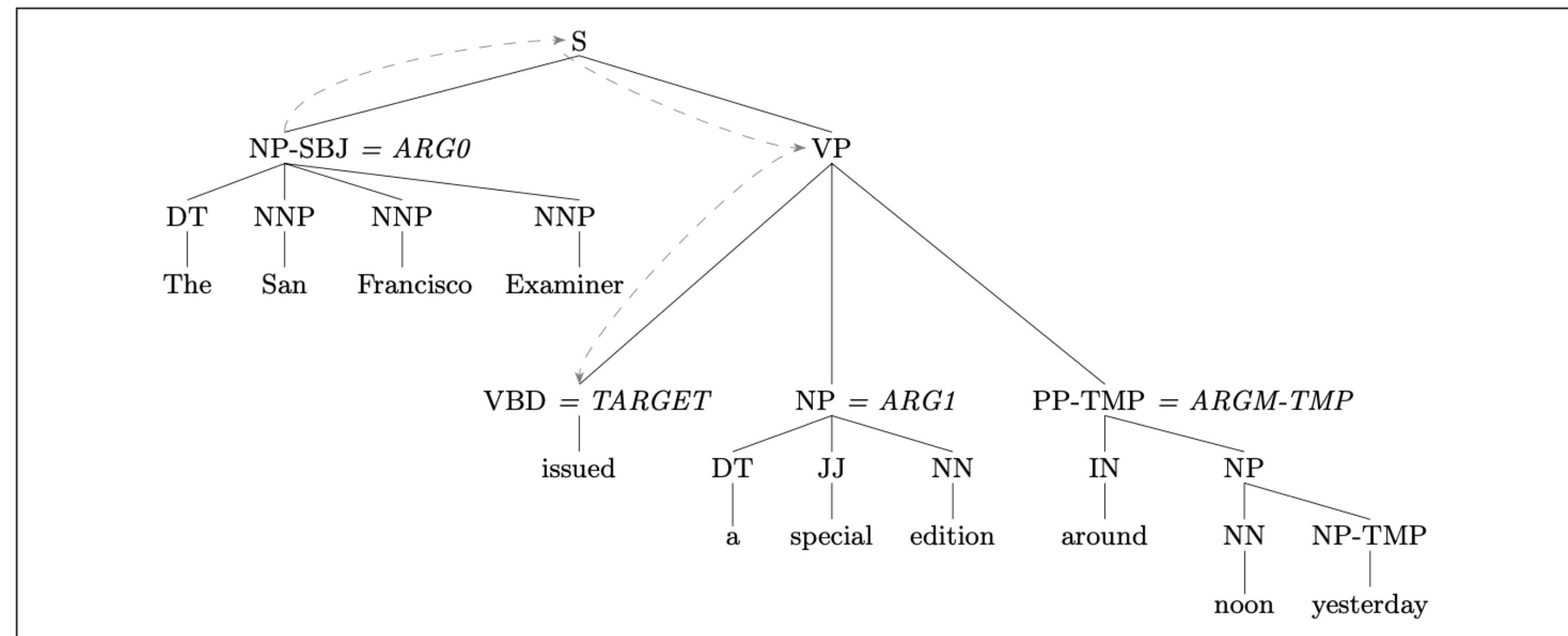


Figure 19.5 Parse tree for a PropBank sentence, showing the PropBank argument labels. The dotted line shows the **path** feature $\text{NP} \uparrow \text{S} \downarrow \text{VP} \downarrow \text{VBD}$ for ARG0, the NP-SBJ constituent *The San Francisco Examiner*.

