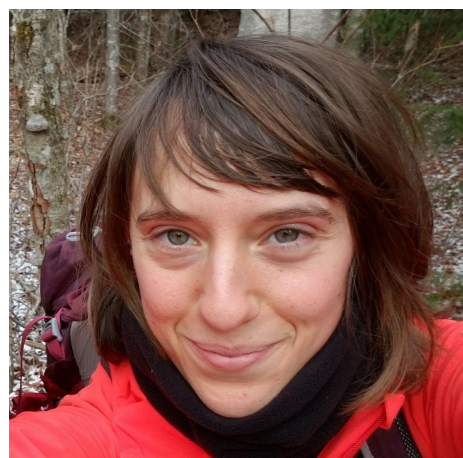


LISA

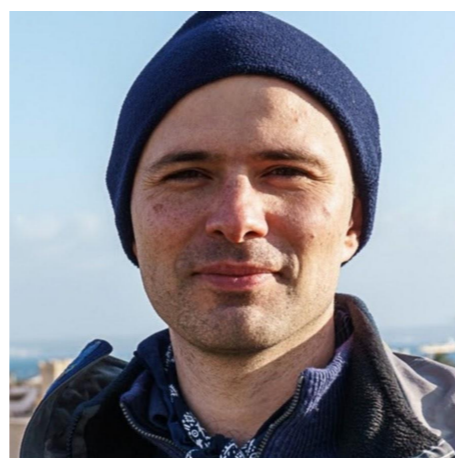
Linguistically-Informed Self-Attention for Semantic Role Labeling



Emma
Strubell¹



Patrick
Verga¹



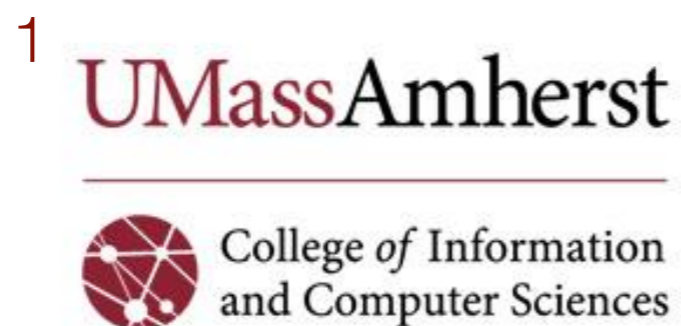
Daniel
Andor²



David
Weiss²



Andrew
McCallum¹



Want fast, accurate, robust NLP

Nobel laureate Donna Strickland: 'I see myself as a scientist not a woman'

For Just the Third Time in 117 Years, a Woman Wins the Nobel Prize in Physics



The Washington Post
Democracy Dies in Darkness

Nobel Prize in physics awarded for 'tools made of light'; first woman in 55 years honored

By Sarah Kaplan
October 2

The 2018 Nobel Prize in physics was awarded Tuesday to Arthur Ashkin, Gérard Mourou and Donna Strickland for their pioneering work to turn lasers into powerful tools.

Ashkin, a researcher at Bell Laboratories in New Jersey, invented "optical tweezers" — focused beams of light that can be used to grab particles, atoms and even living cells and are now widely used to study the machinery of life.

Mourou, of École Polytechnique in France and the University of Michigan, and Strickland, of the University of Waterloo in Canada, "paved the way" for the most powerful lasers ever created by humans via a technique that stretches and then amplifies the light beam.

"Billions of people make daily use of optical disk drive, laser printers and optical scanners . . . millions undergo laser surgery," Nobel committee member Olga Botner said. "The laser is truly one of the many examples of how a so-called blue sky discovery in a fundamental science eventually may transform our daily lives."

Strickland is the first woman to be awarded the physics prize since 1963, when Maria Goeppert-Mayer was recognized for her work on the structure of atomic nuclei. Marie Curie won the physics prize in 1903 and the chemistry Nobel Prize in 1911.

Volume 56, number 3

OPTICS COMMUNICATIONS

1 December 1985

COMPRESSION OF AMPLIFIED CHIRPED OPTICAL PULSES

Donna STRICKLAND and Gerard MOUROU

Laboratory for Laser Energetics, University of Rochester, 250 East River Road, Rochester, NY 14623-1299, USA

Received 5 July 1985

We have demonstrated the compression of a 1.06 μm laser pulse to a duration of 100 fs.

The onset of self-focusing limits the amplification of a similar problem arises for short, yet energetic pulses capable of handling the amplification for radar transmission by passing it through a medium before amplifying an echo is compressed to a duration of 100 fs.

We wish to report the technique employed and that in principle short (≤ 1 ps) pulses A long pulse is deliberately stretched to a duration of 100 ps. The pulse is linearly modulated in frequency before amplification. The pulse is then compressed by amplifying the stretched pulse before self-focusing. It does not appear to affect the gain of amplifying a chirped pulse in a gain medium is gain sweet spot.

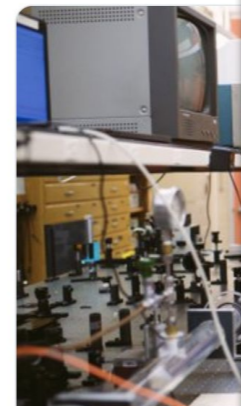
* This is a corrected version of Comm. 55 (1985) 447 was printed as fig. 1.

0 030-4018/85/\$03.00 (North-Holland Physics Publishing Co.)

