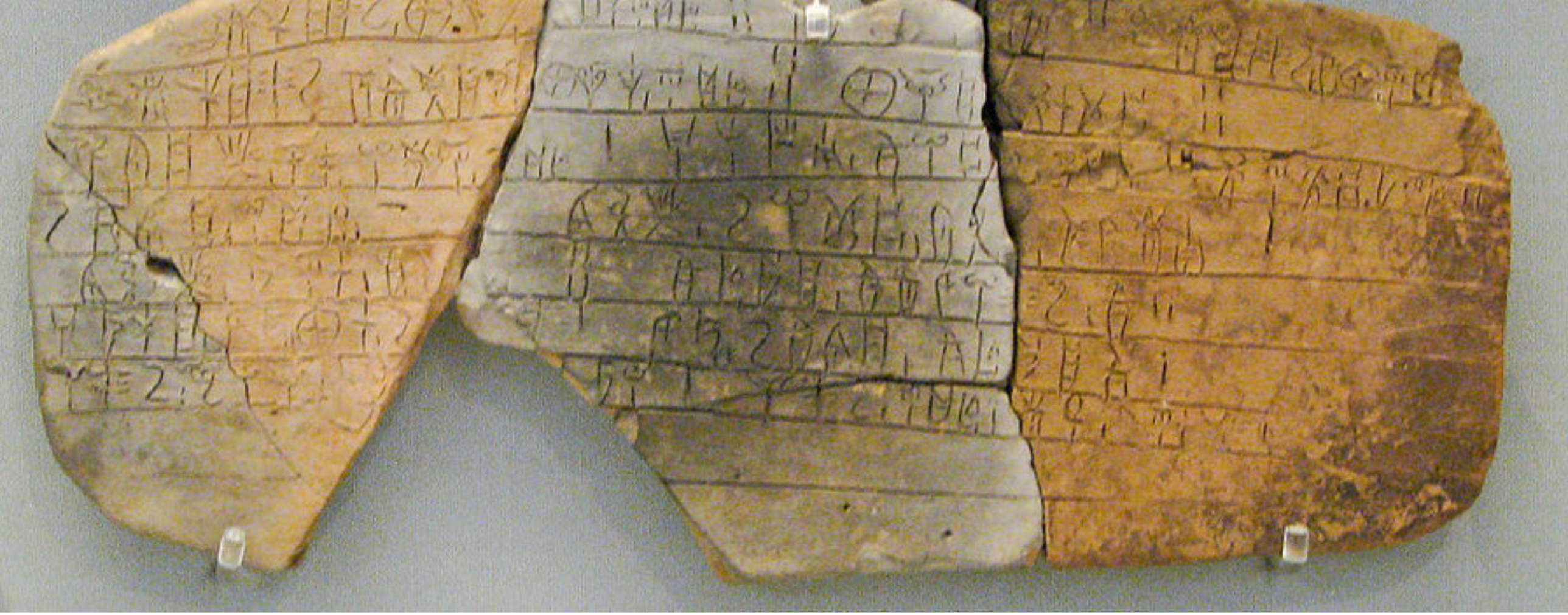

Natural Language Processing

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Lecture 20: Semantic roles (Nov. 2, 2017)

David Bamman, UC Berkeley

Semantic parsing

- Semantic parsing with CCG is simply syntactic parsing, assuming mapping from syntactic primitives to logical forms.
- But this encounters two problems:
    - We don't have those manual mappings (task-specific).
    - We can't parse anything not in our lexicon.

From last time

Learning from logical forms

- We can train a semantic parser in a number of ways:
    - Full derivational trees (CCGBank)
    - Logical forms (Zettlemoyer and Collins 2005)
    - Denotations (Berant et al. 2013)

Learning from trees

S
λx.state(x) ^ (borders(x,texas)

(S/S\NP)
λg.λx.state(x) ^ g(x)

(S\NP)
λy(borders(y,texas)

(S/S\NP)/N	N	(S\NP)/NP	NP
λf.λg.λx.f(x) ^ g(x)	**λx.state(x)**	**λx.λy(borders(y,x)**	**texas**
what	states	border	texas

Learning from logical forms

sentence	what states border texas
logical form	λx.state(x) ^ borders(x, texas)

Two core ideas:

