Information Extraction

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(many slides from Greg Durrett, Luheng He, Emma Strubell)

This Lecture

- How do we represent information for information extraction?
- Semantic role labeling / abstract meaning representation
- Relation extraction
- Slot filling
- Open Information Extraction

IE: The Big Picture

- How do we represent information? What do we extract?
  - Semantic roles
  - Abstract meaning representation
  - Slot fillers
  - Entity-relation-entity triples (fixed ontology or open)

Semantic Role Labeling

Semantic Role Labeling

- Find out 5W in text — “who did what to whom, when and where”
- Identify predicate, disambiguate it, identify that predicate’s arguments

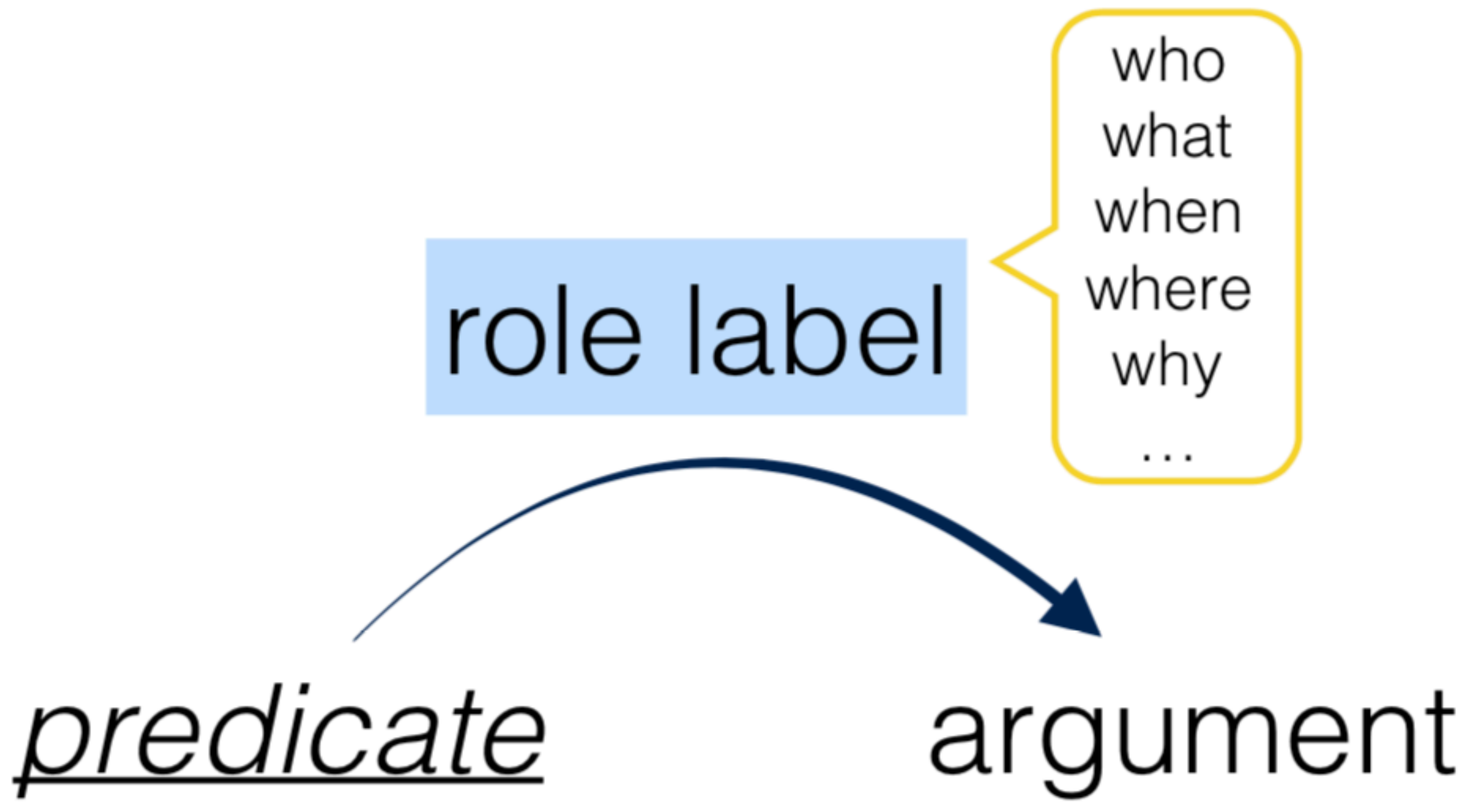

Figure from He et al. (2017)

Semantic Role Labeling

The robot <u>*broke*</u> my favorite mug with a wrench.

My mug <u>*broke*</u> into pieces immediately.

Figure from He et al. (2017)

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Semantic Role Labeling

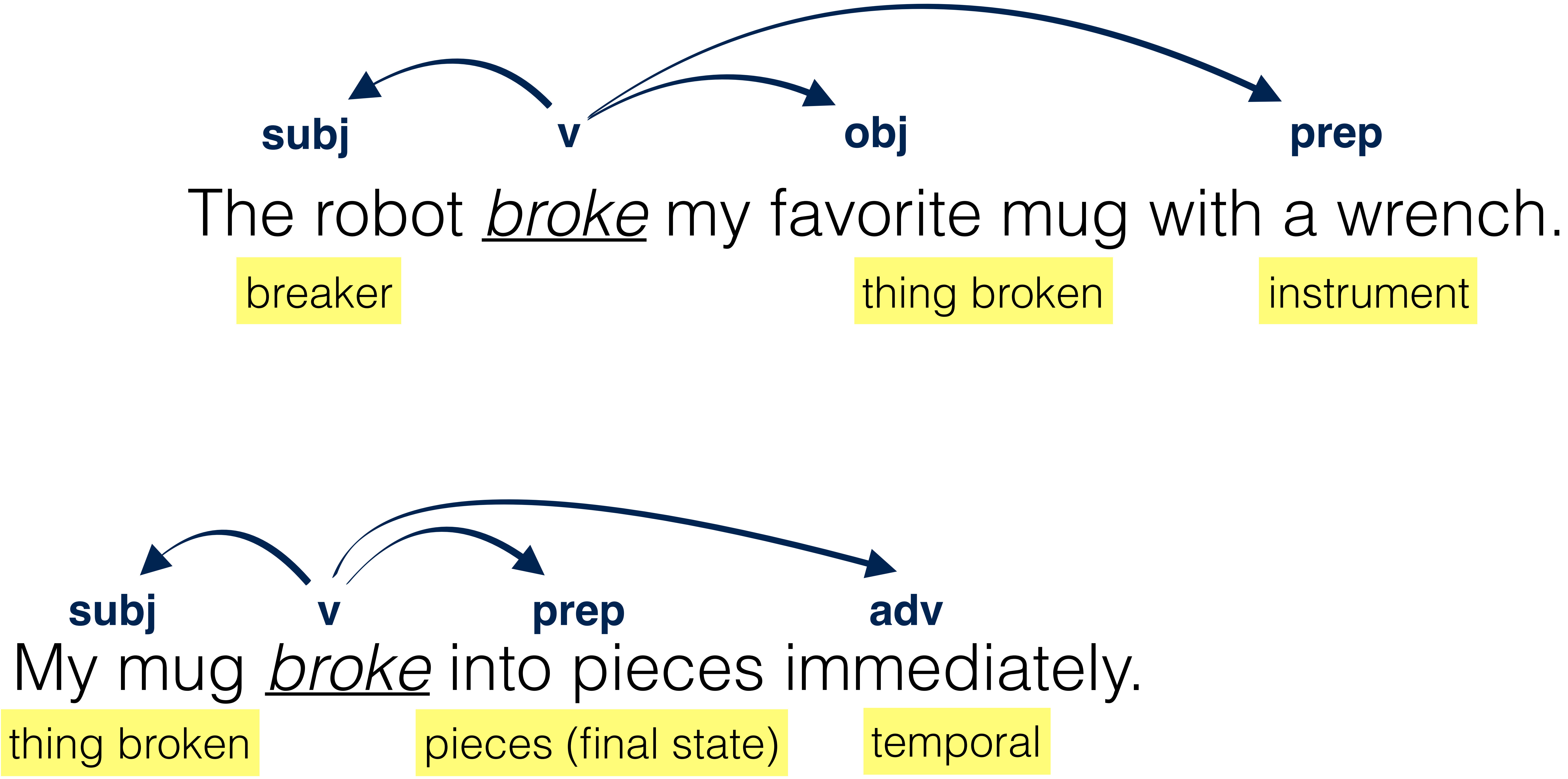


Figure from He et al. (2017)

Semantic Role Labeling

subj v obj prep

The robot *broke* my favorite mug with a wrench.

breaker — ARG0; thing broken — ARG1; instrument — ARG2

subj v prep adv

My mug *broke* into pieces immediately.

thing broken — ARG1; pieces (final state) — ARG3; temporal — ARGM-TMP

Frame: *break.01*

role	description
ARG0	breaker
ARG1	thing broken
ARG2	instrument
ARG3	pieces
ARG4	broken away from what?

The Proposition Bank (PropBank)

Core roles:
Verb-specific roles (ARG0-ARG5) defined in frame files

Frame: *break.01*

role	description
ARG0	breaker
ARG1	thing broken
ARG2	instrument

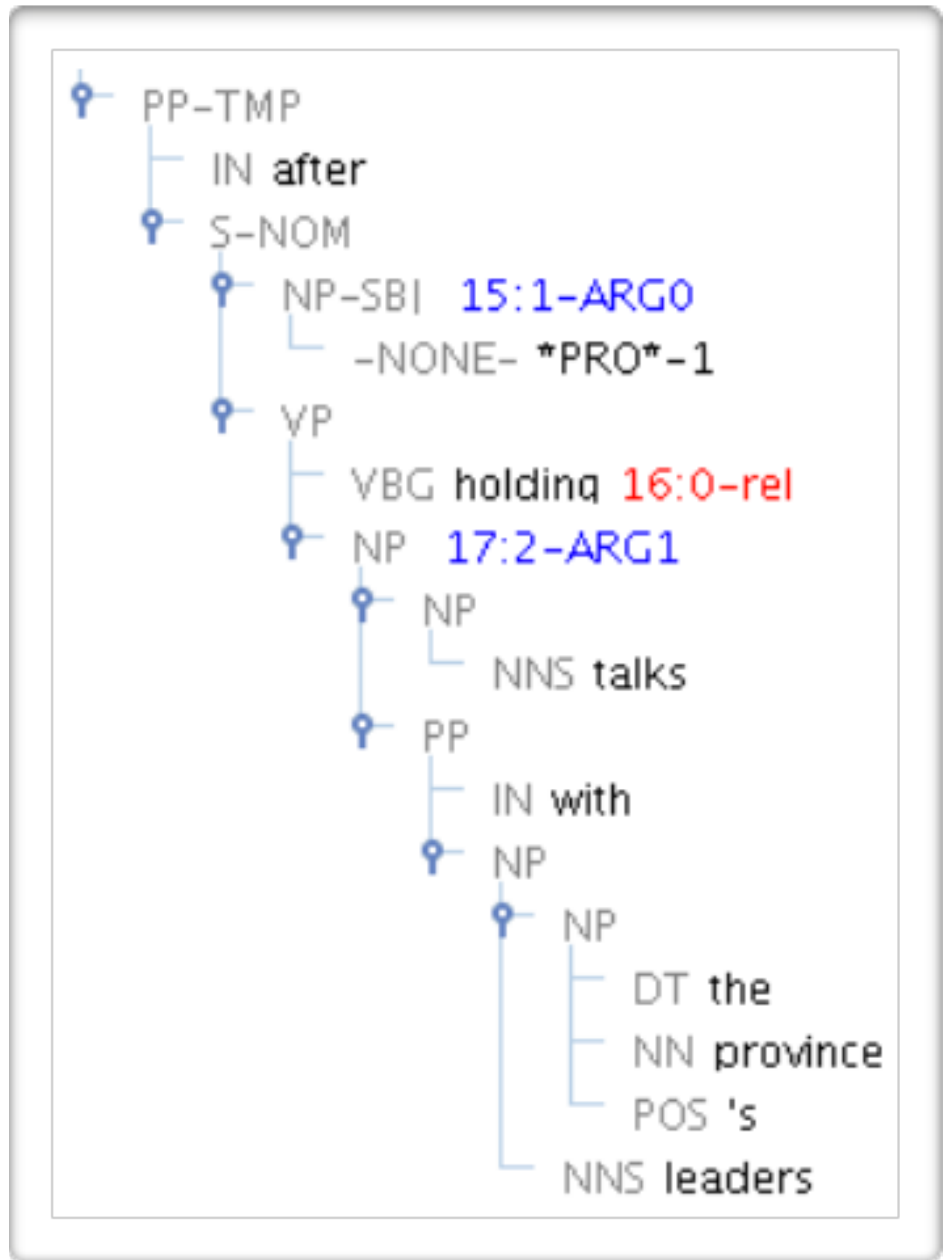
Frame: *buy.01*

role	description
ARG0	buyer
ARG1	thing bough
ARG2	seller
ARG3	price paid
ARG4	benefactive

Adjunct roles:
(ARGM-) shared across verbs

role	description
TMP	temporal
LOC	location
MNR	manner
DIR	direction
CAU	cause
PRP	purpose
…	

Annotated on top of the Penn Treebank Syntax



PropBank Annotation Guidelines, Bonial et al., 2010

Figure from He et al. (2017)

Syntax vs. Semantics

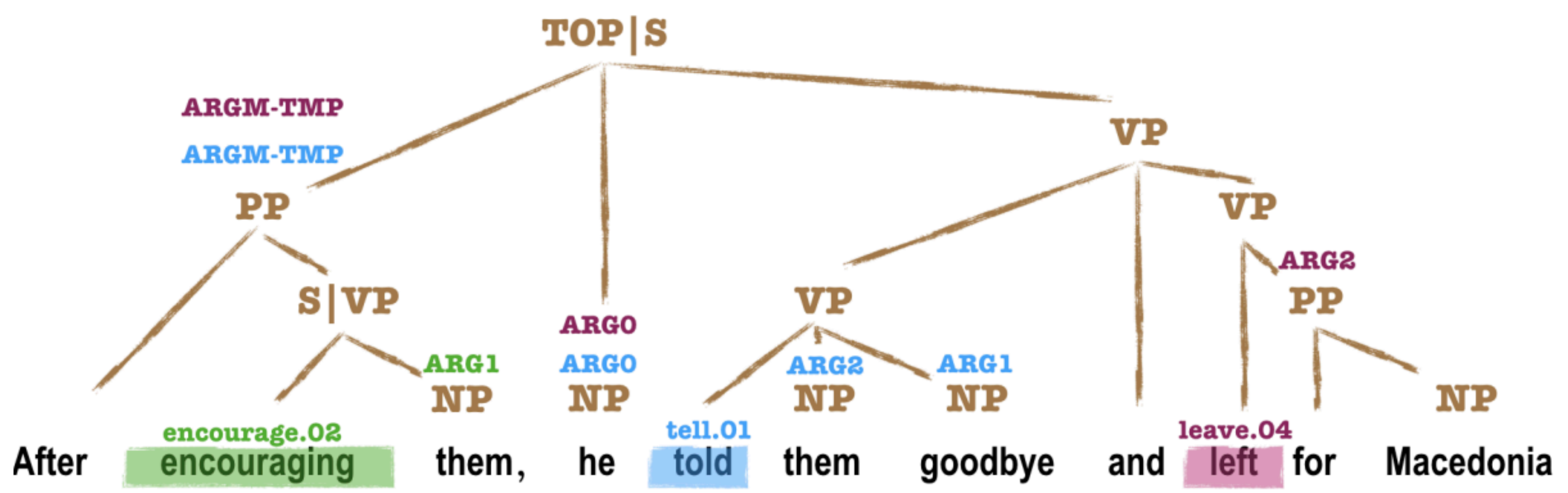


Figure 1.2: Syntax and semantics are closely related. The phrase-syntactic tree is shown in brown above the sentence. Semantic role labeling (SRL) structures from PropBank (Palmer et al., 2005) are shown alongside, in green, blue and magenta. Under SRL, words in the sentence that indicate stand-alone events are selected as predicates. These are shown as highlighted leaf nodes—"encouraging", "told" and "left". Each predicate is disambiguated to its relevant sense shown above it. Arguments to the predicates are are annotated on top of syntactic nodes, with the role labels color-coded by the predicate. SRL substructures (predicates, arguments) thus fully overlap with phrase-syntactic nodes.