STEM Gems
@STEMGemsBook

Follow

#STEMGems "Physicist #DonnaStrickland, a self-described 'laser jock' who prefers to keep a low profile, won the @NobelPrize 3rd woman ever and she calls 'surprise' #GirlsInSTEM"



Physicist Donna Strickland
She is only the third woman to win the Nobel Prize in physics.
time.com

6:02 AM - 23 Oct 2018

9 Retweets 30 Likes

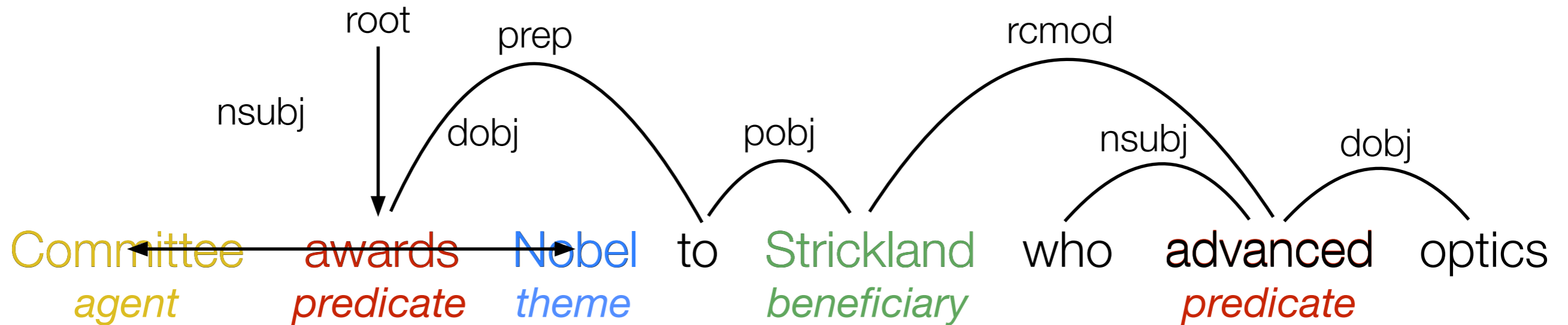
SECOND EDITION

NOBEL PRIZE WOMEN IN SCIENCE

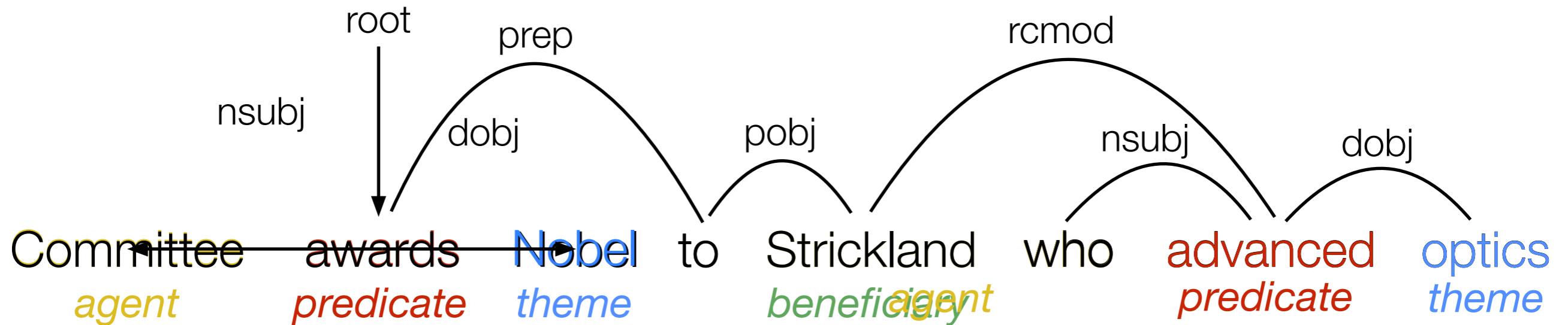
Their Lives, Struggles, AND Momentous Discoveries

SHARON BERTSCH MCGRAYNE

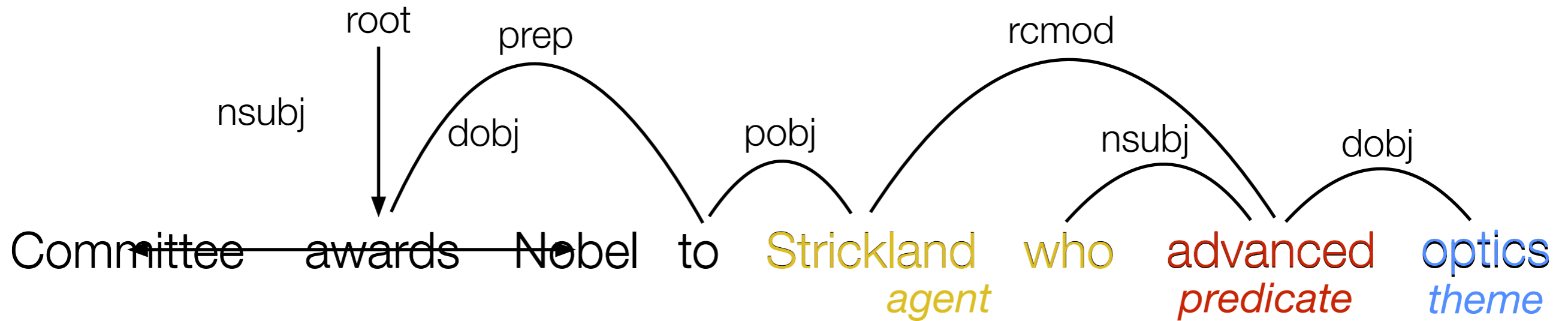
SRL: Who did what to whom?