- We'll learn the lexicon (including the lambda expressions)
- We'll learn CCG parser from that lexicon, and treat the true tree as a latent variable

Learning from logical forms

- For all <sentence, logical form> pairs in training data, maximize the probability of the logical form by marginalizing over the joint probability:

$$P(L \mid S; \theta) = \sum_{T} P(L, T \mid S; \theta)$$

Start with random values for θ; update with SGD

- Where

$$P(L, T \mid S; \theta) = \frac{\exp(f(L, T, S)^{\top}\theta)}{\sum_{L,T} \exp(f(L, T, S)^{\top}\theta)}$$

Learning from logical forms

- Learning from logical forms is means we don't need training data in the form of full CCG derivations + semantically enriched lexicon.
- But we do still need training data in the form of logical forms.

Utah borders Idaho	borders(utah,idaho)
number of dramas starring tom cruise	???

Learning from denotations

sentence	what states border texas
logical form	λx.state(x) ^ borders(x, texas)
denotation	**new_mexico, oklahoma, arkansas, louisiana**

sentence	number of dramas starring tom cruise
logical form	count(λx.genre(x,drama) ^ ∃y.performance(x,y) ^ actor(y,tom_cruise))
denotation	**28**

Learning from denotations

sentence	what states border texas
logical form	λx.state(x) ^ borders(x, texas)
denotation	**new_mexico, oklahoma, arkansas, louisiana**

sentence	number of dramas starring tom cruise
logical form	count(λx.genre(x,drama) ^ ∃y.performance(x,y) ^ actor(y,tom_cruise))
denotation	**28**

Learning from denotations

- How could we use the principles of learning from logical forms to learn from denotations?

- The meaning of a sentence is the set of possible worlds consistent with that statement.

Utah borders Idaho	TRUE
number of dramas starring tom cruise	28

Learning from denotations

- Basic idea: maximize the probability of the tree T/ logical form z that, when executed against a knowledge base $\mathcal{K}$, yield the correct denotation y

$$\sum_{i=1}^{N} \log \sum_{T:[\![T.z]\!]_{\mathcal{K}}=y_i} P(T \mid S_i, \theta)$$

objective function

Why do we need CCG (or a syntactic representation) at all?

- It provides the scaffolding for learning by encoding our assumptions about the problem (compositionality)

- Meaning is built from parts, so let's learn to decompose our answers (denotations, logical forms) into those parts.

Event semantics

Pat gives Sal a book

$\exists x.\text{book}(x) \wedge \textsc{give}(\text{Pat},\text{Sal},x)$

Eisenstein 2017

Event semantics

Yesterday, Pat gives Sal a book reluctantly

$\exists x.\text{book}(x) \wedge \text{GIVE}(\text{Pat, Sal, x, yesterday, reluctantly})$

- One option: extend the arity of the relation (require more arguments)
- But that's not great because we need a separate predicate for every possible combination of arguments (even those that aren't required).

Eisenstein 2017

Event semantics

We can reify the event to an existentially quantified variable of its own, and then use it as a argument in other relations.

$\exists$e,x.GIVE-EVENT(e)
$\wedge$ GIVER(e,Pat)
$\wedge$ GIFT(e,x)
$\wedge$ BOOK(e,x)
$\wedge$ RECIPIENT(e,Sal)
$\wedge$ TIME(e,yesterday)
$\wedge$ MANNER(e,reluctanctly)

Eisenstein 2017

Event semantics

Neo-Davidson event semantics: the event is central, and relations are predicated of the event. Each argument of an event holds its own relation.

$\exists$e,x.GIVE-EVENT(e)
$\wedge$ GIVER(e,Pat)
$\wedge$ GIFT(e,x)
$\wedge$ BOOK(e,x)
$\wedge$ RECIPIENT(e,Sal)
$\wedge$ TIME(e,yesterday)
$\wedge$ MANNER(e,reluctanctly)

In model-theoretic semantics, each of these has a denotation in a world model

Eisenstein 2017

Event semantics

Sasha broke the window

$\exists$e,y.BREAKING-EVENT(e)
$\wedge$ BREAKER(e,Sasha)
$\wedge$ BROKEN-THING(e,y)
$\wedge$ WINDOW(e,y)

Pat opened the door

$\exists$e,y.OPENING-EVENT(e)
$\wedge$ OPENER(e,Pat)
$\wedge$ OPENED-THING(e,y)
$\wedge$ DOOR(e,y)

Event semantics

In model-theoretic semantics, each of these has some denotation in the world model.