Figure from Swayamdipta (2019)

Question-Answer Driven SRL

In 1950 Alan M. Turing ***published*** "Computing machinery and intelligence" in Mind, in which he ***proposed*** that machines could be ***tested*** for intelligence ***using*** questions and answers.

Predicate		Question	Answer
published	1	Who published something?	Alan M. Turing
	2	What was published?	"Computing Machinery and Intelligence"
	3	When was something published?	In 1950
proposed	4	Who proposed something?	Alan M. Turing
	5	What did someone propose?	that machines could be tested for intelligent using questions and answers
	6	When did someone propose something?	In 1950
tested	7	What can be tested?	machines
	8	What can something be tested for?	intelligence
	9	How can something be tested?	using questions and answers
using	10	What was being used?	questions and answers
	11	Why was something being used?	tested for intelligence

Figure from FitzGerald et al. (2018)

SRL Systems

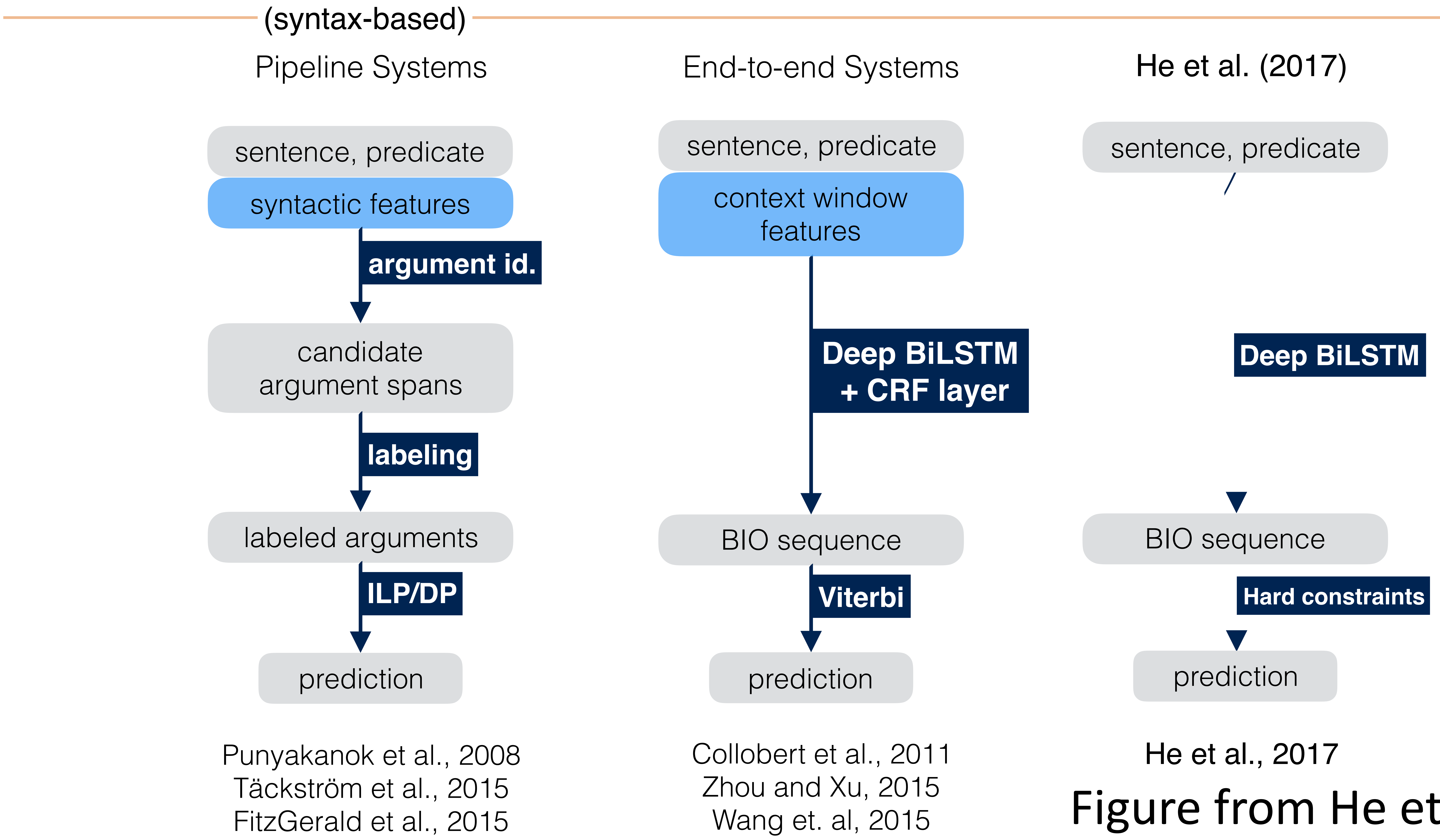


Figure from He et al. (2017)

Semantic Role Labeling

- Identify predicates (*love*) using a classifier (not shown)
- Identify ARG0, ARG1, etc. as a tagging task with a BiLSTM conditioned on *love*
- Other systems incorporate syntax, joint predicate-argument finding

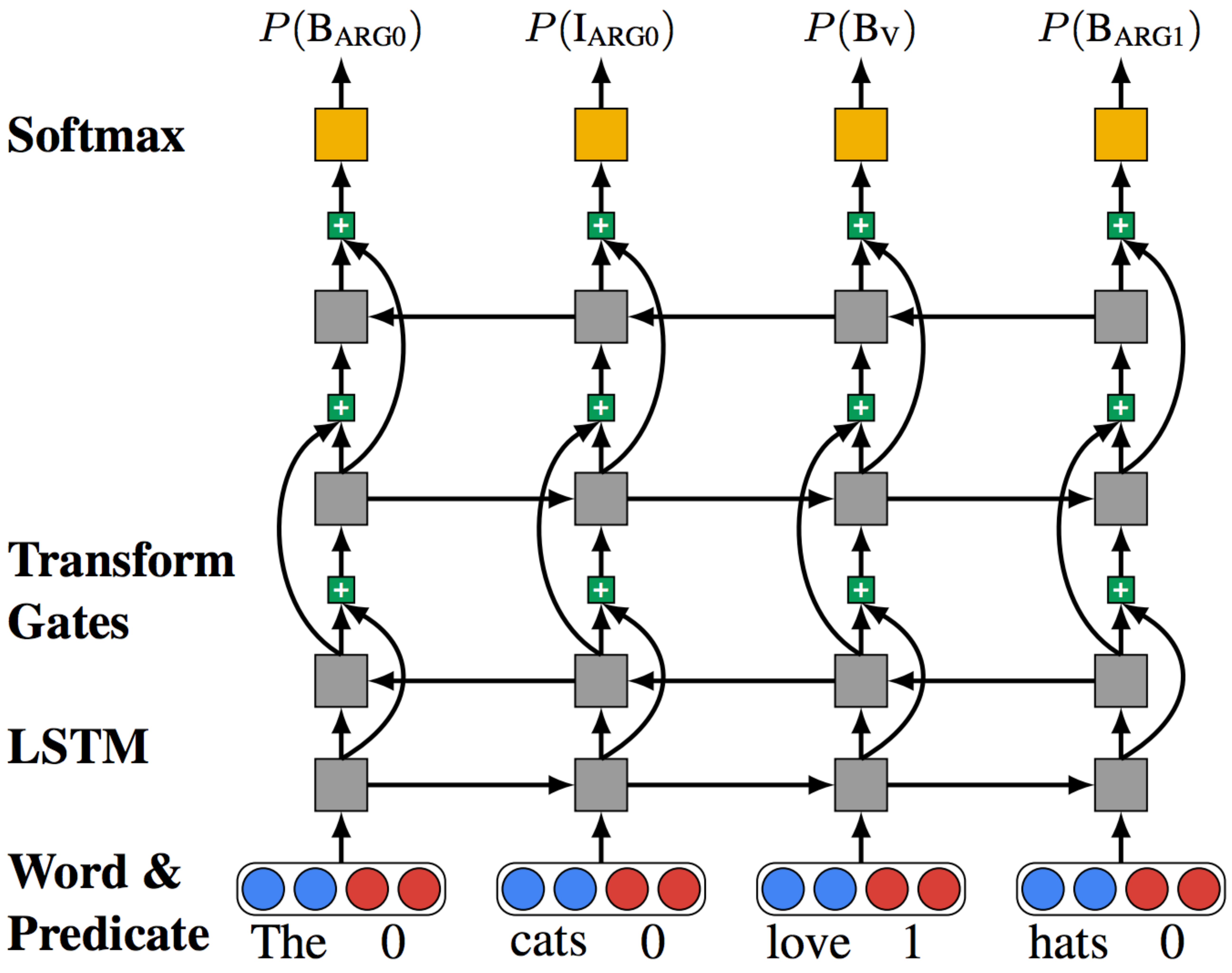
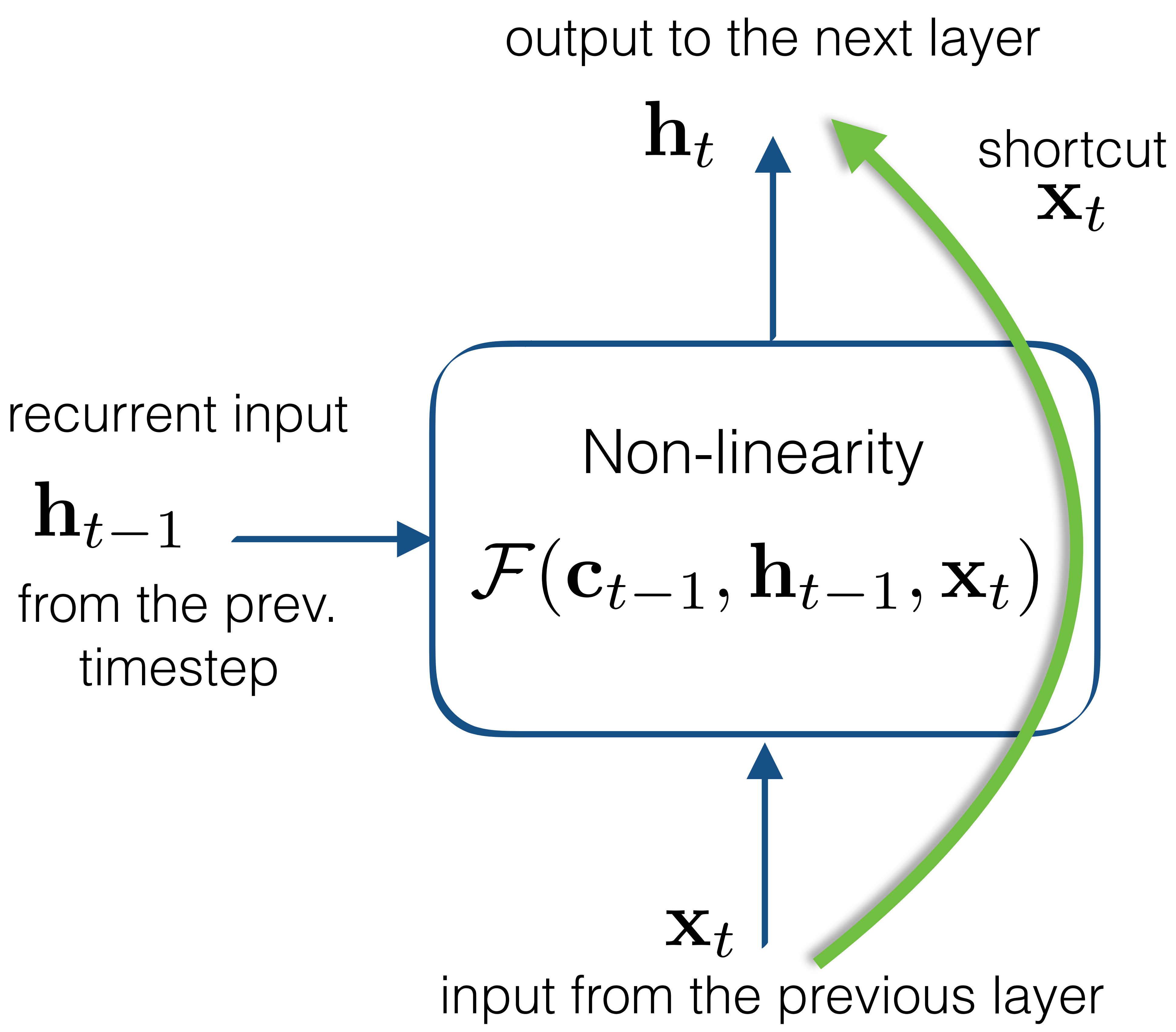


Figure from He et al. (2017)

Residual / Highway Connections



new output:

residual net $\mathbf{h}_t + \mathbf{x}_t$

gated highway network:

$$\mathbf{r}_t \circ \mathbf{h}_t + (1 - \mathbf{r}_t) \circ \mathbf{x}_t$$

$$\mathbf{r}_t = \sigma(f(\mathbf{h}_{t-1}, \mathbf{x}_t))$$

References:
Deep Residual Networks, Kaiming He, ICML 2016 Tutorial
Training Very Deep Networks, Srivastava et al., 2015

Figure from He et al. (2017)