SRL: Who did what to whom?



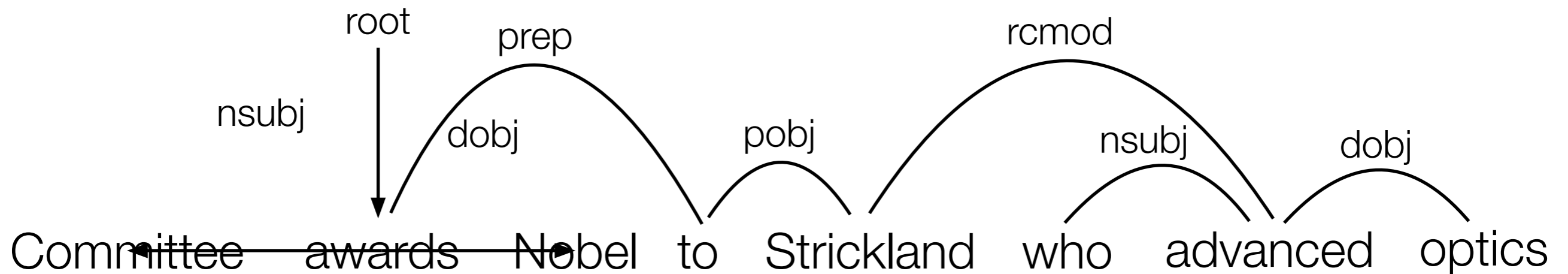
SRL: Who did what to whom?



Committee awards Nobel to Strickland who advanced optics

agent *predicate* *theme* *beneficiary*

PropBank SRL: Who did what to whom?



Committee awards Nobel to Strickland who advanced optics
ARG₀ *predicate* *ARG₁* *to* *ARG₂* *who* *advanced* *ARG₁*

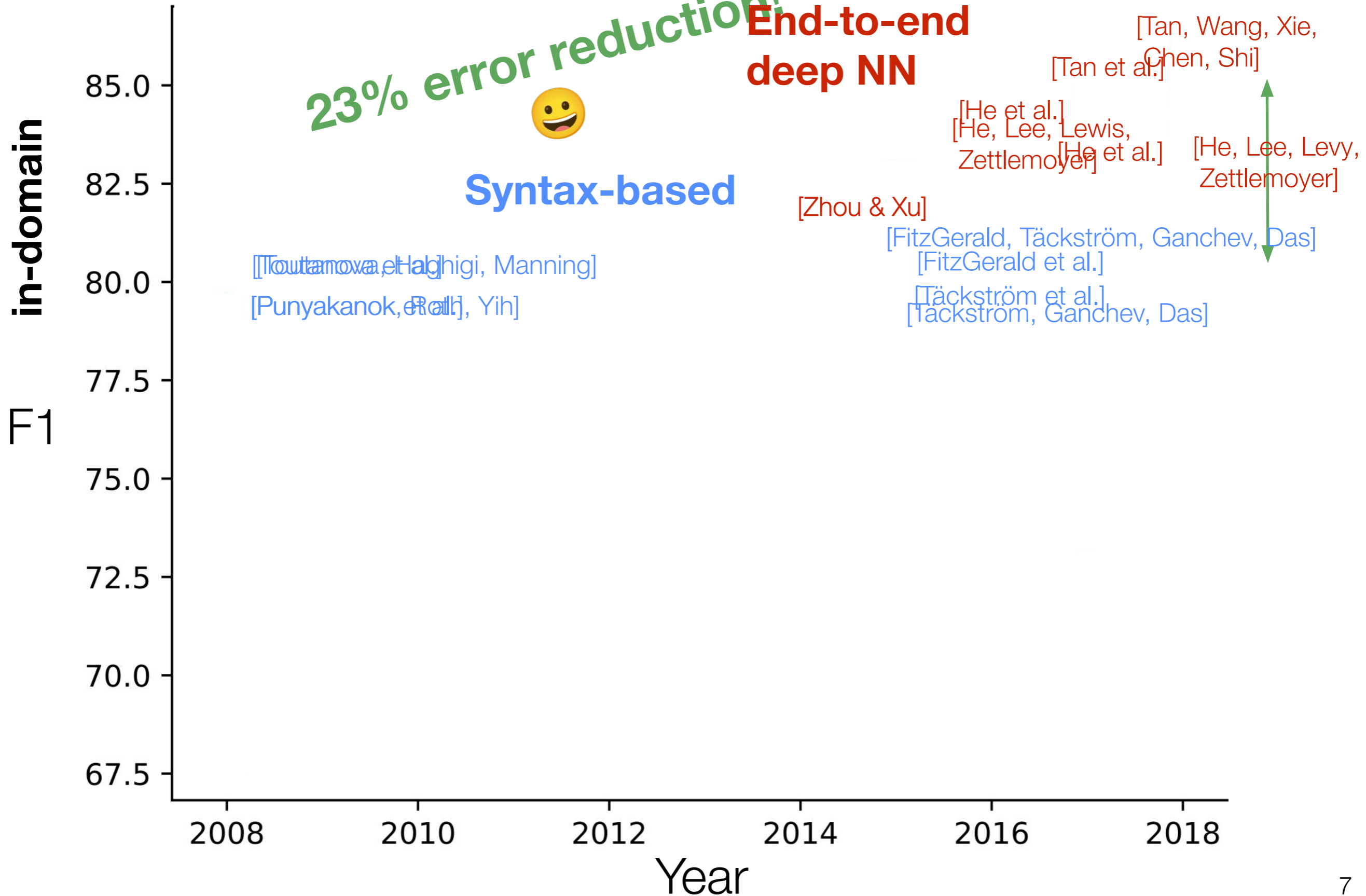
Committee awards Nobel to Strickland who advanced optics
ARG₀ *predicate* *ARG₁* *to* *beneficiary* *ARG₂* *advanced* *ARG₁*