Example: WINDOW has a identifier in some knowledge base (e.g., Freebase) uniquely identifying its properties.

$\exists$e,y.BREAKING-EVENT(e)
$\wedge$ BREAKER(e,Sasha)
$\wedge$ BROKEN-THING(e,y)
$\wedge$ WINDOW(e,y)

$\exists$e,y.OPENING-EVENT(e)
$\wedge$ OPENER(e,Pat)
$\wedge$ OPENED-THING(e,y)
$\wedge$ DOOR(e,y)

Event semantics

This requires a comprehensive representation of the world

$\exists$e,y.BREAKING-EVENT(e)
$\wedge$ BREAKER(e,Sasha)
$\wedge$ BROKEN-THING(e,y)
$\wedge$ WINDOW(e,y)

$\exists$e,y.OPENING-EVENT(e)
$\wedge$ OPENER(e,Pat)
$\wedge$ OPENED-THING(e,y)
$\wedge$ DOOR(e,y)

Shallow semantics

∃e,y.EVENT(e)
∧ CAUSER-OF-ACTION(e,Sasha)
∧ RECIPIENT-OF-ACTION(e,y)
∧ “window”(y)

∃e,y.BREAKING-EVENT(e)
∧ BREAKER(e,Sasha)
∧ BROKEN-THING(e,y)
∧ WINDOW(e,y)

∃e,y.EVENT(e)
∧ CAUSER-OF-ACTION(e,Pat)
∧ RECIPIENT-OF-ACTION(e,y)
∧ “door”(y)

∃e,y.OPENING-EVENT(e)
∧ OPENER(e,Pat)
∧ OPENED-THING(e,y)
∧ DOOR(e,y)

These roles have a lot in common: direct causal responsibility for the events, have volition, often animate

Shallow semantics

∃e,y.EVENT(e)
∧ AGENT(e,Sasha)
∧ THEME(e,y)
∧ “window”(y)

∃e,y.BREAKING-EVENT(e)
∧ BREAKER(e,Sasha)
∧ BROKEN-THING(e,y)
∧ WINDOW(e,y)

∃e,y.EVENT(e)
∧ AGENT(e,Pat)
∧ THEME(e,y)
∧ “door”(y)

∃e,y.OPENING-EVENT(e)
∧ OPENER(e,Pat)
∧ OPENED-THING(e,y)
∧ DOOR(e,y)

Shallow semantics

Agent: Sasha
Theme: window

$\exists$e,y.BREAKING-EVENT(e)
$\wedge$ BREAKER(e,Sasha)
$\wedge$ BROKEN-THING(e,y)
$\wedge$ WINDOW(e,y)

Agent: Pat
Theme: door

$\exists$e,y.OPENING-EVENT(e)
$\wedge$ OPENER(e,Pat)
$\wedge$ OPENED-THING(e,y)
$\wedge$ DOOR(e,y)

Thematic roles

Thematic roles capture the semantic commonality among arguments for different relations (predicates)

- John broke the window
- The window was broken by John

Different syntactic roles, but the same thematic role.

Thematic roles

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

Thematic roles

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 makes hotel reservations for *her boss*...
Source	I flew in from *Boston*.
Goal	I drove to *Portland*.

Thematic roles

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

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

Thematic roles

The thematic roles for verbs generally are predictable by the syntactic position of the argument (specific to each verb class). Some allow for consistent alternations:

Agent Theme Goal

Doris gave the book to Cary

Agent Goal Theme

Doris gave Cary the book

Thematic roles

- Thematic roles are very useful but different to formally define AGENT, THEME, etc.
- At the same time, they may be too coarse for some applications.

Thematic roles

Intermediary instruments can be subjects

- The cook opened the jar with the new gadget
- The new gadget opened the jar

- Shelly ate the sliced banana with a fork
- *The fork ate the sliced banana

Enabling instruments cannot

Levin and Rappaport Hovav 2005; SLP3

Coarsening: Proto-roles

- Proto-roles = generalized thematic roles
- Proto-agent: causing an event, having volition wrt event, moving, acting with intention
- Proto-patient: change of state, causally affected by event)

Propbank

- Sentences from the Penn Treebank annotated with proto-roles, along with lexical entries for each sense of a verb identifying the specific meaning of each proto-role for that verb sense.

https://propbank.github.io

Propbank

(22.11) **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].