10 Years of PropBank SRL

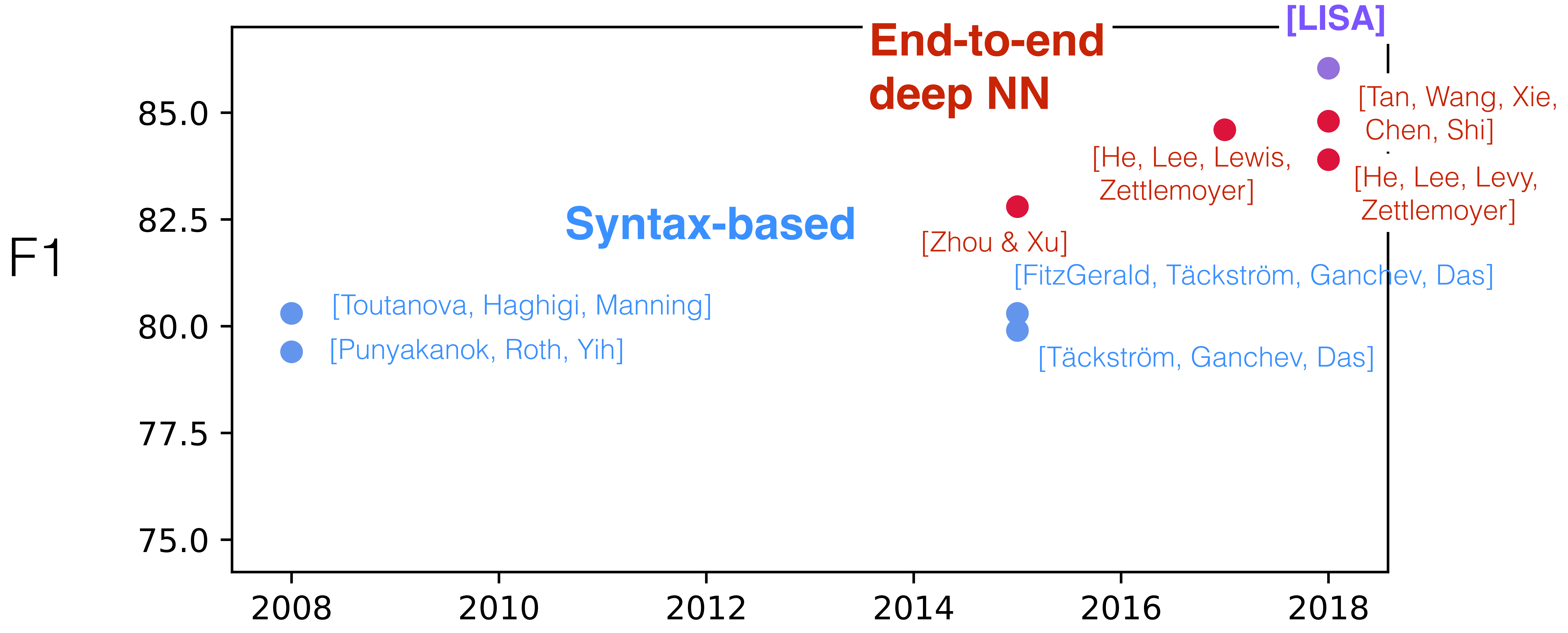
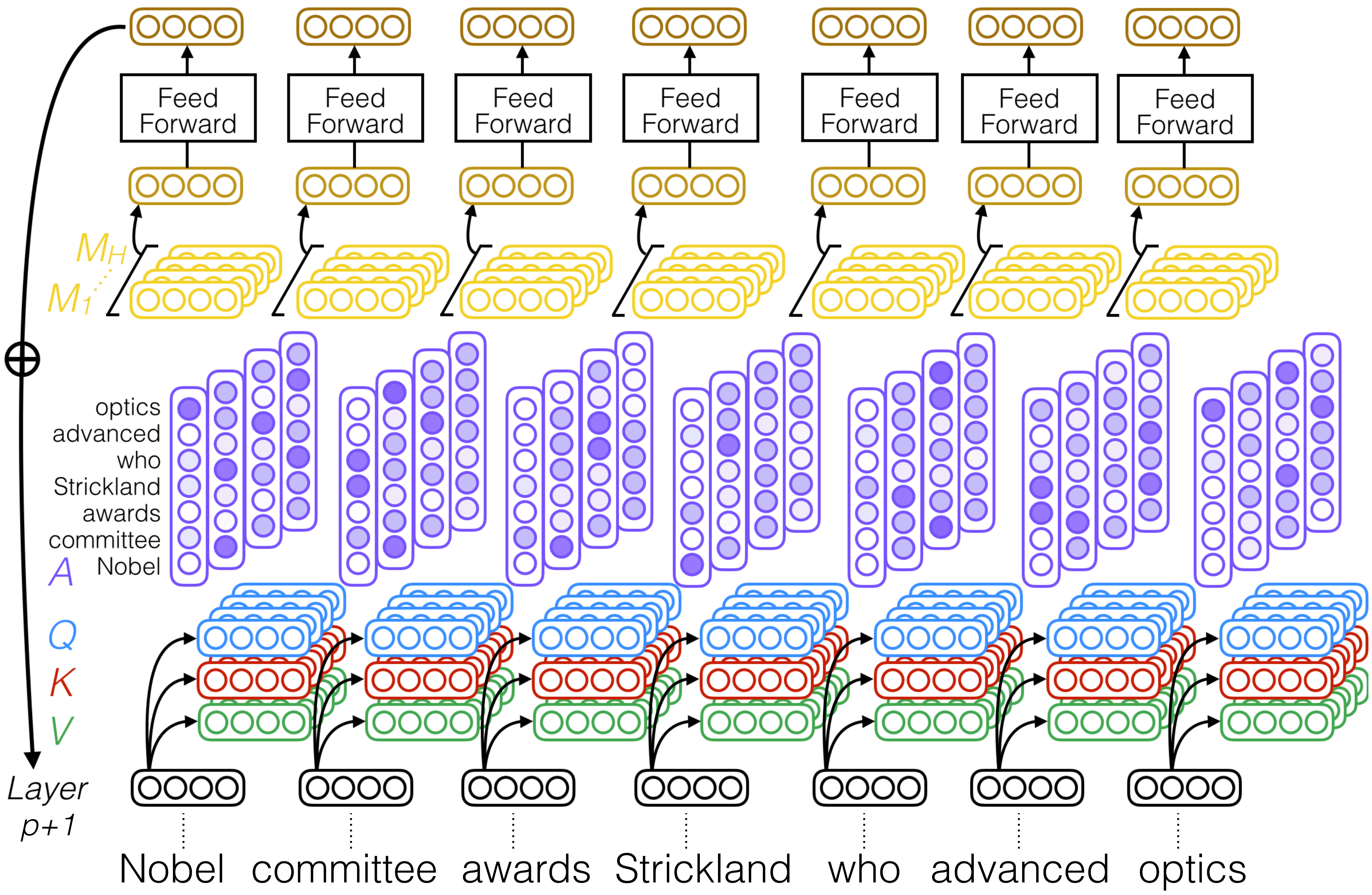


Figure from Strubell et al. (2018)

Semantic Role Labeling

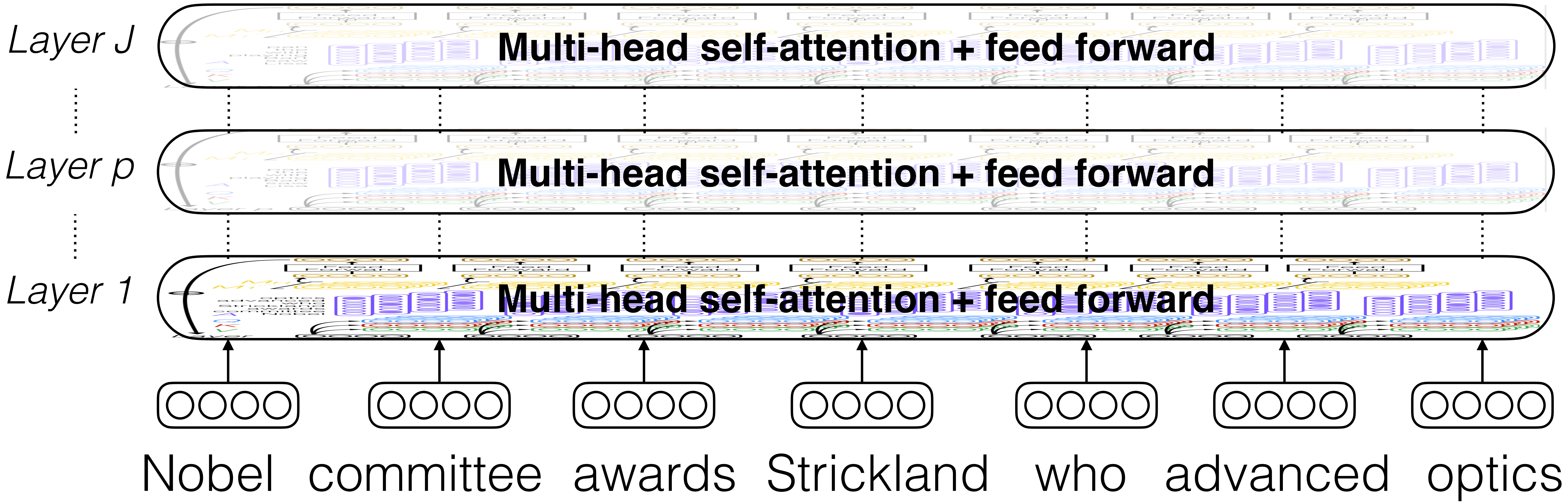
- Can we combine the two approaches — incorporate syntactic information into neural networks?
- Multi-task learning with related tasks, e.g., part-of-speech tagging, dependency parsing …
- Syntactically-informed self-attention: use the Transformer to encore the sentence; in one head, token attends to its likely syntactic parents; in next layer, tokens observe all other parents.

Recall: Transformer (multi-head self-attention)

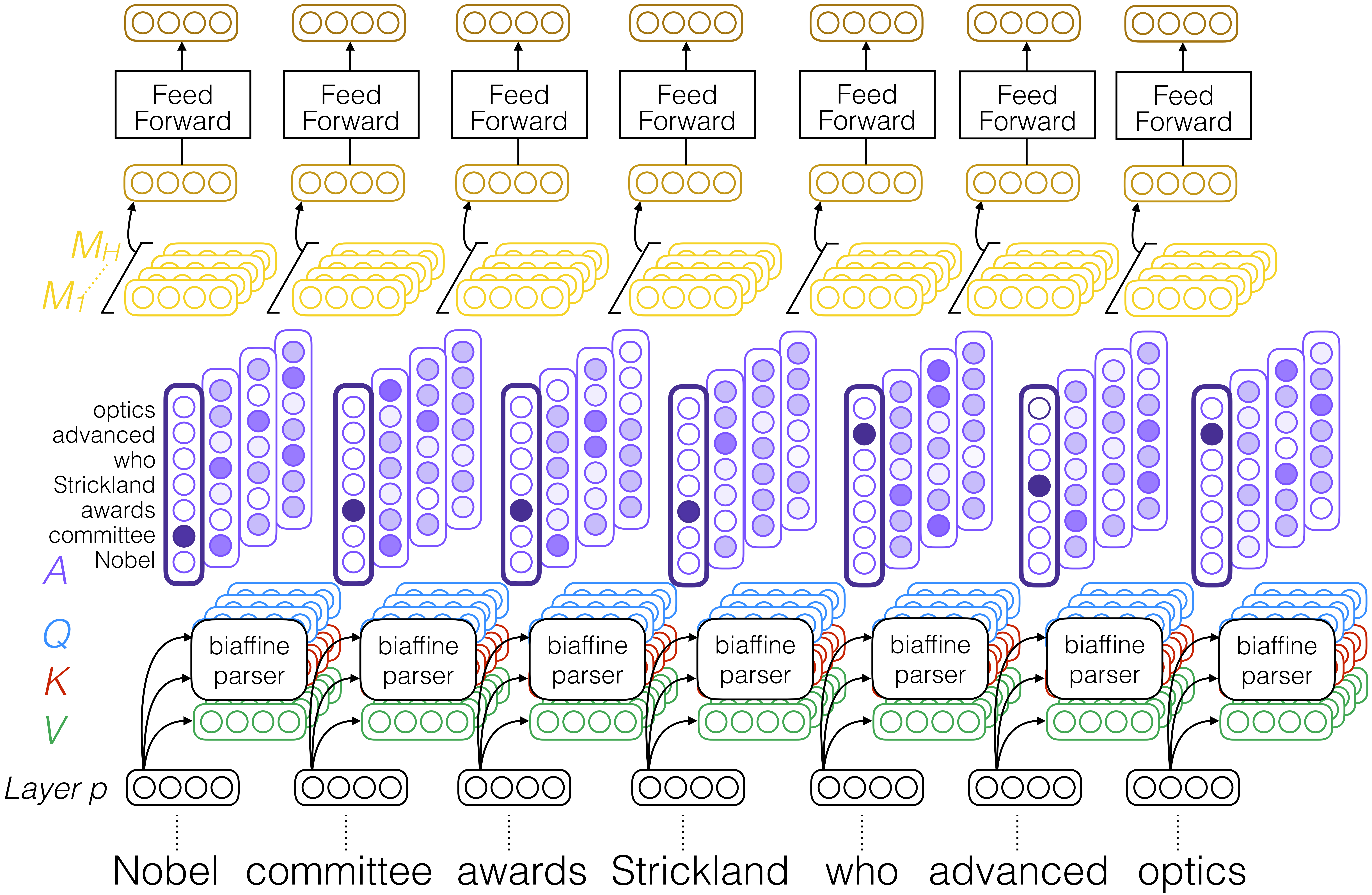


Recall: Transformer (multi-head self-attention)

Figure from Strubell et al. (2018)

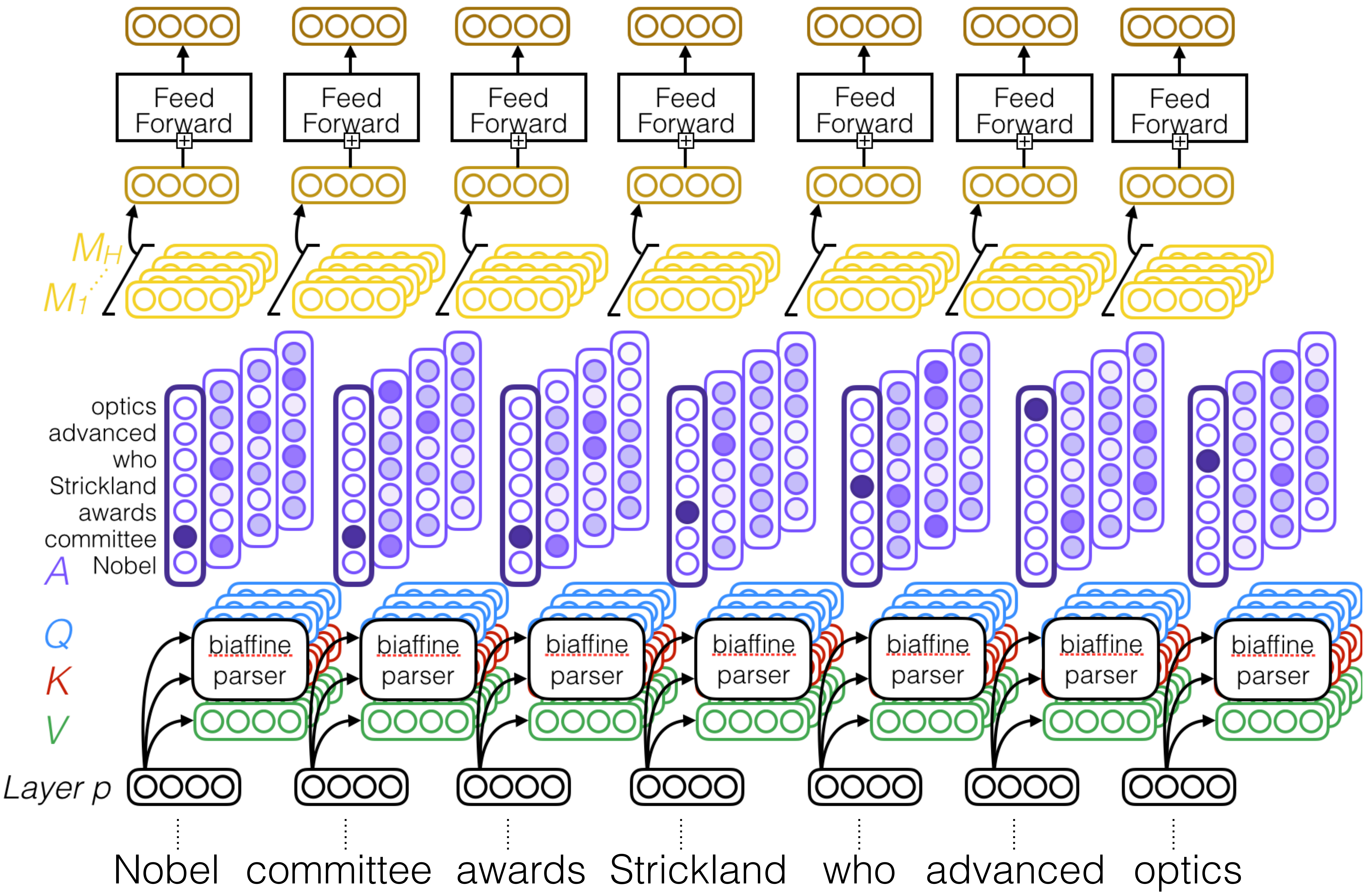


Syntactically-Informed Self-Attention



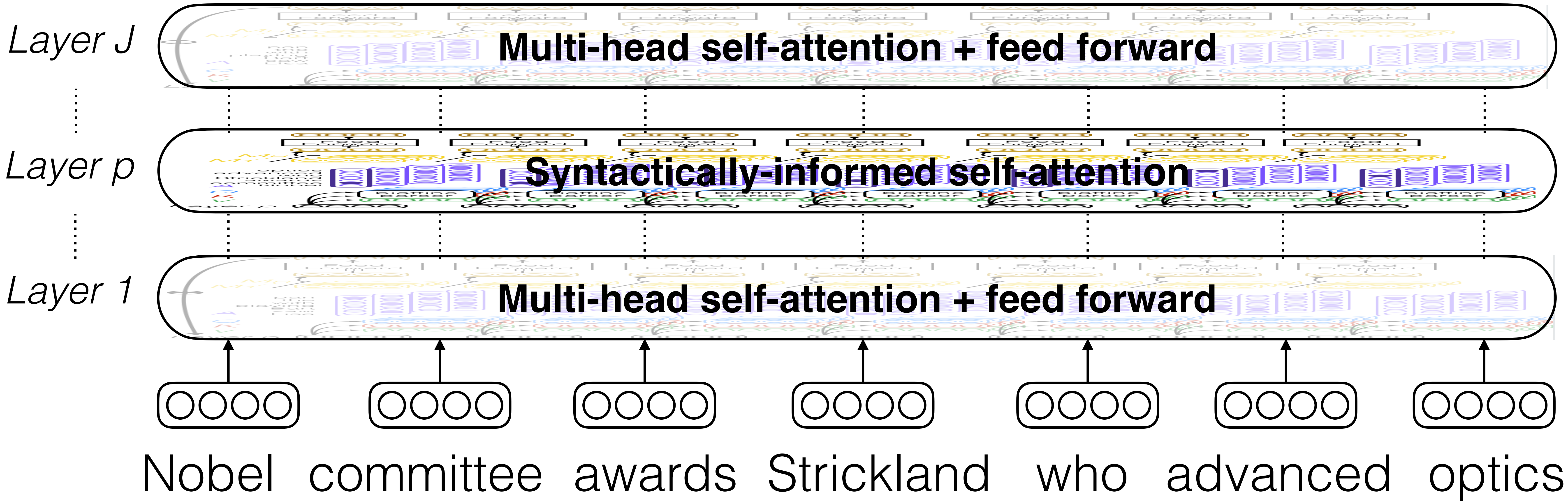
[Dozat and Manning 2017]