Neural-based

Standard structure

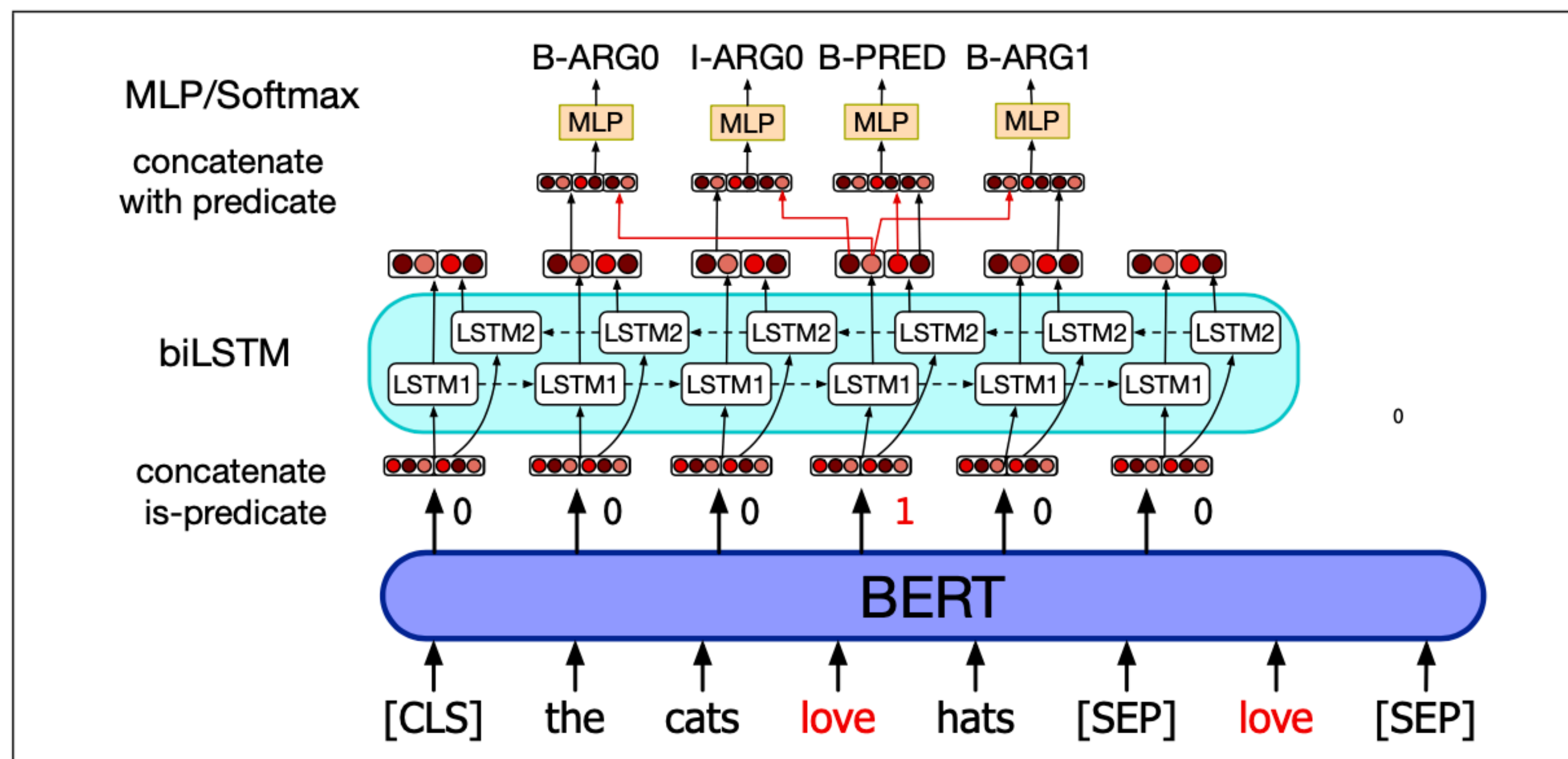


Figure 19.6 A BERT + biLSTM approach to semantic role labeling. The input sentence is followed by [SEP] and an extra input for the predicate, in this case *love*. The BERT outputs are concatenated to an indicator variable which is 1 for the predicate and 0 for all other words, passed through a biLSTM, and then the output embedding at each token position is concatenated with the embedding for the predicate, and passed through a single-layer MLP. After [Shi and Lin \(2019\)](#) and [He et al. \(2017\)](#).

Multilingual

X-SRL: A Parallel Cross-Lingual Semantic Role Labeling Dataset