(22.12) **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%].

Propbank

- Verb-specific argument structures lets us map the commonalities among the different surface forms
    - [$_{Arg0}$ Big Fruit Co.] increased [$_{Arg1}$ the price of bananas].
    - [$_{Arg1}$ The price of bananas] was increased again [$_{Arg0}$ by Big Fruit Co.]
    - [$_{Arg1}$ The price of bananas] increased [$_{Arg2}$ 5%].

Propbank

- Verb-specific argument structures lets us map the commonalities among the different surface forms
    - [$_{Arg0}$ Big Fruit Co.] increased [$_{Arg1}$ the price of bananas].
    - [$_{Arg1}$ The price of bananas] was increased again [$_{Arg0}$ by Big Fruit Co.]
    - [$_{Arg1}$ The price of bananas] increased [$_{Arg2}$ 5%].

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

FrameNet

- Propbank maps argument structure for individual verb senses
- FrameNet maps argument structure for frames, which are evoked by a lexical unit (typically a verb)

https://framenet.icsi.berkeley.edu/fndrupal/framenet_data

Frames

AI

- Schank and Abelson 1975, 1977
- Minksky 1974

Linguistics

- Fillmore 1975, 1982, Tannen 1979

Cognitive Psychology

- Rumelhart 1975, 1980

Sociology

- Goffman 1975

Media Studies

- Entman 1993

Frames

John went into a restaurant. He ordered a hamburger and coke. He asked the waitress for the check and left.

(Schank & Abelson 75)

Frames

- “A frame is a data-structure for representing a stereotyped situation” (Minsky 1975)
- By the term ‘frame’ I have in mind any system of concepts related in such a way that to understand any one of them you have to understand the whole structure in which it fits; when one of the things in such a structured is introduced … all of the others are automatically made available.” (Fillmore 1982)

Who did what to whom?

commercial_transaction

- John bought the car at the dealership
- The car was bought by John
- John's purchase of the car
- The sale of the car cleared their inventory.

Who did what to whom?

Buyer

- John bought the car at the dealership
- The car was bought by John
- John's purchase of the car
- The sale of the car cleared their inventory.

Who did what to whom?

Thing bought

- John bought the car at the dealership
- The car was bought by John
- John’s purchase of the car
- The sale of the car cleared their inventory.

Semantic Frame

APPLY_HEAT

- Lexical units:

bake.v, barbecue.v, blanch.v, boil.v, braise.v, broil.v, brown.v, char.v, coddle.v, cook.v, deep fry.v, fry.v, grill.v, microwave.v, parboil.v, plank.v, poach.v, roast.v, saute.v, scald.v, sear.v, simmer.v, singe.v, steam.v, steep.v, stew.v, toast.v

- Core Frame Elements:

Cook	The Cook applies heat to the Food.
Food	Food is the entity to which heat is applied by the Cook.
Heating instrument	The entity that directly supplies heat to the Foo
Container	The Container holds the Food to which heat is applied.
Temperature setting	The Temperature_setting of the Heating_instrument for the Food.

Semantic Frame

DESTROY

- Lexical units:

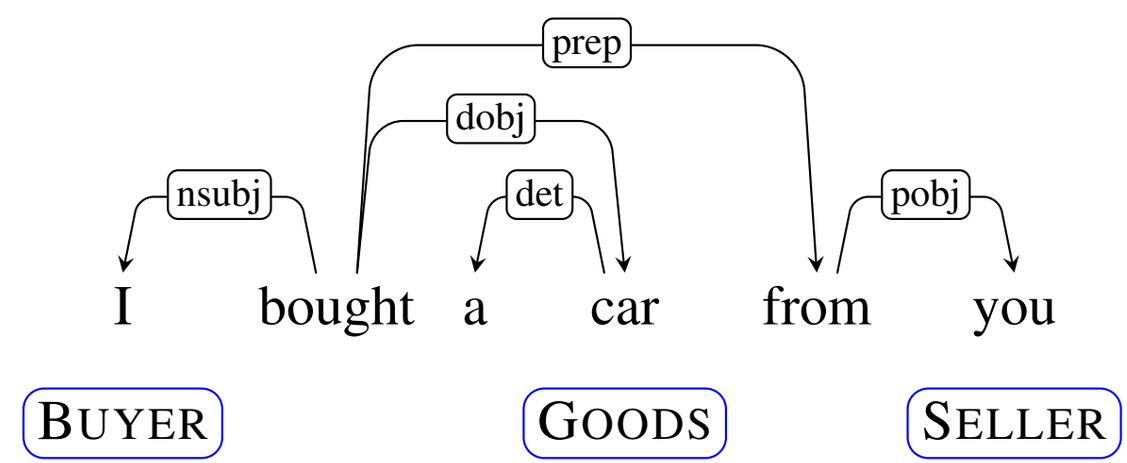
annihilate.v, annihilation.n, blast.v, blow up.v, demolish.v, demolition.n, destroy.v, destruction.n, destructive.a, devastate.v, devastation.n, dismantle.v, dismantlement.n, lay waste.v, level.v, obliterate.v, obliteration.n, raze.v, ruin.v, take out.v, unmake.v, vaporize.v

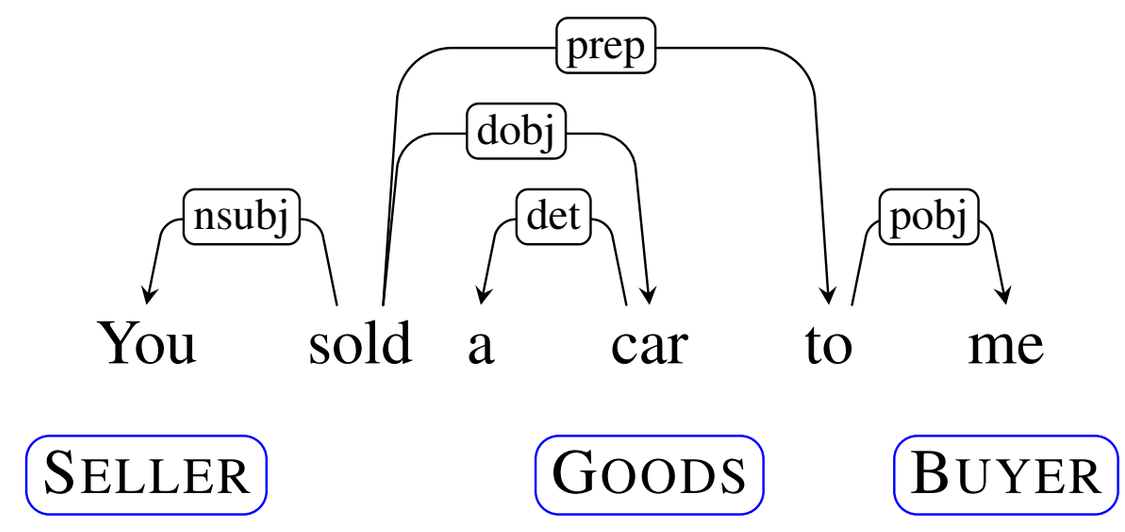
- Core Frame Elements:

Cause	The event or entity which is responsible for the destruction of the Patient.
Destroyer	The conscious entity, generally a person, that performs the intentional action that results in the Patient's destruction.
Patient	The entity which is destroyed by the Destroyer.