Syntactically-Informed Self-Attention



Linguistically-Informed Self-Attention

Figure from Strubell et al. (2018)



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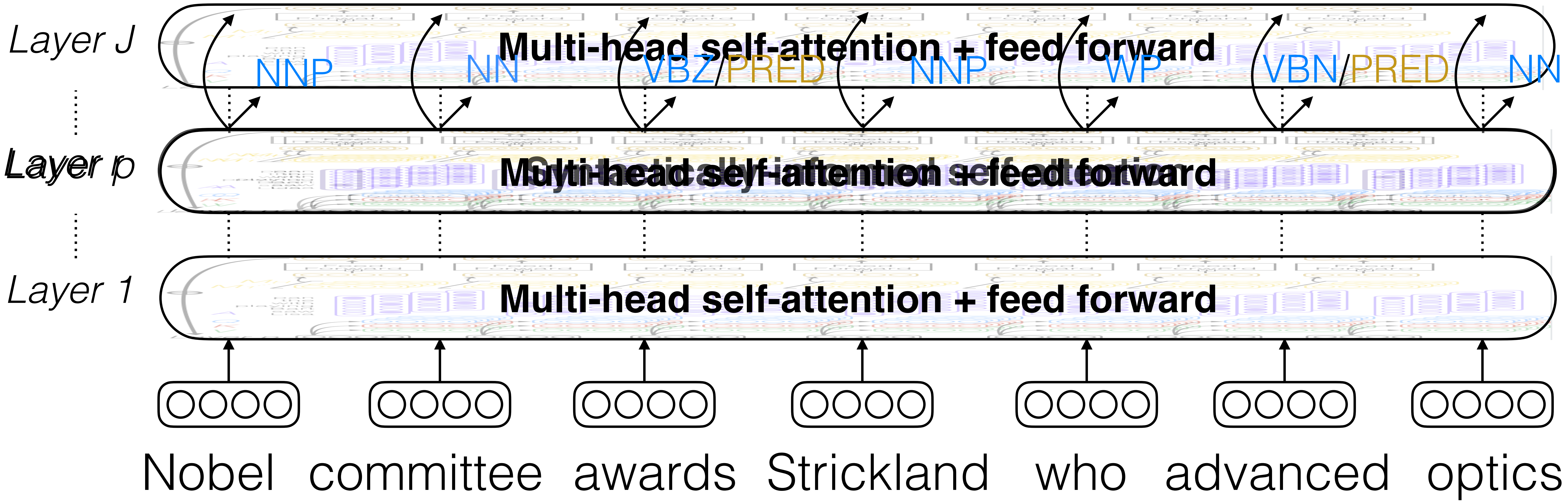

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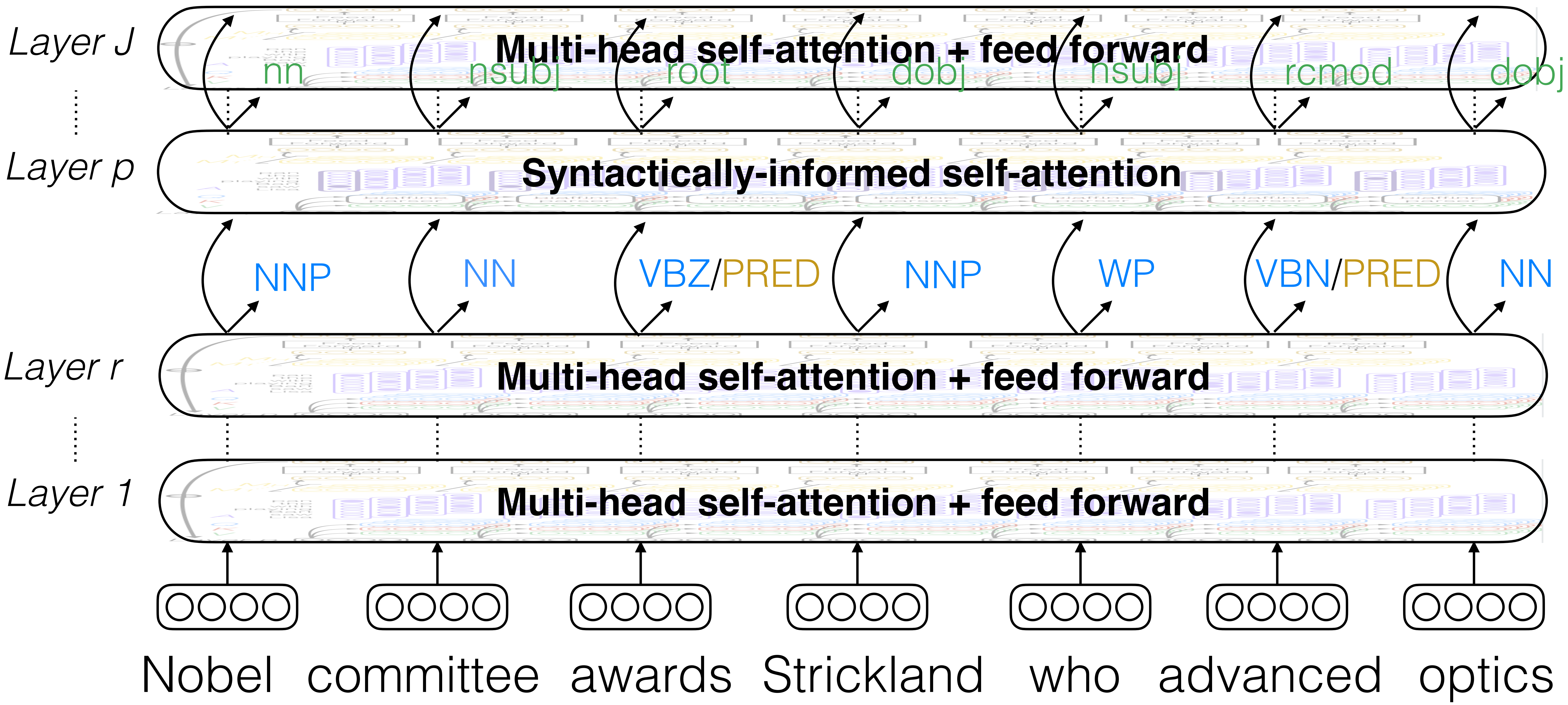

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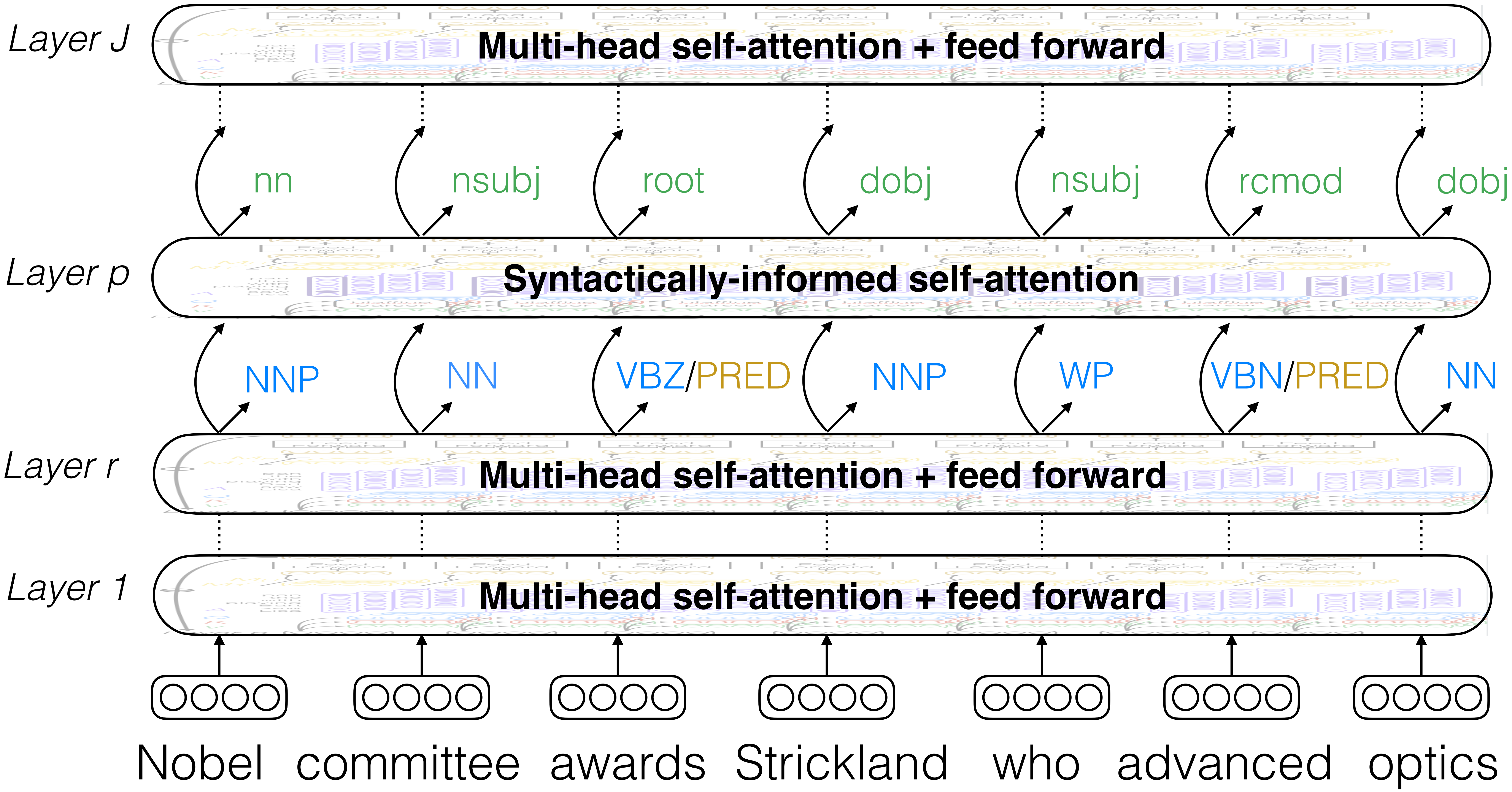

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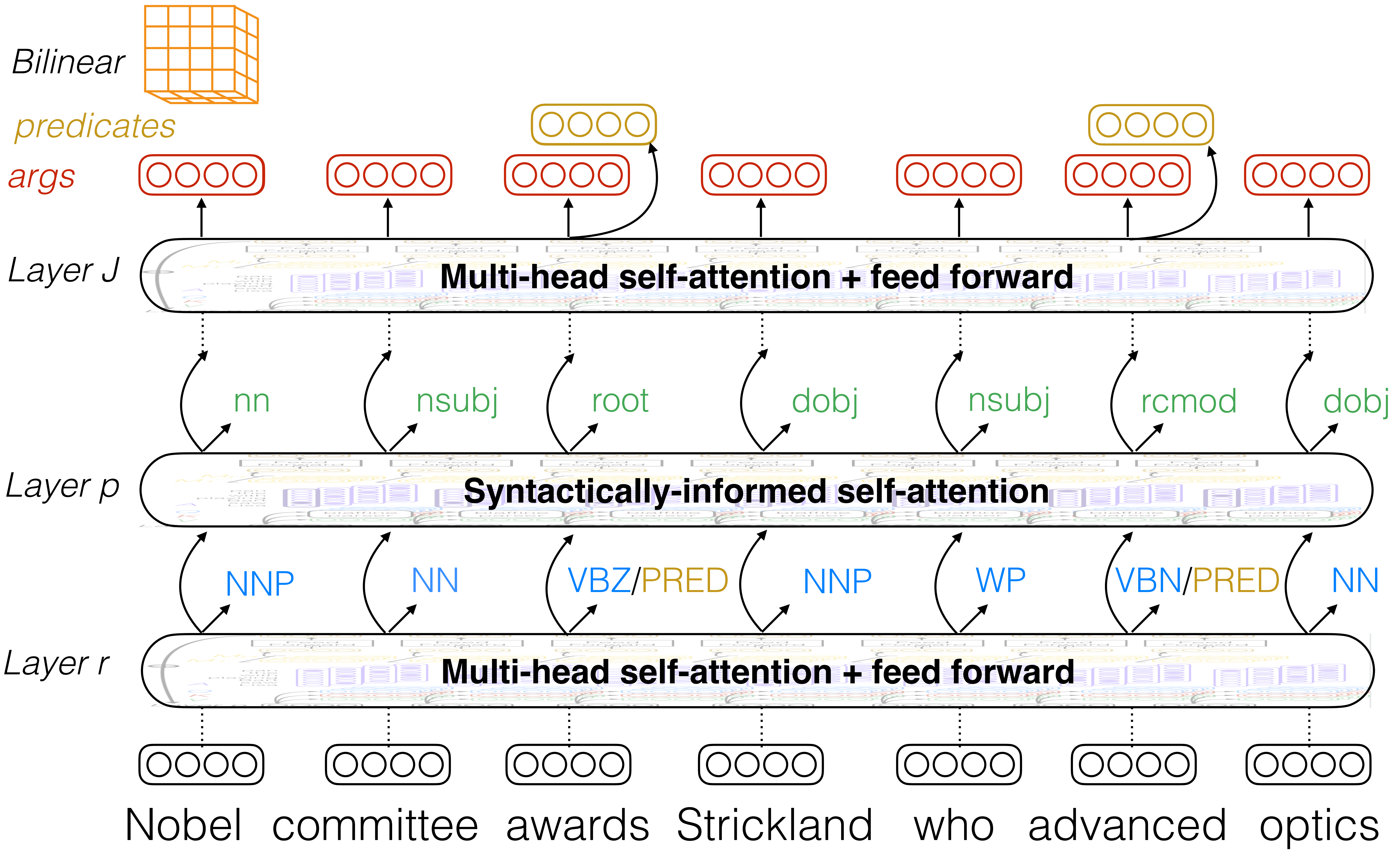

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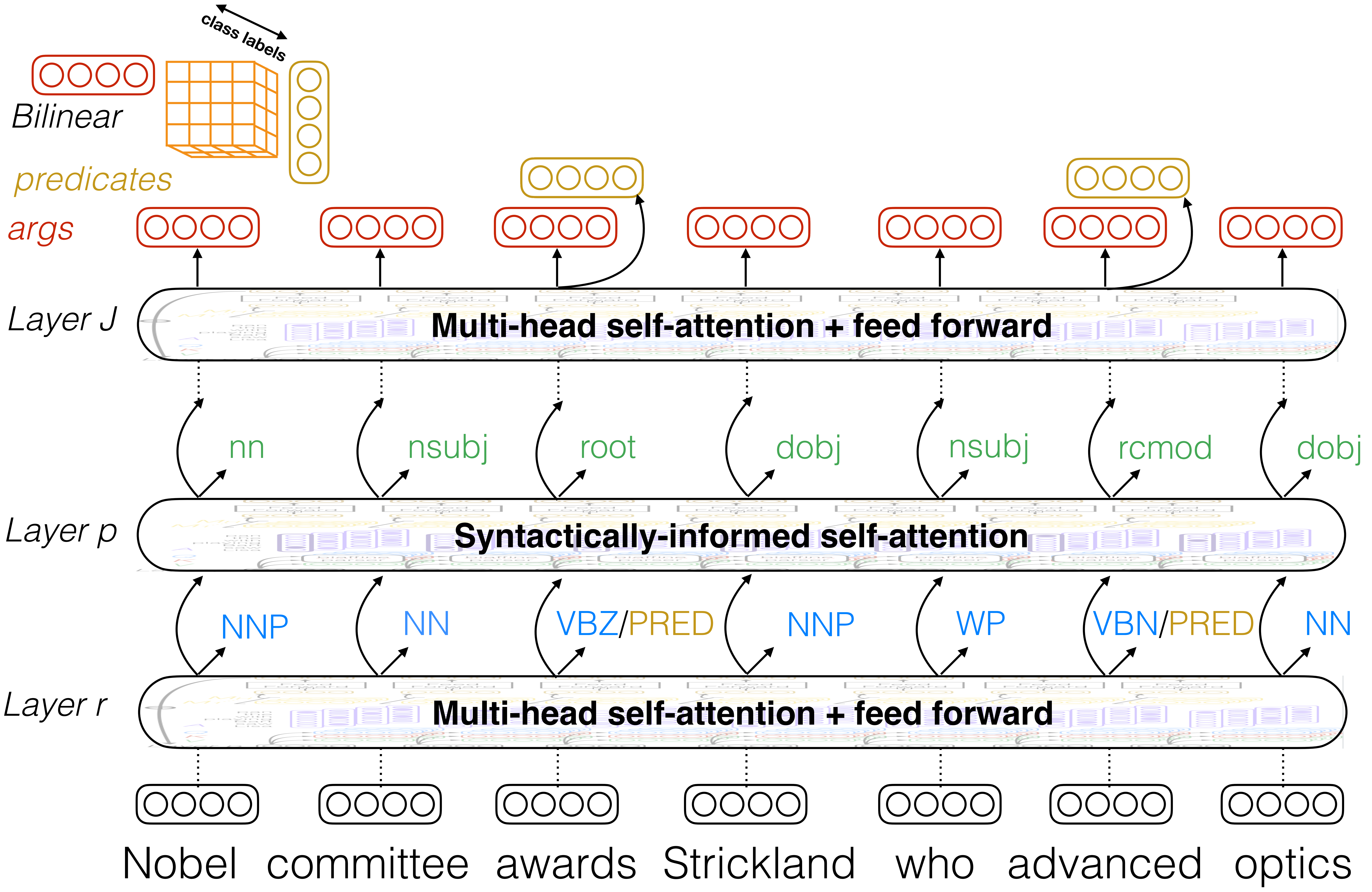