10 years of PropBank SRL

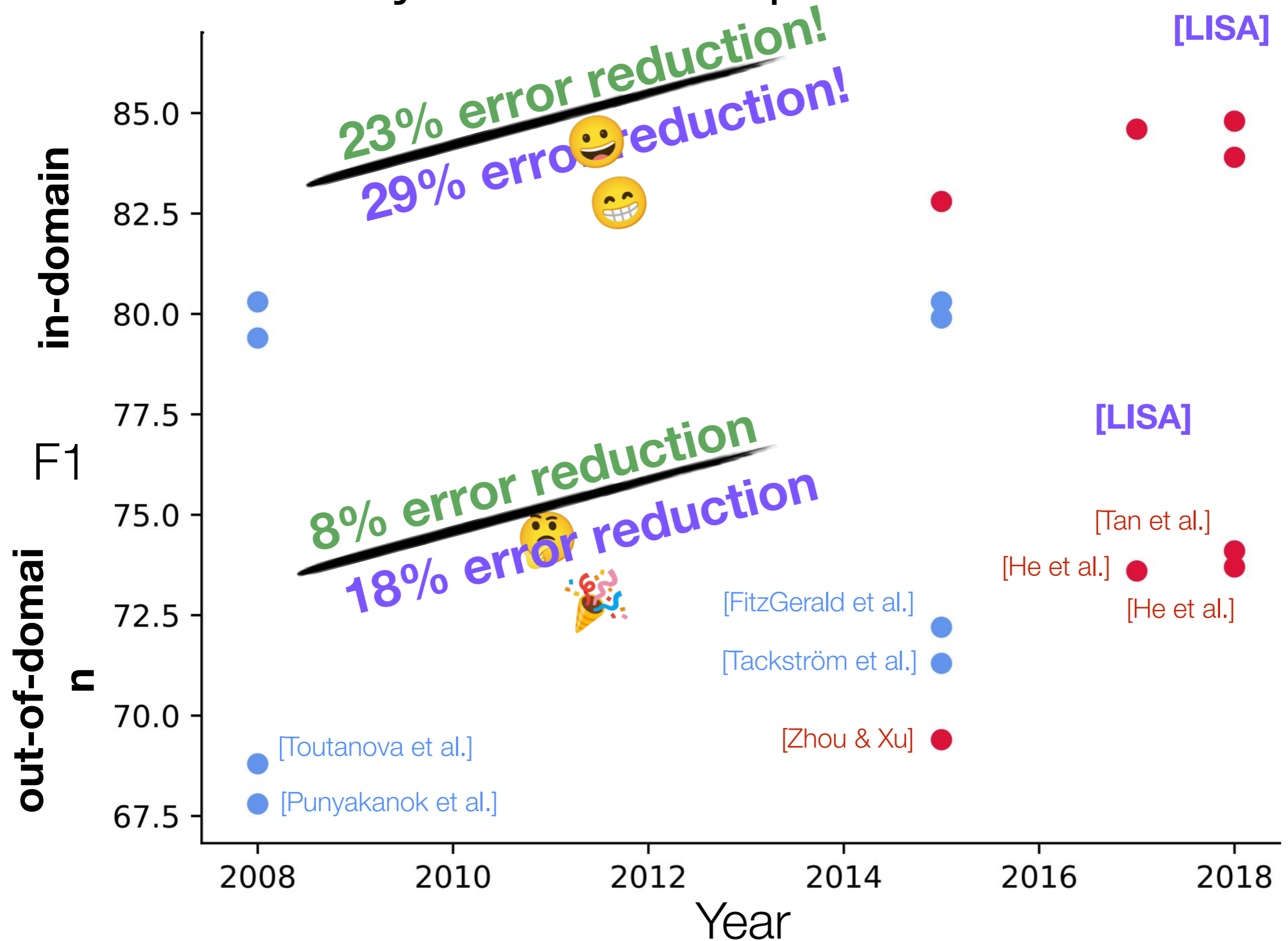
23% error reduction!
😊

End-to-end
deep NN

Syntax-based

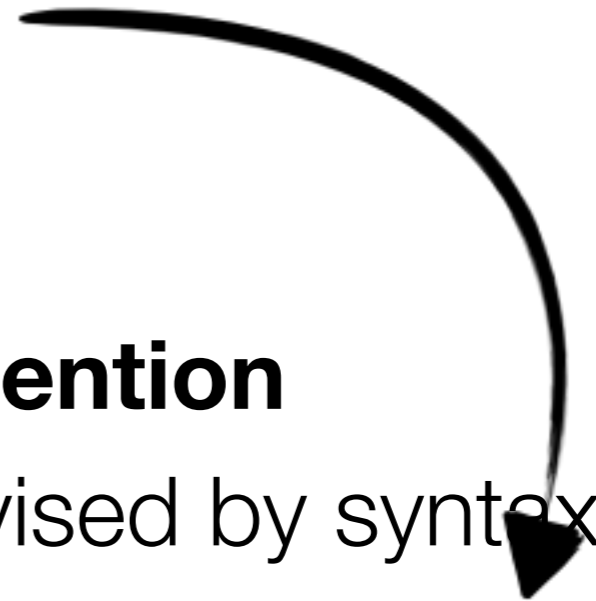


10 years of PropBank SRL



Linguistically-Informed Self-Attention

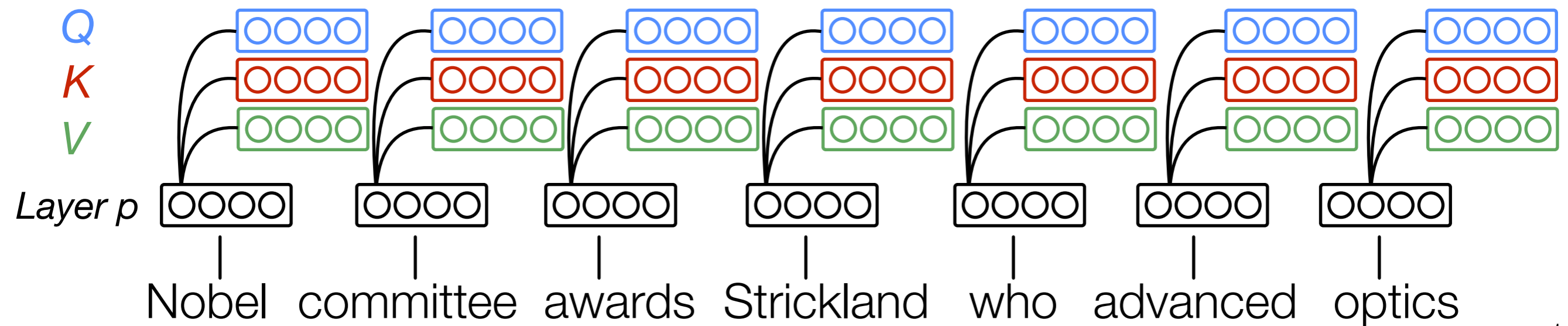
- **Multi-task learning, single-pass inference**
 - Part-of-speech tag
 - Labeled dependency parsing
 - Predicate detection
 - Semantic role spans & labeling
- **Syntactically-informed self-attention**