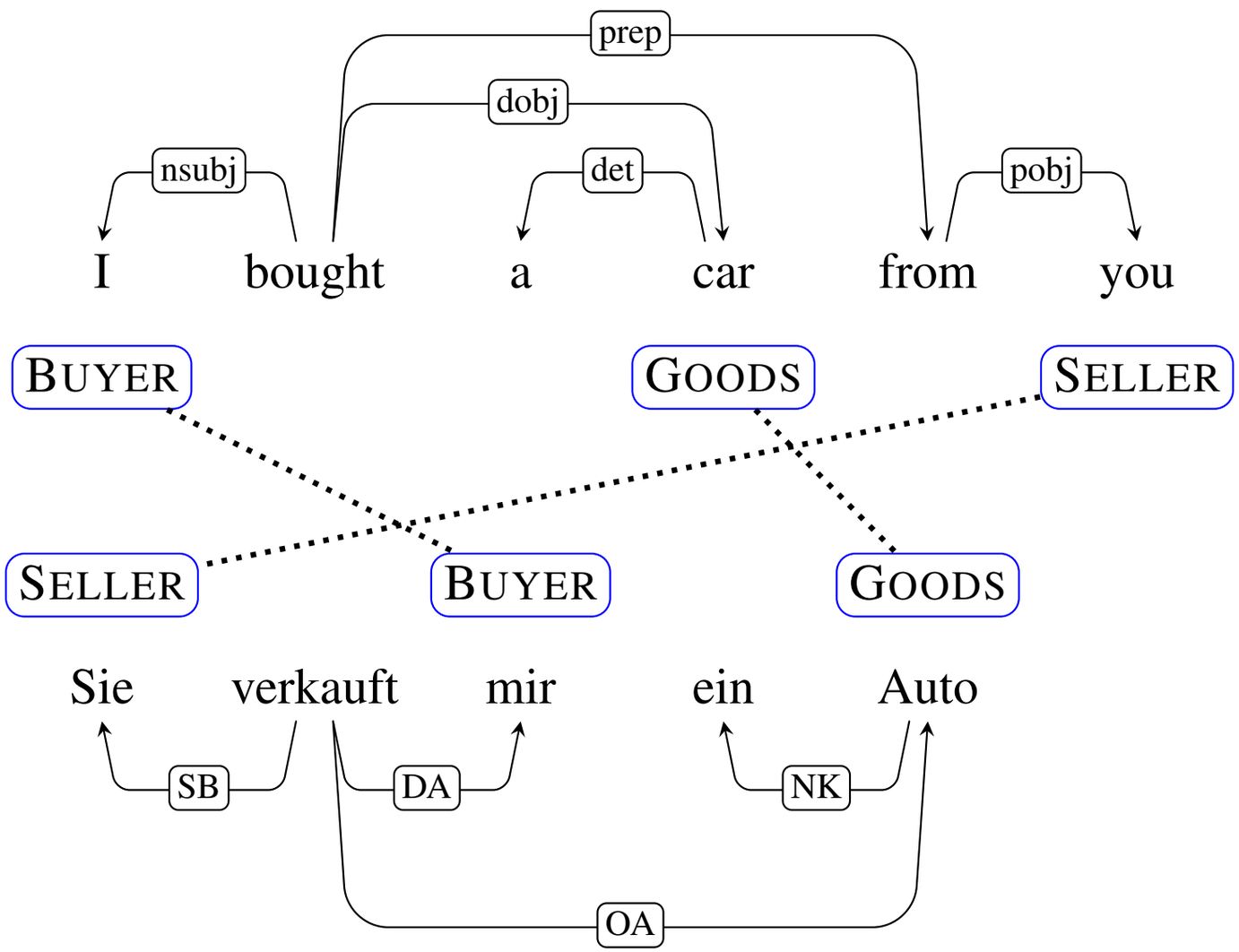
Semantic representations

Two different perspectives on a commercial transaction





Multilingual frames



Multilingual frames

- French
- Chinese
- Brazilian Portuguese
- German
- Spanish
- Japanese
- Swedish
- Korean

https://framenet.icsi.berkeley.edu/fndrupal/framenets_in_other_languages

Semantic role labeling

- Input: a sentence
- Output:
  - A list of predicates, each containing:
    - a label (e.g., Framenet frame)
    - a span
    - a set of arguments, each containing:
      - a label (thematic role, FrameNet role)
      - a span

Smith 2017

Semantic role labeling

FrameNet	[You]	can't	[blame]	[the program]	[for being unable to identify it]
	COGNIZER		TARGET	EVALUEE	REASON
PropBank	[The San Francisco Examiner]	issued	[a special edition]	[yesterday]	
	ARG0	TARGET	ARG1	ARGM-TMP	