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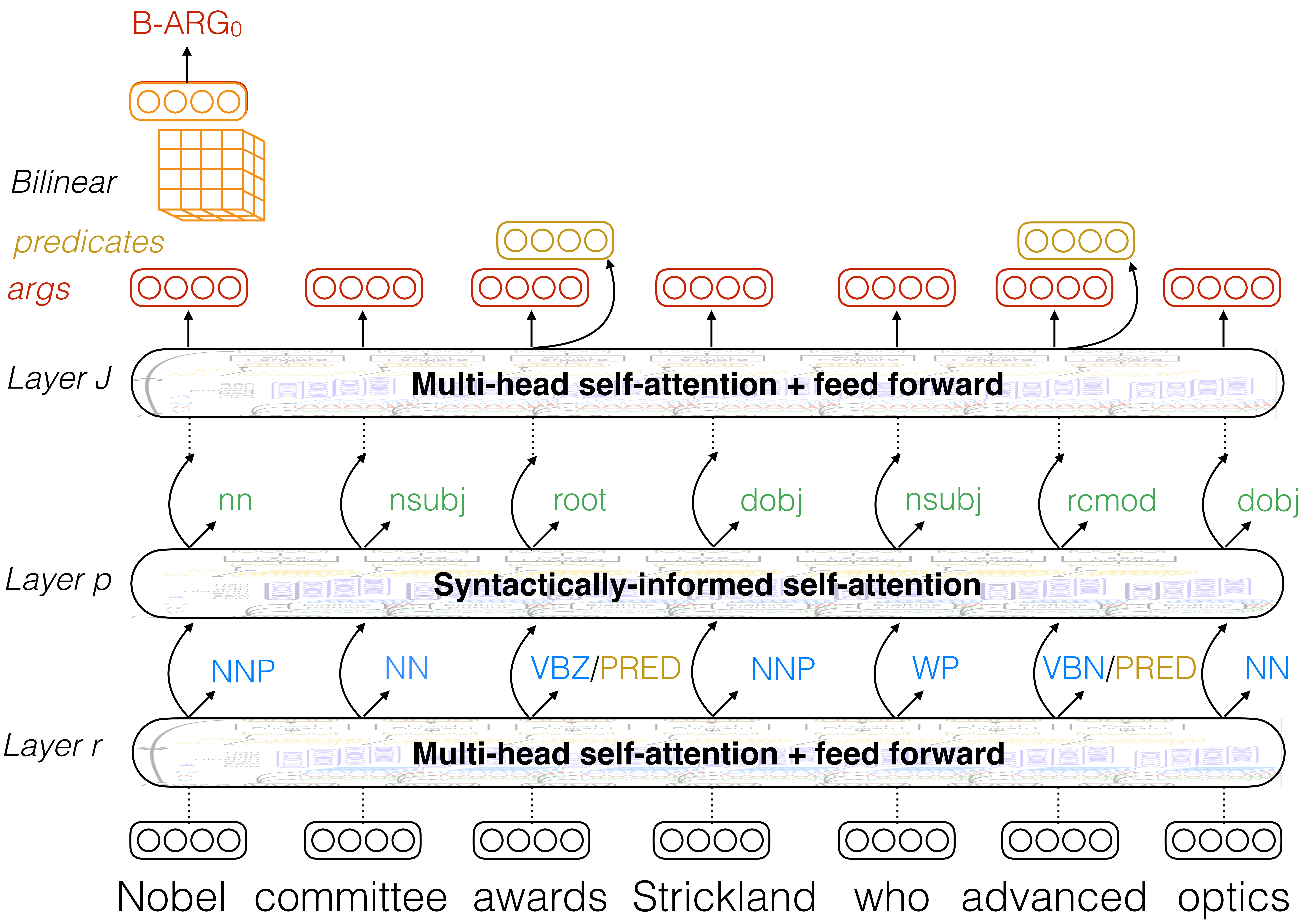

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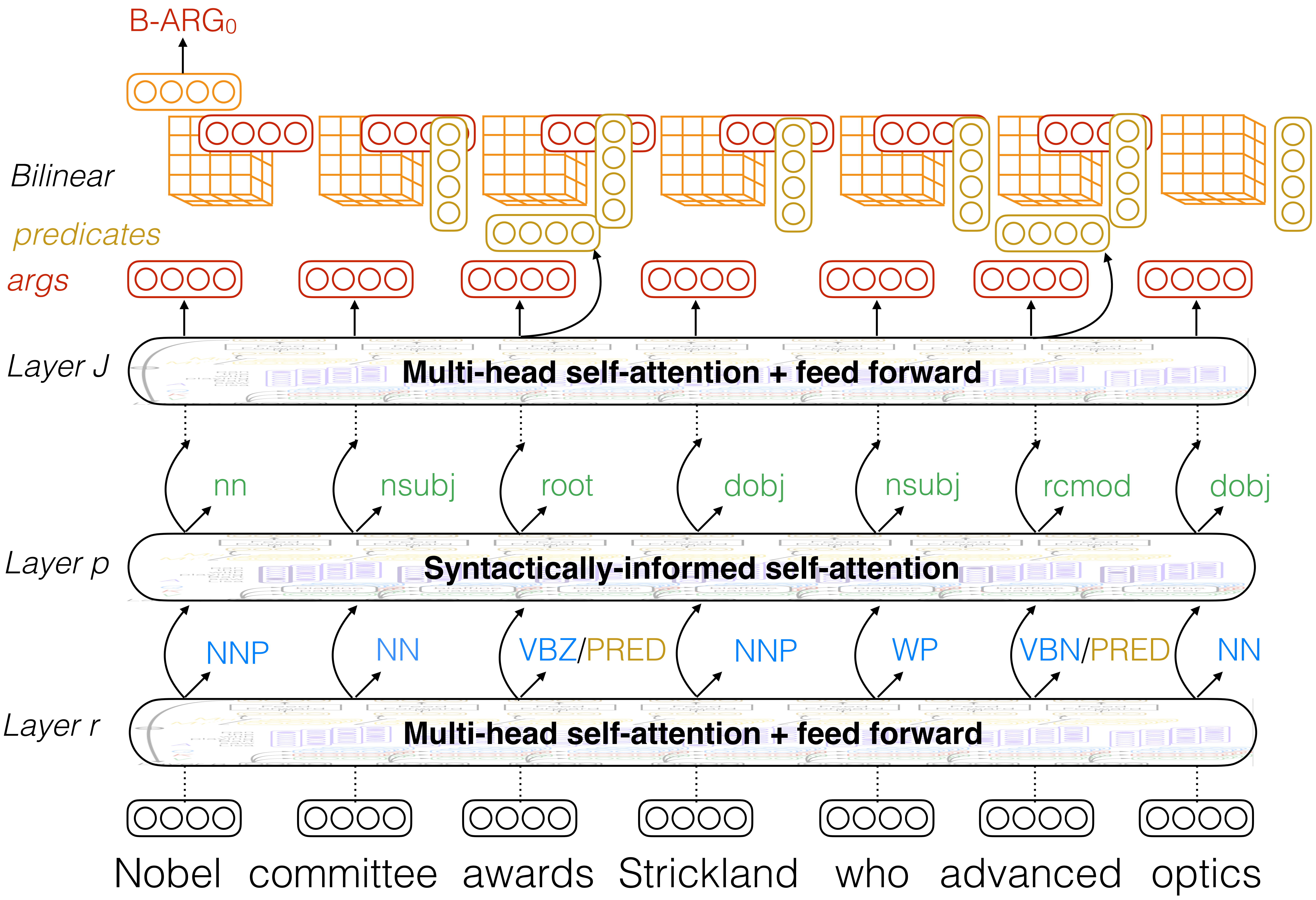

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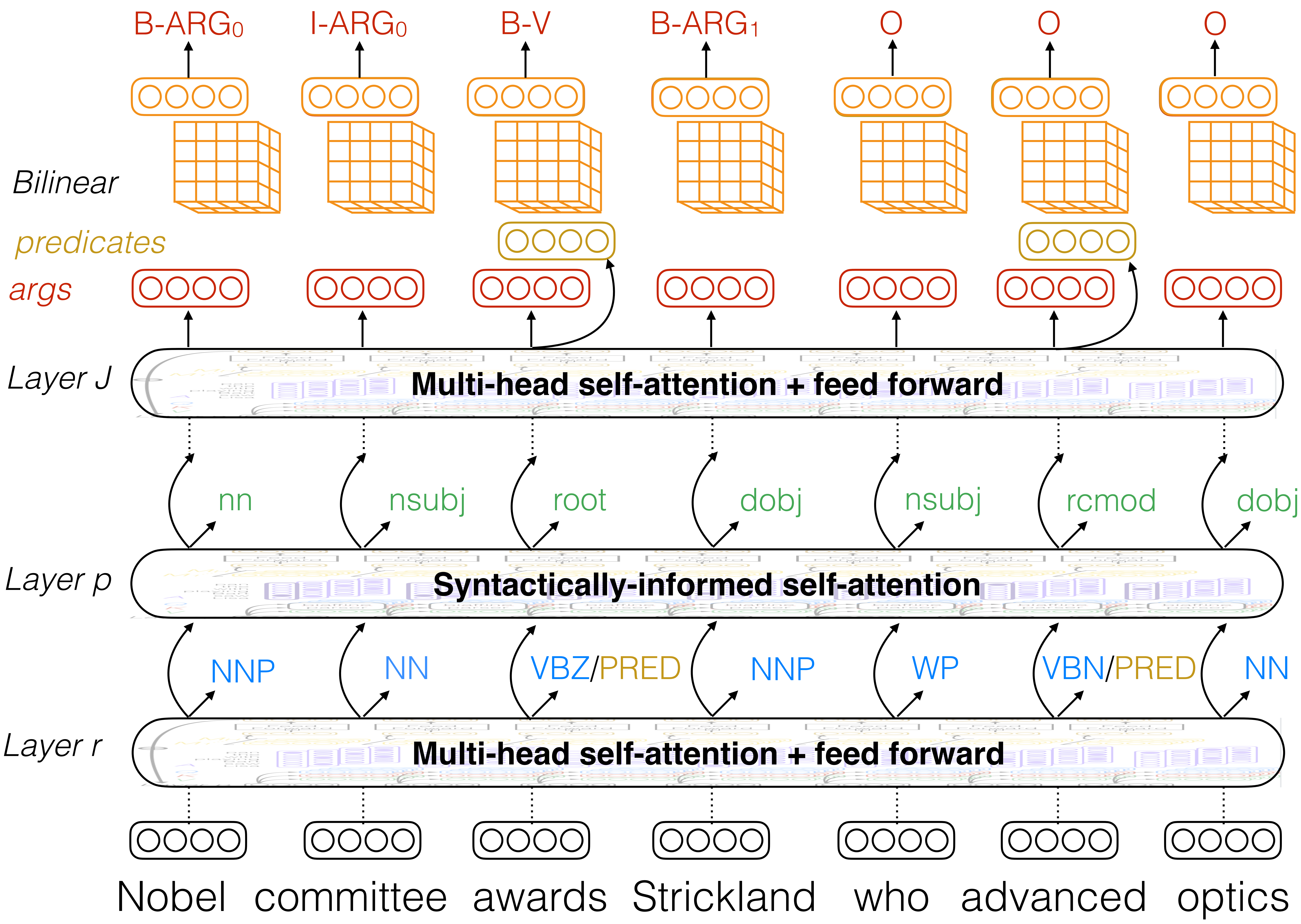

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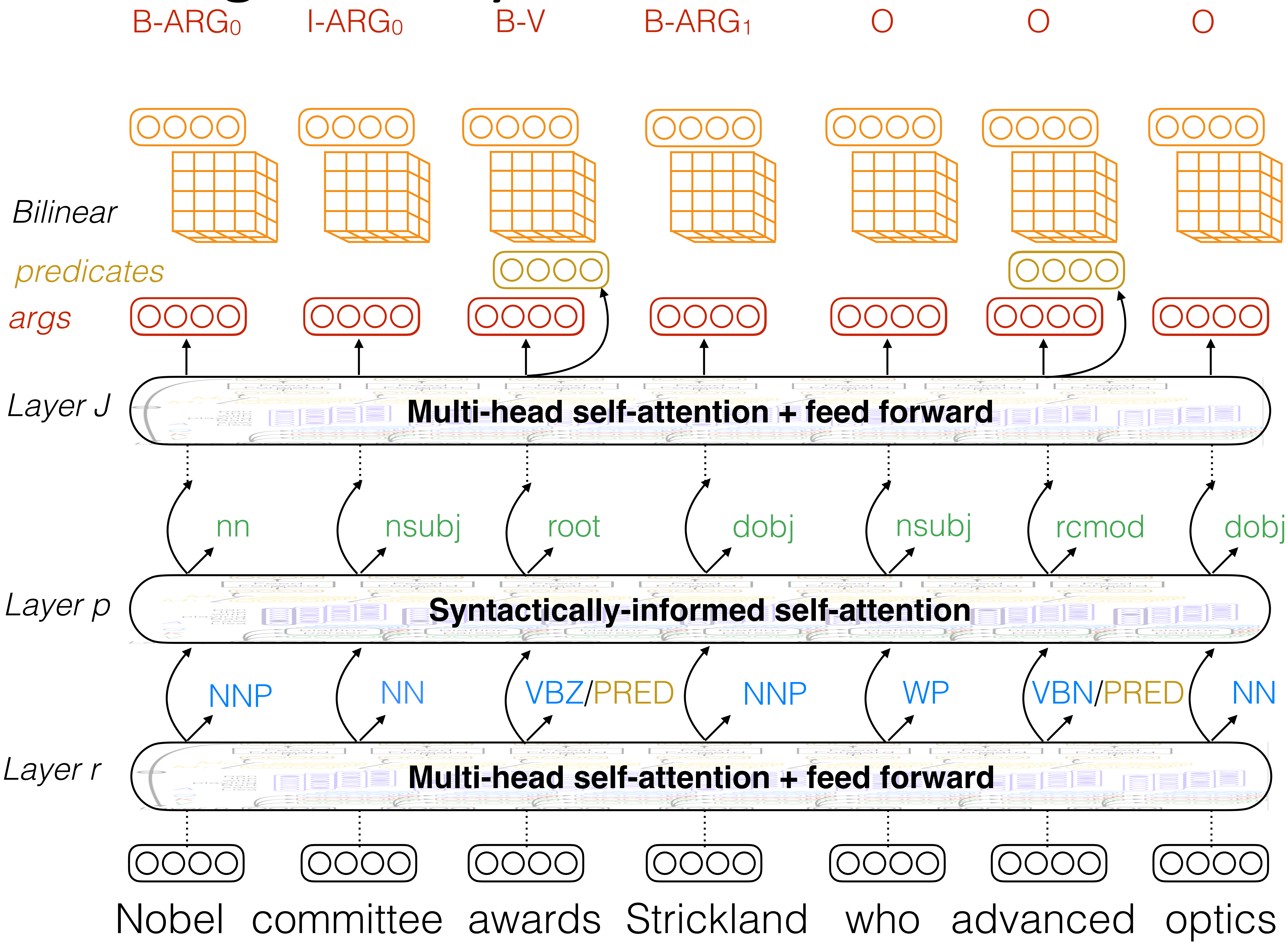