 - Multi-head self-attention supervised by syntax
 - Multi-head self-attention supervised by **syntax**



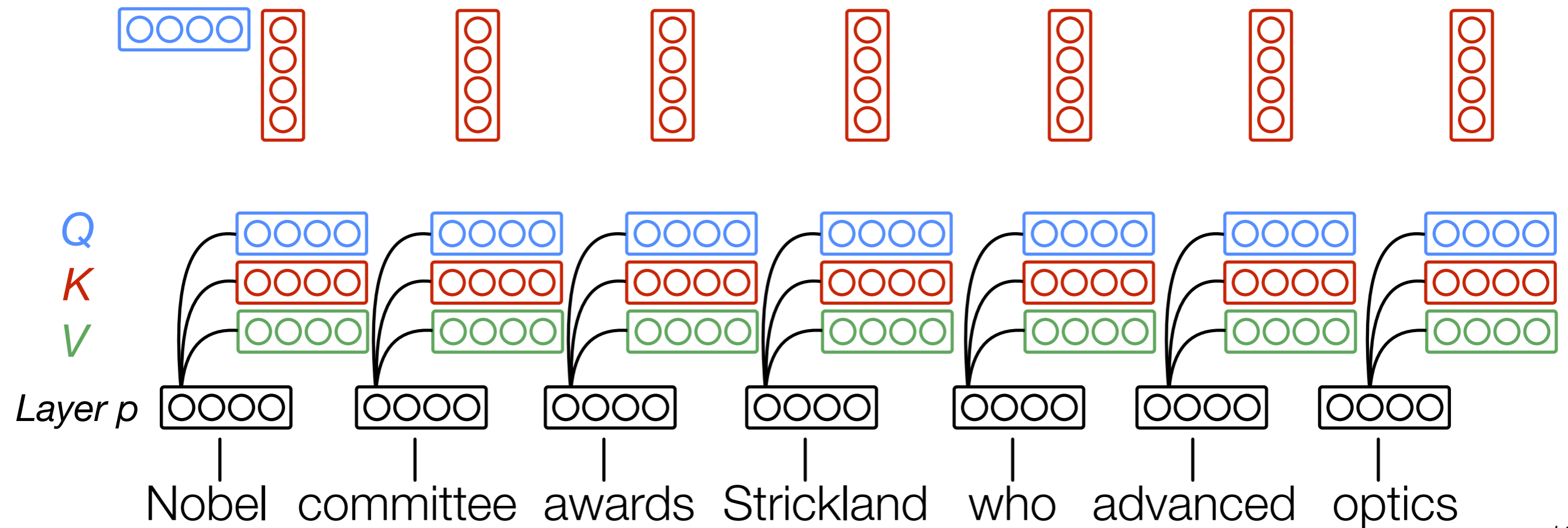
Outline

- Want fast, accurate, robust NLU
- PropBank SRL: Who did what to whom?
- 10 years of PropBank SRL
- LISA: Linguistically-informed self attention
 - Multi-head self-attention [Vaswani et al. 2017]
 - Syntactically-informed self-attention
 - Multi-task learning, single-pass inference
- Experimental results & error analysis