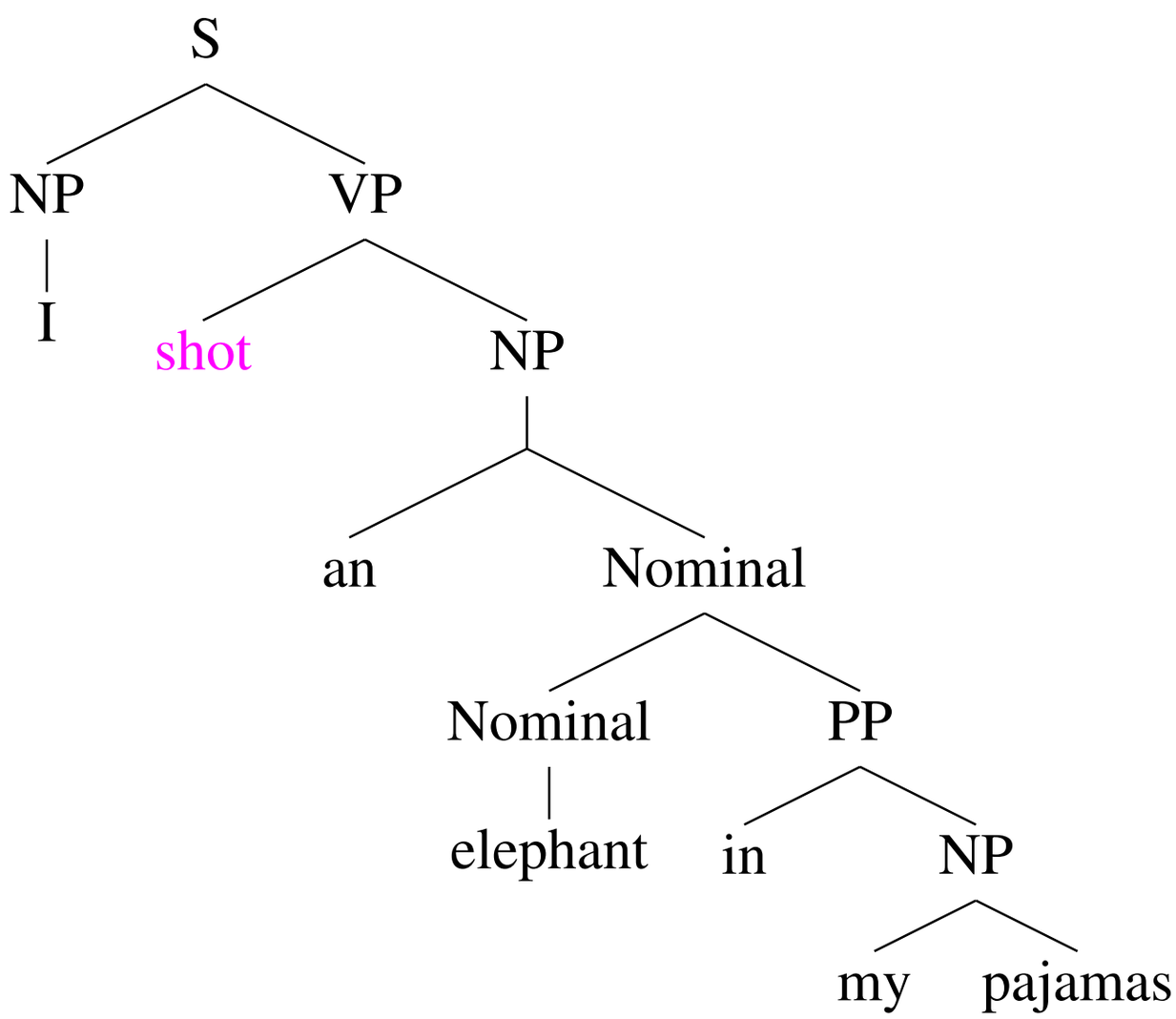
Semantic role labeling

```
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)
```