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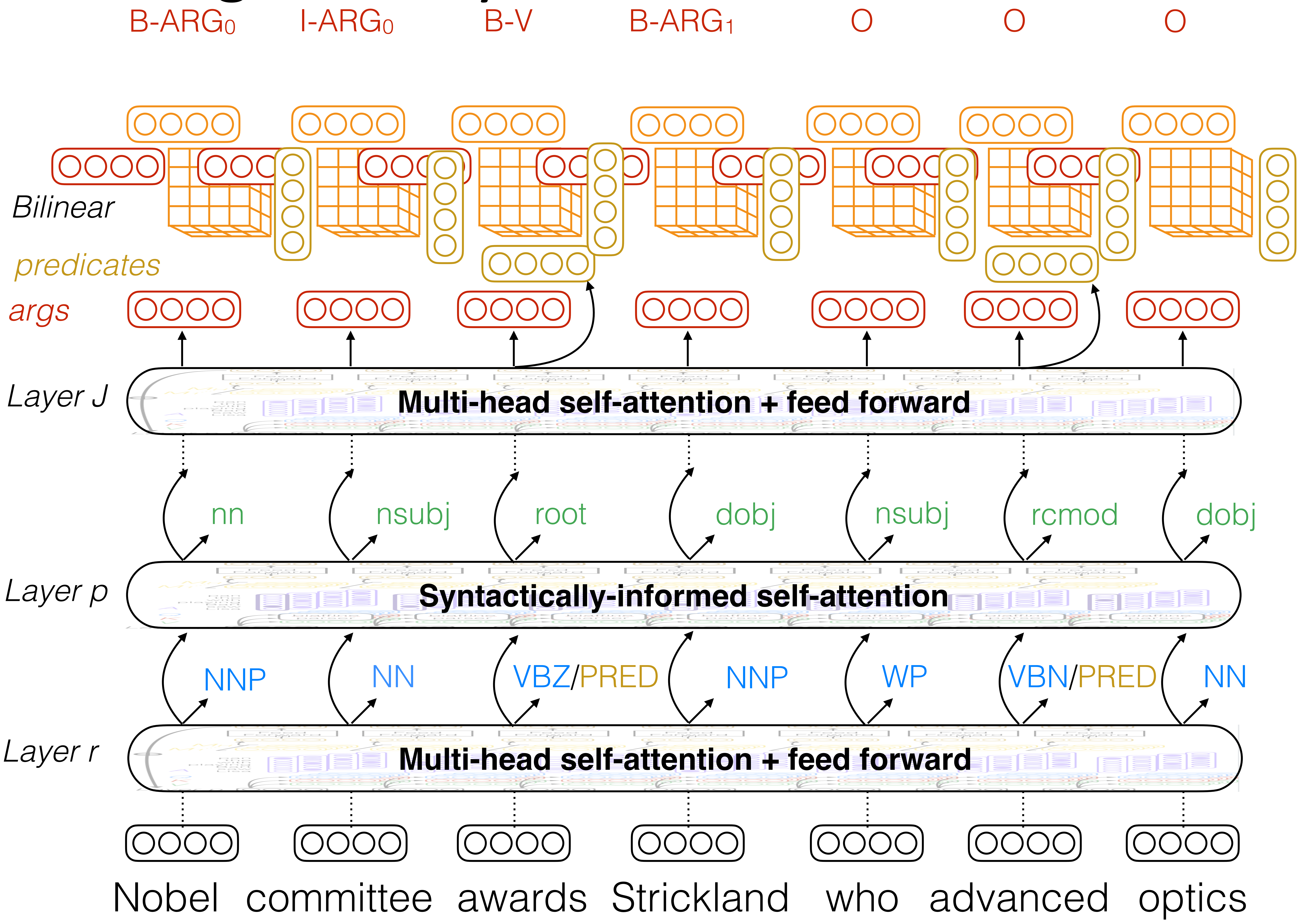

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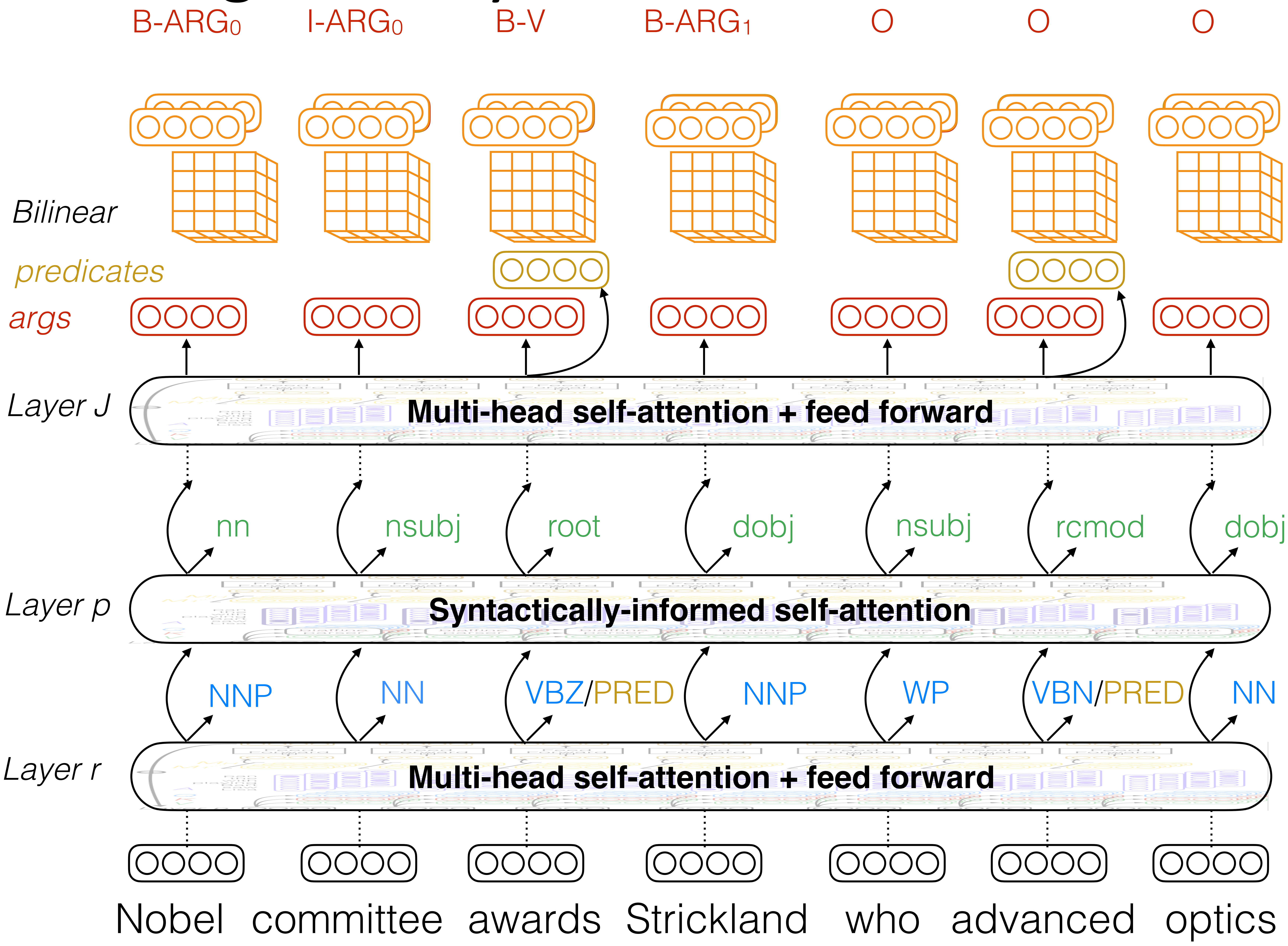

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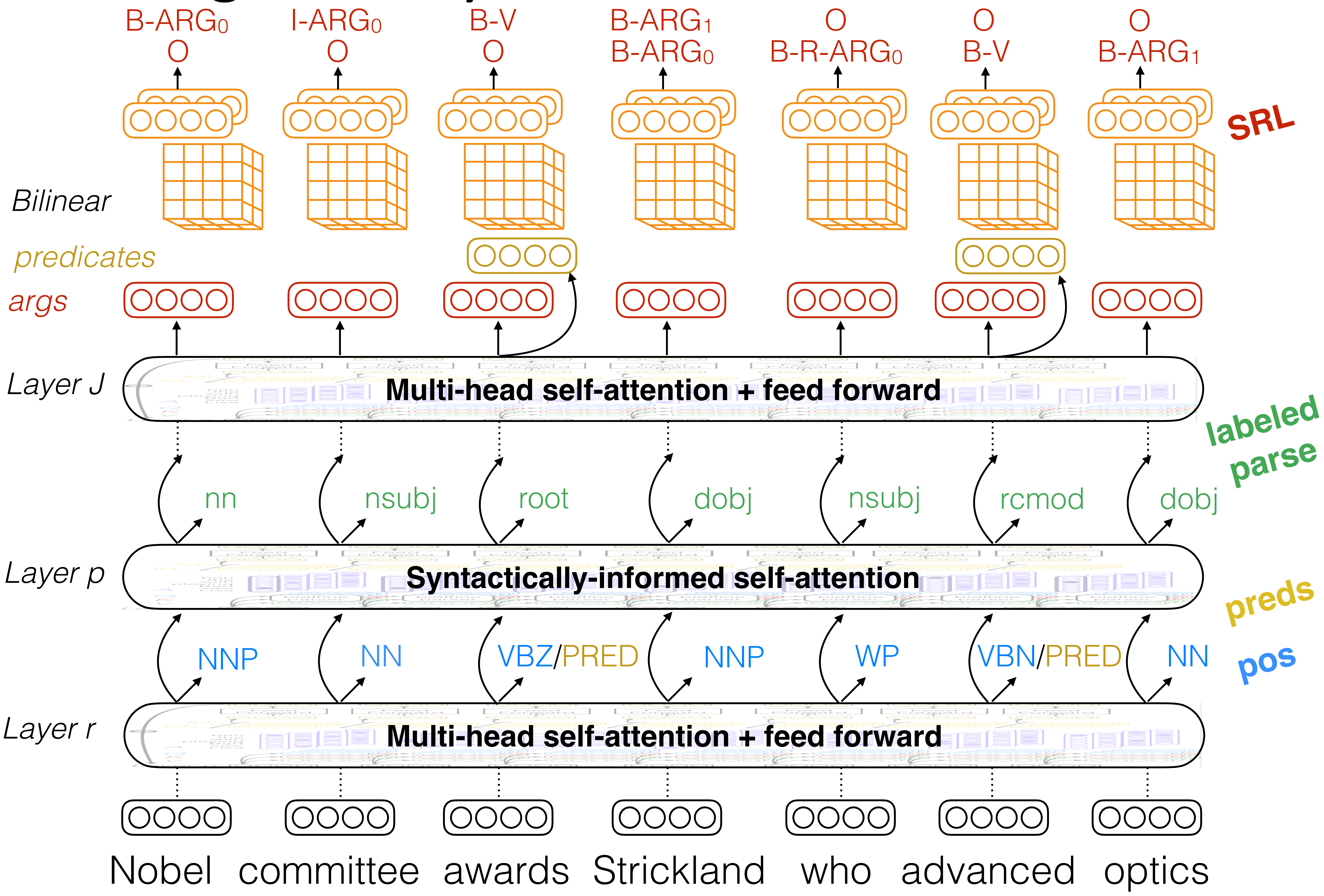


Linguistically-Informed Self-Attention

	 **GloVe**	**ELMo** 
	in-domain (dev)	**in-domain (dev)**
He et al. 2017	81.5	---
He et al. 2018	81.6	85.3
SA	82.39	85.26
LISA	**82.24**	**85.35**
+D&M	83.58	85.17
+Gold	*86.81*	*87.63*

Strubell et al. (2018)

Why SRL is difficult? or NLP in general

- Syntactic Alternation

The robot *plays* piano.

ARG0 player — ARG2 instrument

The cafe is *playing* my favorite song.

ARG0 player — ARG1 thing performed

The music *plays* softly.

ARG1 thing performed — ARGM-MNR

subjects

objects

Why SRL is difficult? or NLP in general

- Prepositional Phrase (PP) Attachment

I *eat* [pasta] [with delight].

ARG0 ARG1 ARGM-MNR

eater meal manner

I *eat* [pasta with broccoli].

ARG0 ARG1

eater meal

Why SRL is difficult? or NLP in general

- Long Dependencies

We *flew* to Chicago.

ARG1 — passenger; ARGM-GOL — goal

We remember the nice view *flying* to Chicago.

ARG1 — passenger; ARGM-GOL — goal

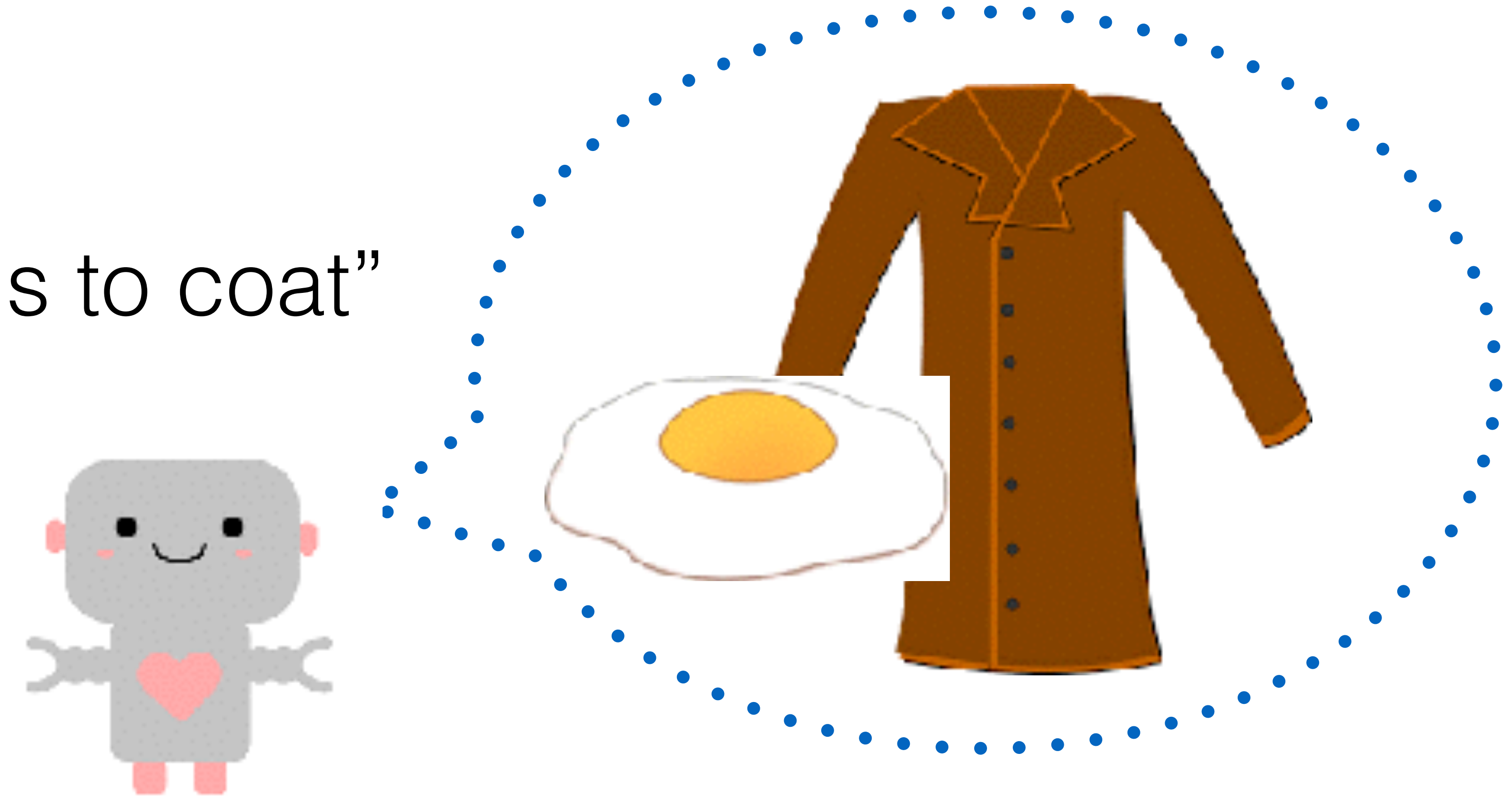
We remember John and Mary *flying* to Chicago.