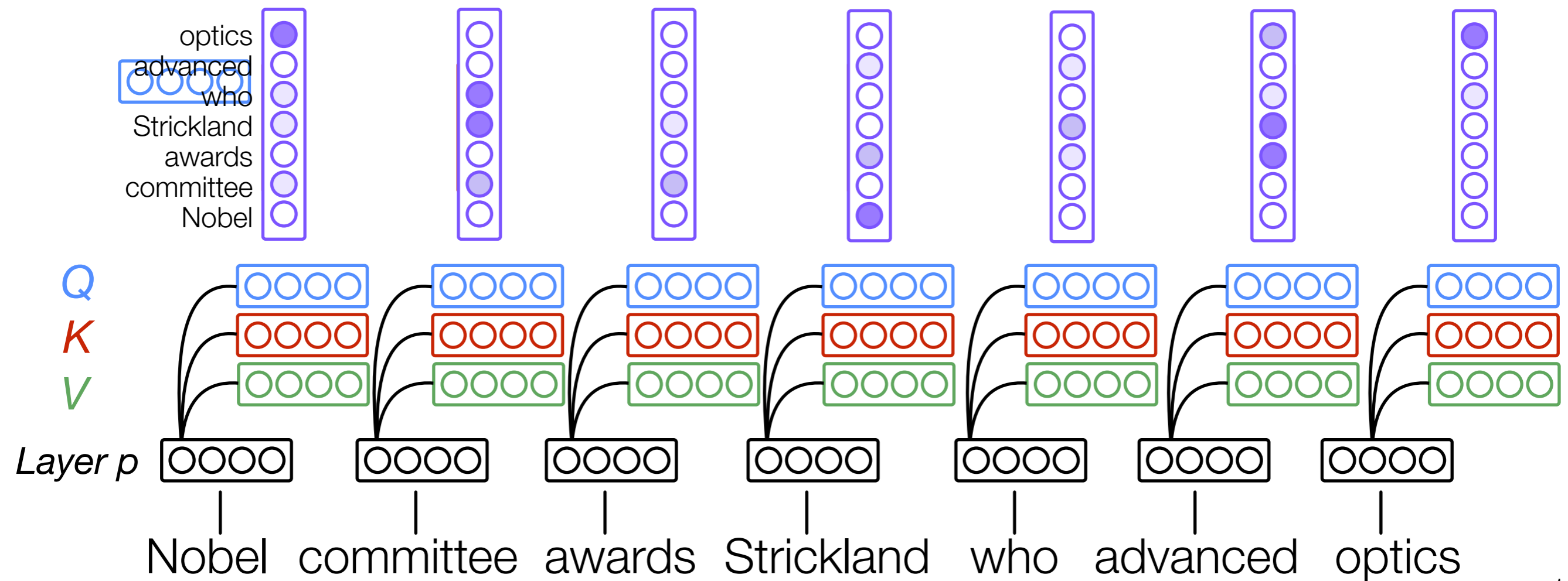
Self-attention



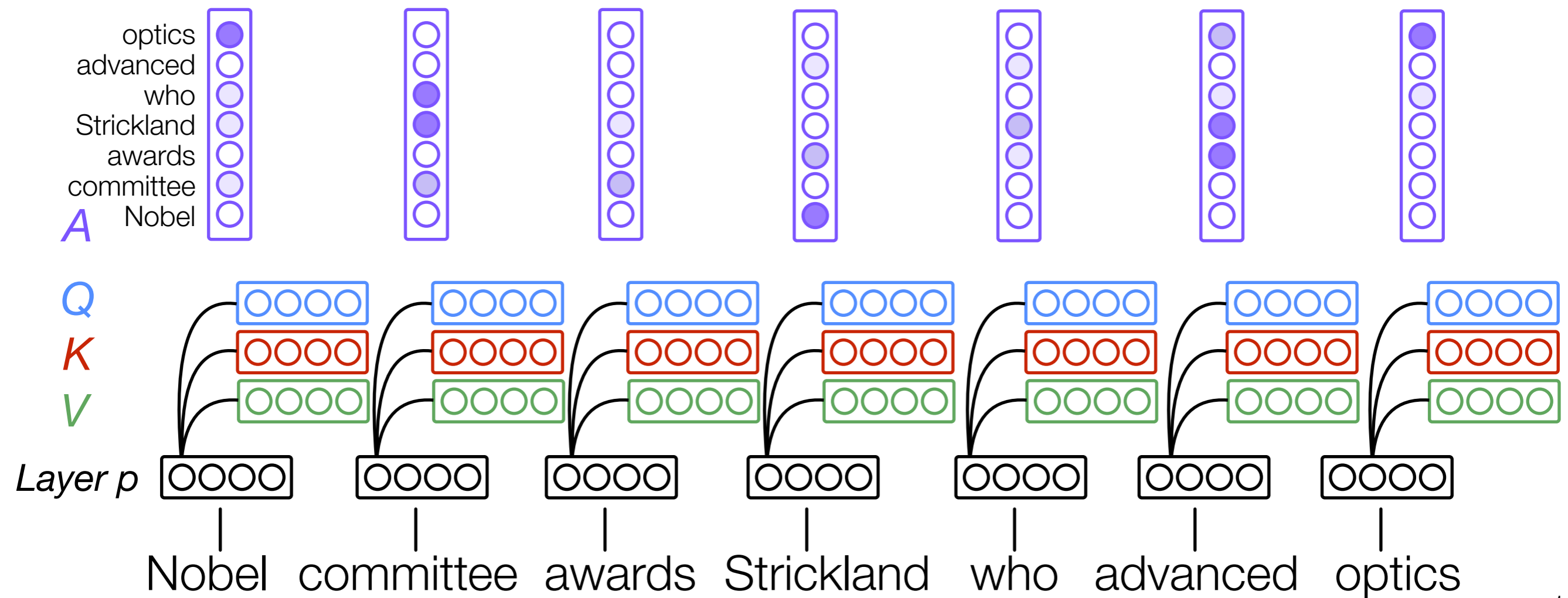