Gildea and Jurafsky 2002; SLP3

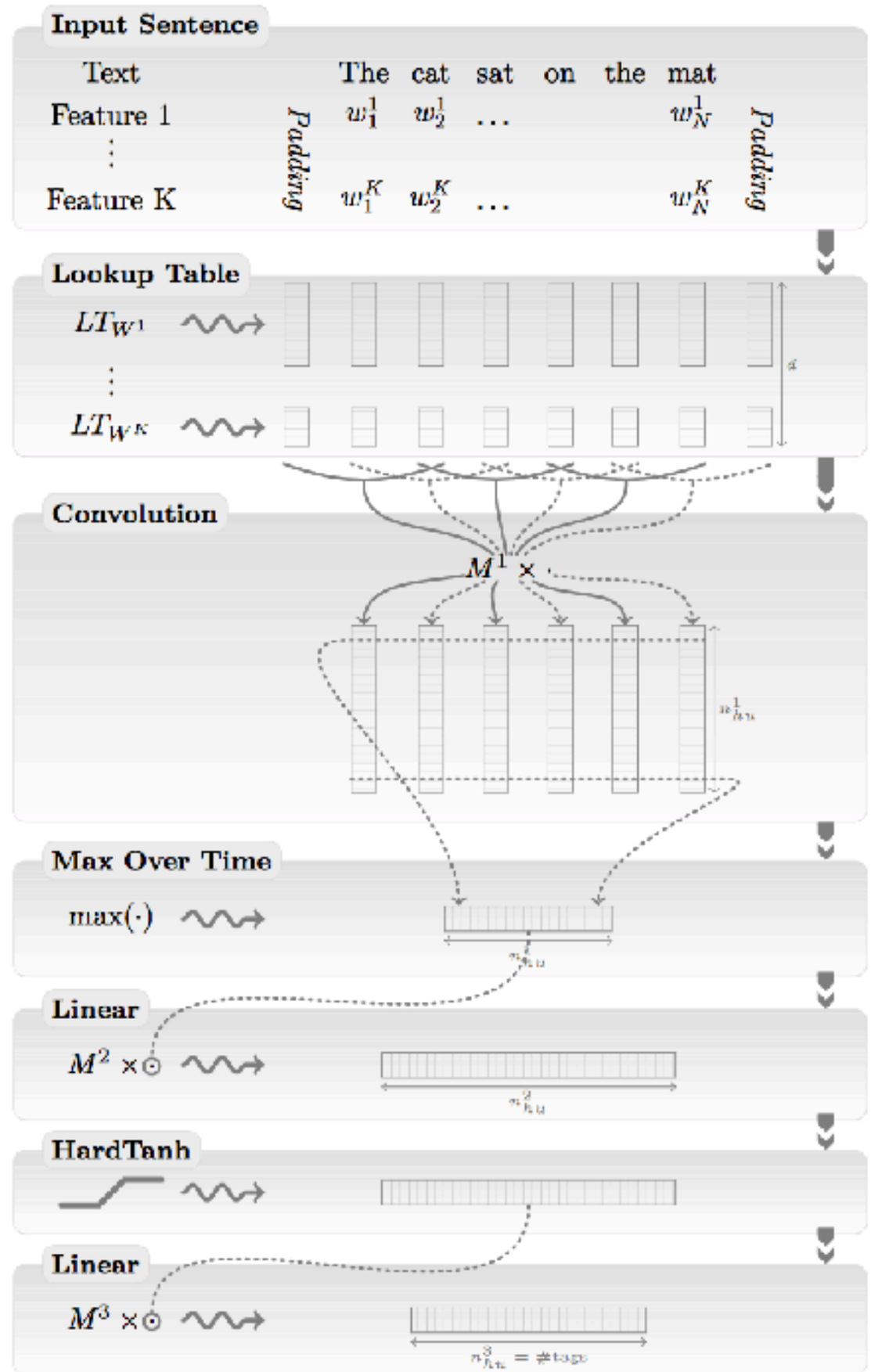
Semantic role labeling



feature
predicate: shot
phrase type = NP
headword of phrase = elephant
path = NP↑S↓VP
voice of verb = active
voice of verb = passive
phrase before verb?
first/last words of phrase

Semantic role labeling

Collobert et al. (2011), Natural Language Processing (Almost) from Scratch



Semantic role labeling

- Sentence-level constraints:
    - Arguments can’t overlap
    - For a given predicate, typically only one argument of each type (e.g., ARG0, BUYER)
- Approximate joint decoding (Das et al. 2010)
- Constrained optimization (e.g., ILP)

Smith 2017

Data

- CCGBank [through UCB Library]
  http://groups.inf.ed.ac.uk/ccg/ccgbank.html

- PropBank
  https://propbank.github.io

- FrameNet
  https://framenet.icsi.berkeley.edu/fndrupal/framenet_data