ARG1 — passenger; ARGM-GOL — goal

Why SRL is difficult? or NLP in general

- Even harder for out-of-domain data

“Dip chicken breasts into eggs to coat”



Active, Ser133-phosphorylated CREB effects transcription of CRE-dependent genes via interaction with the 265-kDa …

Abstract Meaning Representation

Abstract Meaning Representation

- Graph-structured annotation
- Nodes are variables labeled by concepts; edges are semantic relations

“Bob ate four cakes that he bought.”

```
(x2 / eat-01
    :ARG0 (x1 / person
        :name (n / name
            :op1 "Bob")
        :wiki "Bob_X")
    :ARG1 (x4 / cake
        :quant 4
        :ARG1-of (x7 / buy-01
            :ARG0 x1)))
```

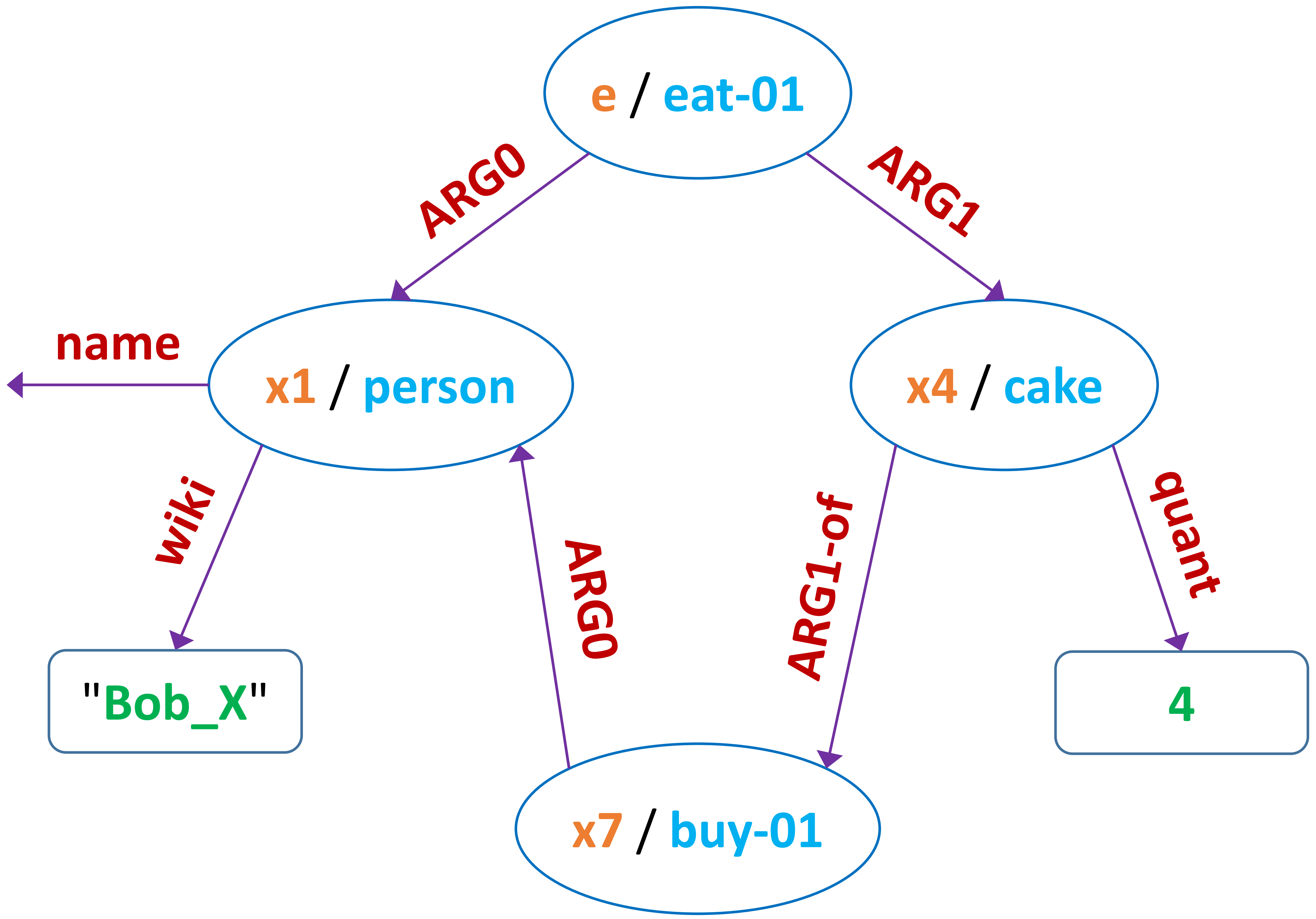


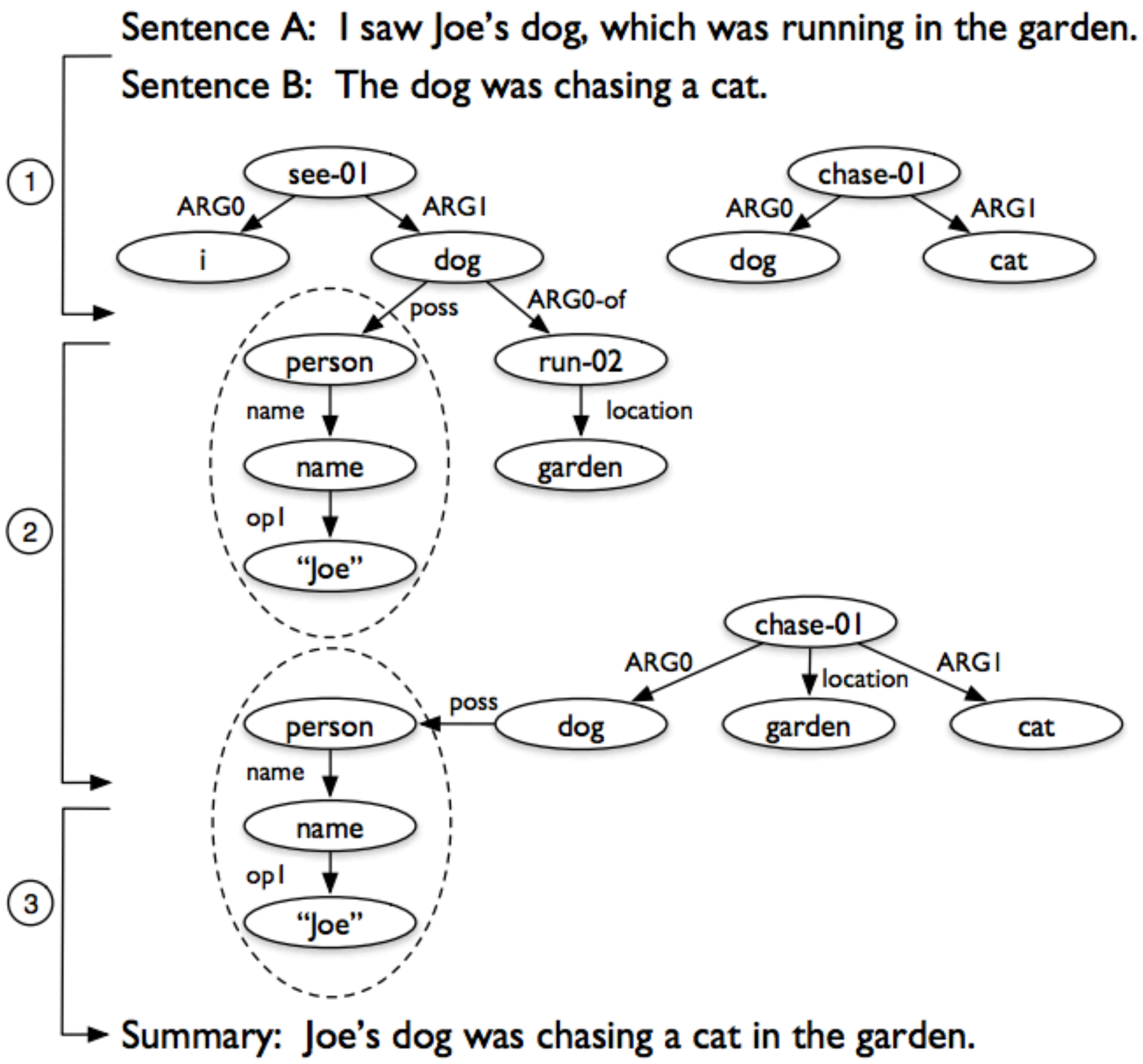
Figure from Gruzitis et al. (2014)

Abstract Meaning Representation

- Superset of SRL: full sentence analyses, contains coreference and multi-word expressions as well
- F1 scores in the 60s: hard!
- So comprehensive that it's hard to predict, but still doesn't handle tense or some other things…

Banarescu et al. (2014)

Summarization with AMR



- Merge AMRs across multiple sentences
- Summarization = subgraph extraction

Liu et al. (2015)

Relation Extraction

Relation Extraction

- Extract entity-relation-entity triples from a fixed inventory

Located_In

Nationality

During the war in Iraq, American journalists were sometimes caught in the line of fire

- Use NER-like system to identify entity spans, classify relations between entity pairs with a classifier
- Systems can be feature-based or neural, look at surface words, syntactic features (dependency paths), semantic roles
- Problem: limited data for scaling to big ontologies

ACE (2003-2005)

Hearst Patterns

- Syntactic patterns especially for finding hypernym-hyponym pairs (“is a” relations)

Y is a X	*Berlin is a city*
X such as [list]	*cities such as Berlin, Paris, and London.*
other X including Y	*other cities including Berlin*

- Totally unsupervised way of harvesting world knowledge for tasks like parsing and coreference (Bansal and Klein, 2011-2012)

Hearst (1992)

Distant Supervision

- Lots of relations in our knowledge base already (e.g., 23,000 film-director relations); use these to bootstrap more training data
- If two entities in a relation appear in the same sentence, assume the sentence expresses the relation

Director

[Steven Spielberg]'s film [Saving Private Ryan] is loosely based on the brothers' story

Allison co-produced the Academy Award-winning [Saving Private Ryan], directed by [Steven Spielberg]

Director

Mintz et al. (2009)

Distant Supervision

- Learn decently accurate classifiers for ~100 Freebase relations
- Could be used to crawl the web and expand our knowledge base

Relation name	100 instances			1000 instances		
	Syn	Lex	Both	Syn	Lex	Both
/film/director/film	**0.49**	0.43	0.44	**0.49**	0.41	0.46
/film/writer/film	**0.70**	0.60	0.65	**0.71**	0.61	0.69
/geography/river/basin_countries	0.65	0.64	**0.67**	**0.73**	0.71	0.64
/location/country/administrative_divisions	0.68	0.59	**0.70**	**0.72**	0.68	**0.72**
/location/location/contains	0.81	**0.89**	0.84	**0.85**	0.83	0.84
/location/us_county/county_seat	0.51	0.51	**0.53**	0.47	**0.57**	0.42
/music/artist/origin	0.64	0.66	**0.71**	0.61	**0.63**	0.60
/people/deceased_person/place_of_death	0.80	0.79	**0.81**	0.80	**0.81**	0.78
/people/person/nationality	0.61	0.70	**0.72**	0.56	0.61	**0.63**
/people/person/place_of_birth	**0.78**	0.77	**0.78**	0.88	0.85	**0.91**
Average	0.67	0.66	**0.69**	**0.68**	0.67	0.67

Mintz et al. (2009)

Distant Supervision

- Inherently have noise in training data, need special methods (e.g., multi-instance learning) to handle false positives AND false negatives.

Freebase

Entity 1	Entity 2	Relation
Thailand	Bangkok	/location/country/capital

Sentences mentioning the two entities:

1. *Bangkok* is the most populous city of *Thailand*.

false positive

2. *Bangkok* grew rapidly during the 1960s through the 1980s and now exerts a significant impact among *Thailand*'s politics, economy, education, media and modern society.

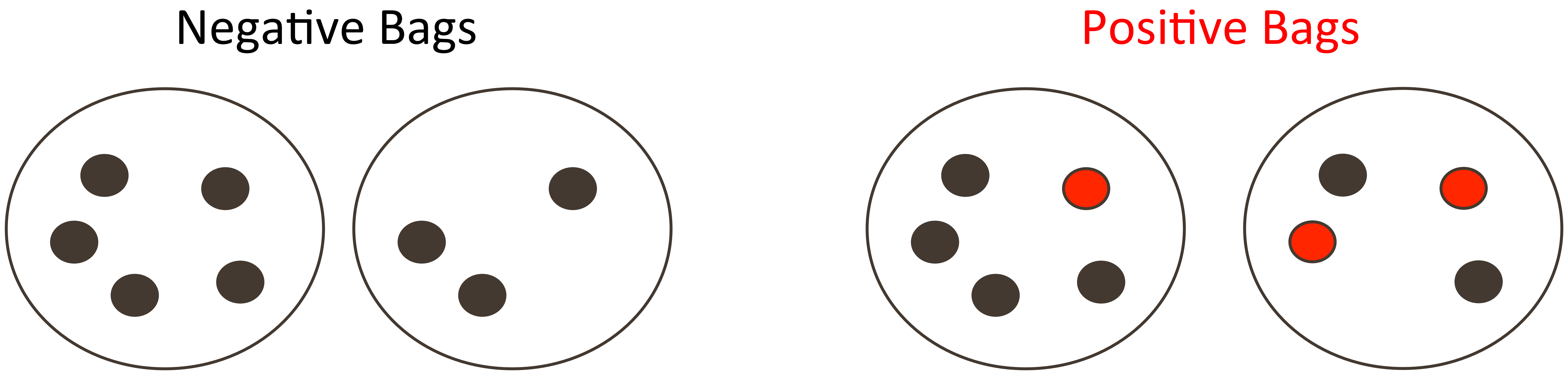
???

3. The nation of *Thailand* is about to get its very first visit ever from a president this weekend, President Obama, so the American Embassy in *Bangkok* is understandably very excited right now.

Figure from Jiang et al. (2016)

Multi-instance Learning

- Instead of labels on each individual instance, the learner only observes labels on bags of instances.