Self-attention



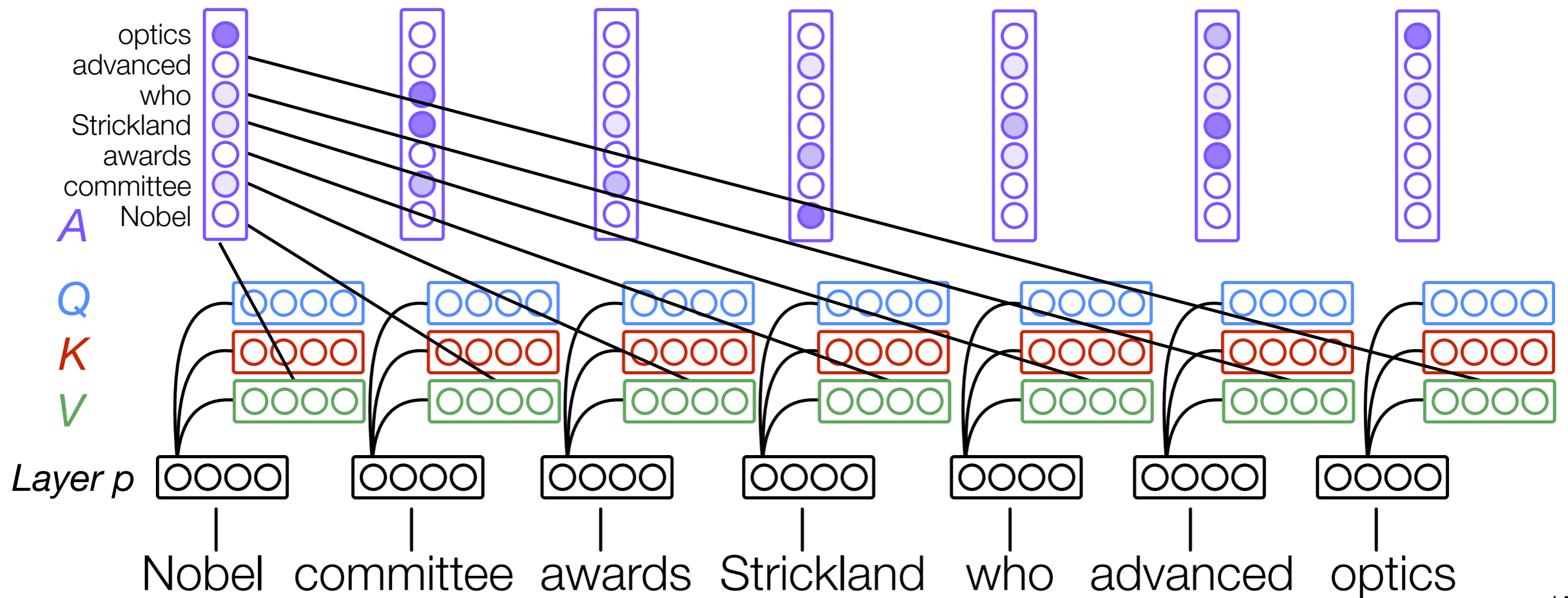
Self-attention