A bag is labeled negative, if
all the examples in it are negative

A bag is labeled positive, if
there is **at least one** positive example

Xu et al. (2013), Pershina et al. (2014), Tabassum (2016)

Multi-instance Learning

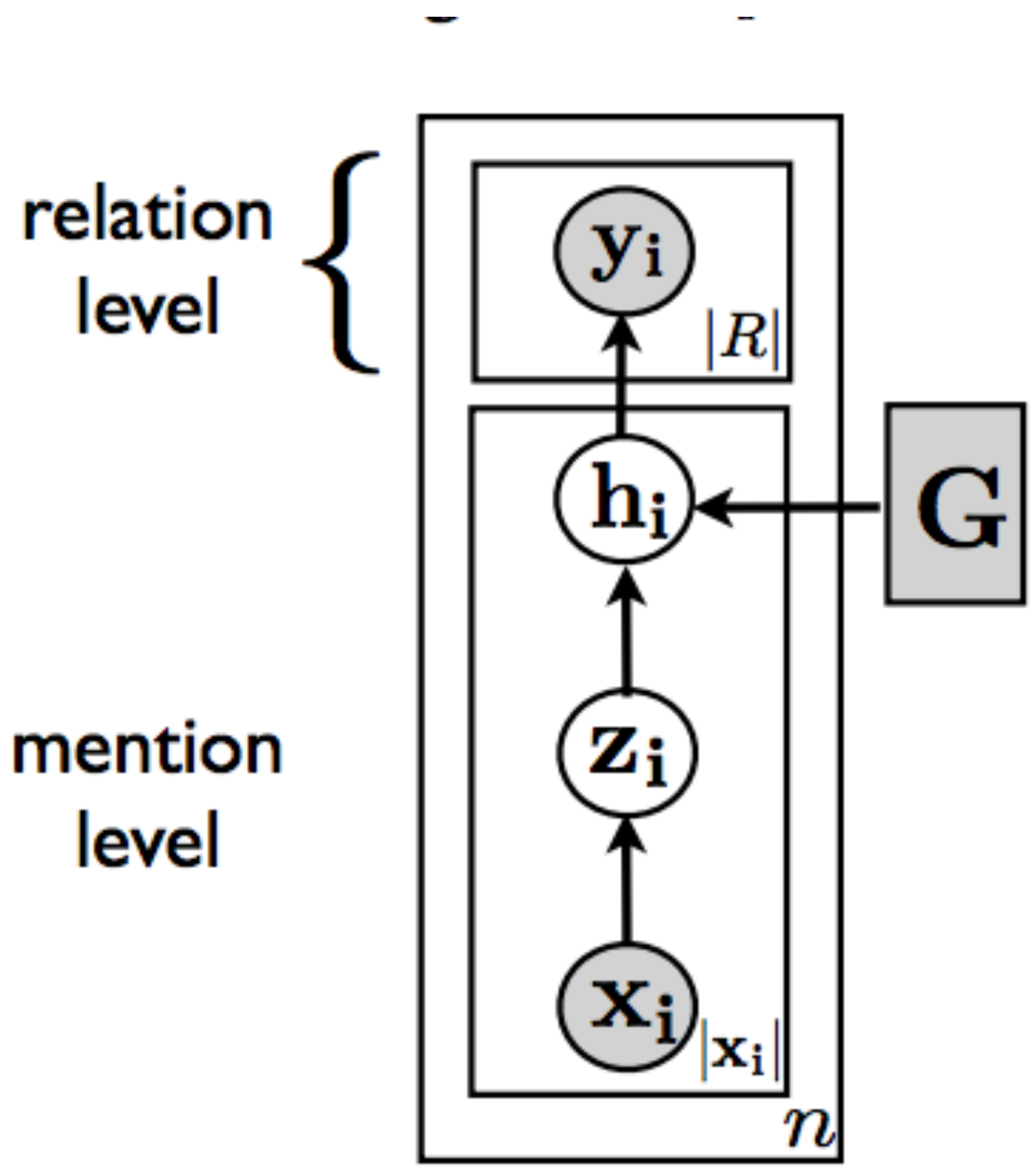
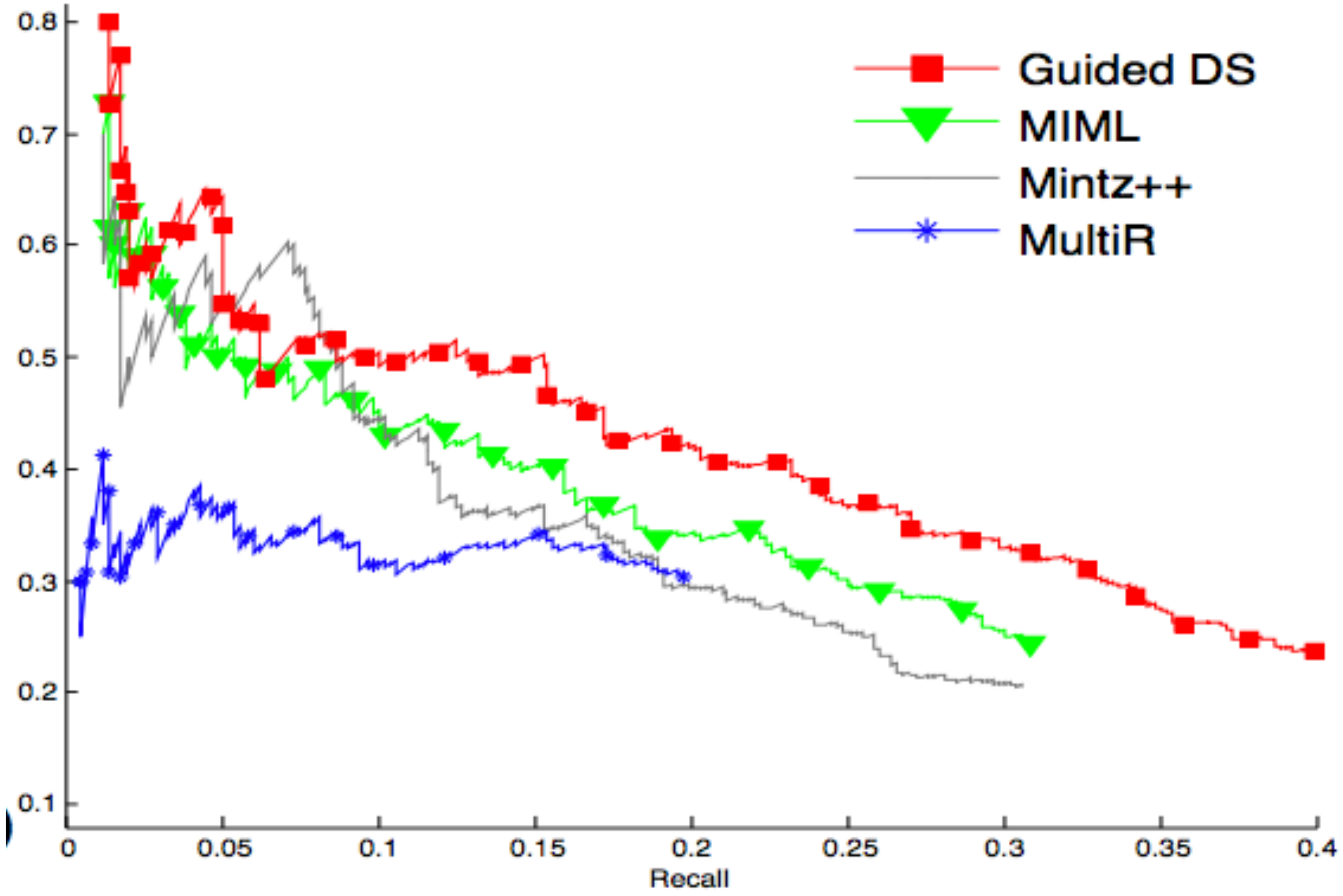


Figure 1: Plate diagram of Guided DS



Xu et al. (2013), Pershina et al. (2014), Tabassum (2016)

Slot Filling

Slot Filling

- Most conservative, narrow form of IE

magnitude time

Indian Express — A massive earthquake of magnitude 7.3 struck Iraq on Sunday, 103 kms (64 miles) southeast of the city of As-Sulaymaniyah, the US Geological Survey said, reports Reuters. US Geological Survey initially said the quake was of a magnitude 7.2, before revising it to 7.3.

epicenter

Speaker: Alan Clark speaker

"Gender Roles in the Holy Roman Empire" title

Allagher Center Main Auditorium location

This talk will discuss...

- Old work: HMMs, later CRFs trained per role

Freitag and McCallum (2000)

Open IE

Open Information Extraction

- “Open”ness — want to be able to extract all kinds of information from open-domain text

- Acquire commonsense knowledge just from “reading” about it, but need to process lots of text (“machine reading”)

- Typically no fixed relation inventory

TextRunner

- Extract positive examples of (e, r, e) triples via parsing and heuristics
- Train a Naive Bayes classifier to filter triples from raw text: uses features on POS tags, lexical features, stopwords, etc.

Barack Obama, 44th president of the United States, was born on August 4, 1961 in Honolulu

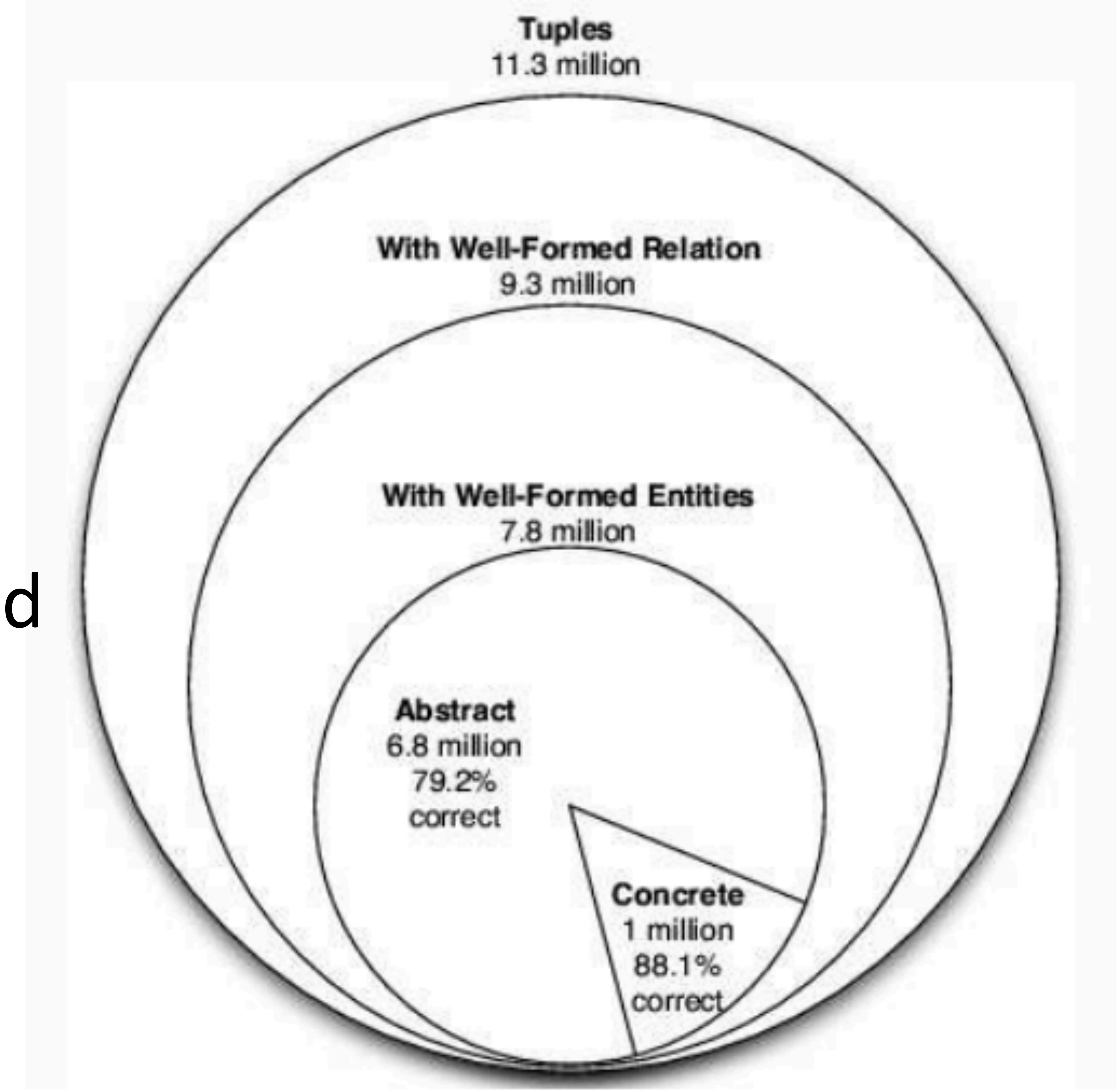
=> Barack_Obama, was born in, Honolulu

- 80x faster than running a parser (which was slow in 2007…)
- Use multiple instances of extractions to assign probability to a relation

Banko et al. (2007)

Exploiting Redundancy

- 9M web pages / 133M sentences
- 2.2 tuples extracted per sentence, filter based on probabilities
- Concrete: definitely true
  Abstract: possibly true but underspecified
- Hard to evaluate: can assess precision of extracted facts, but how do we know recall?



Banko et al. (2007)

ReVerb

- More constraints: open relations have to begin with verb, end with preposition, be contiguous (e.g., *was born on*)

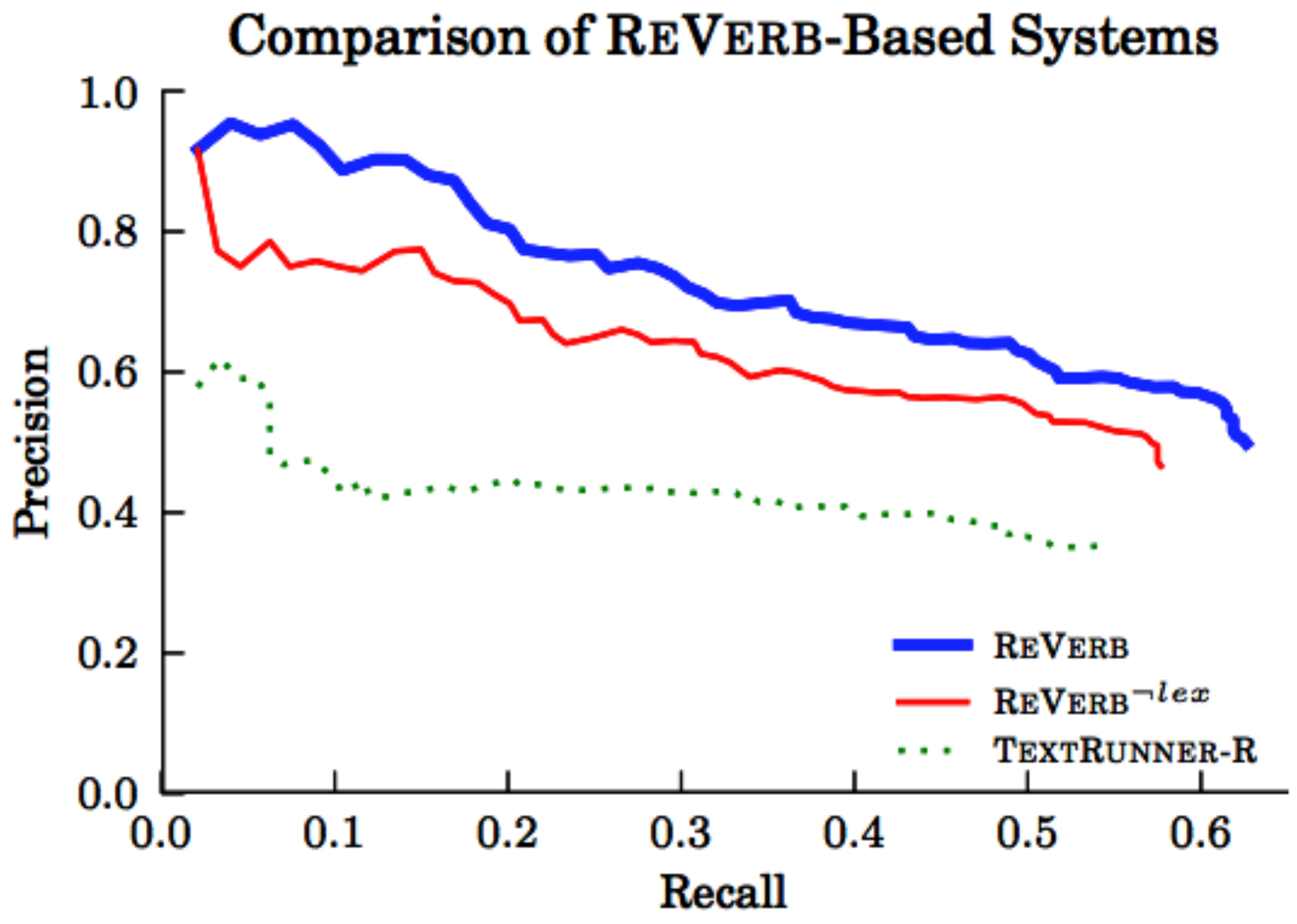
- Extract more meaningful relations, particularly with light verbs

is	is an album by, is the author of, is a city in
has	has a population of, has a Ph.D. in, has a cameo in
made	made a deal with, made a promise to
took	took place in, took control over, took advantage of
gave	gave birth to, gave a talk at, gave new meaning to
got	got tickets to, got a deal on, got funding from

Fader et al. (2011)

ReVerb

- For each verb, identify the longest sequence of words following the verb that satisfy a POS regex (V .* P) and which satisfy heuristic lexical constraints on specificity
- Find the nearest arguments on either side of the relation
- Annotators labeled relations in 500 documents to assess recall



Fader et al. (2011)

Takeaways

- SRL/AMR: handle a bunch of phenomena, but more or less like syntax++ in terms of what they represent
- Relation extraction: can collect data with distant supervision, use this to expand knowledge bases
- Slot filling: tied to a specific ontology, but gives fine-grained information
- Open IE: extracts lots of things, but hard to know how good or useful they are
  - Can combine with standard question answering
  - Add new facts to knowledge bases
- Many, many applications and techniques