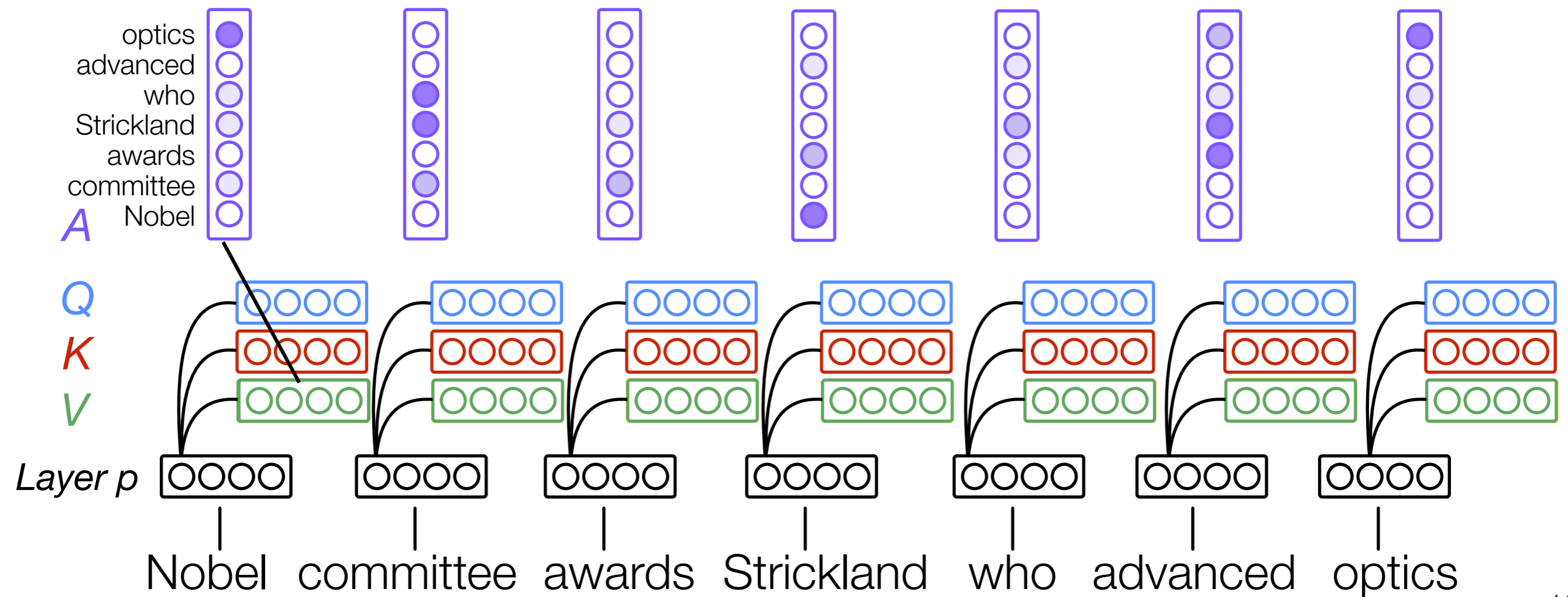
Self-attention



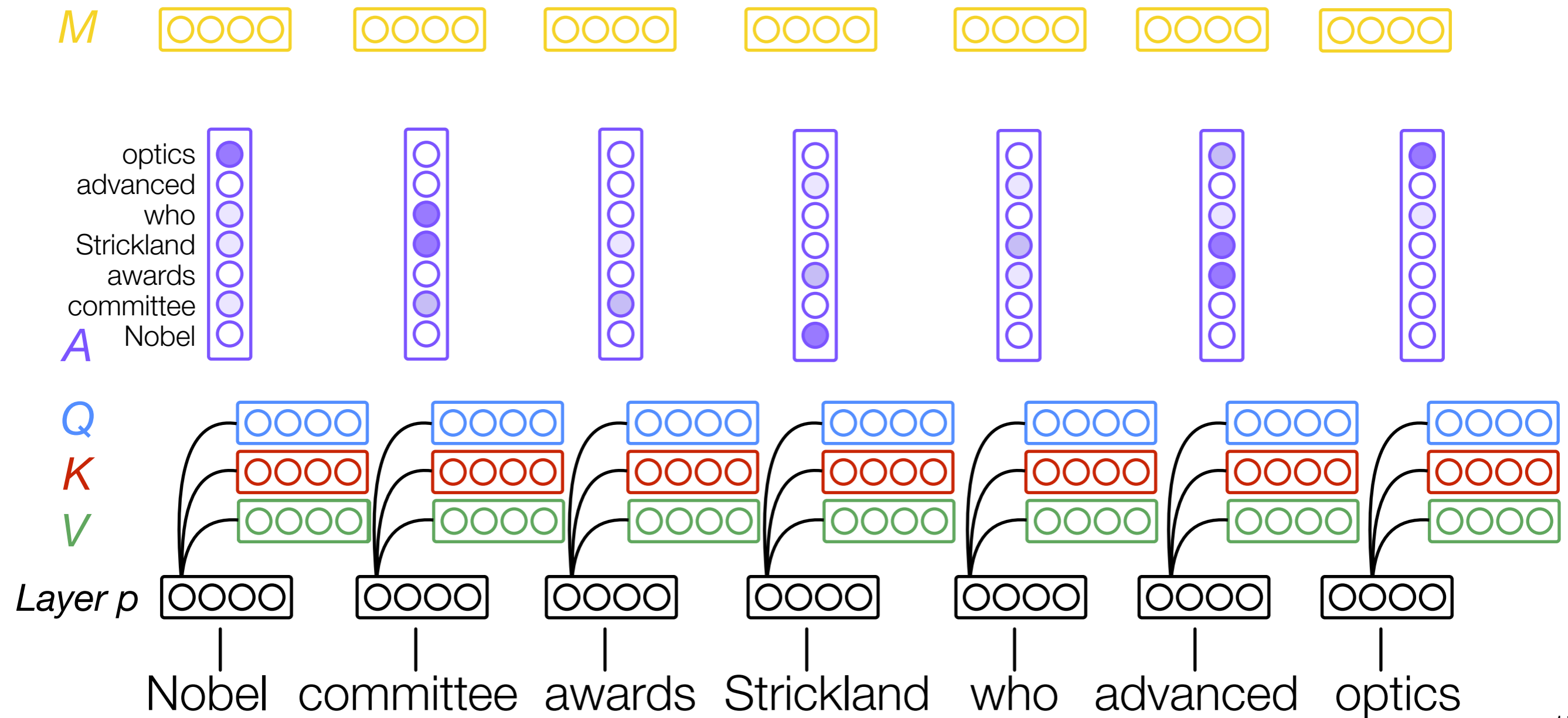
Self-attention



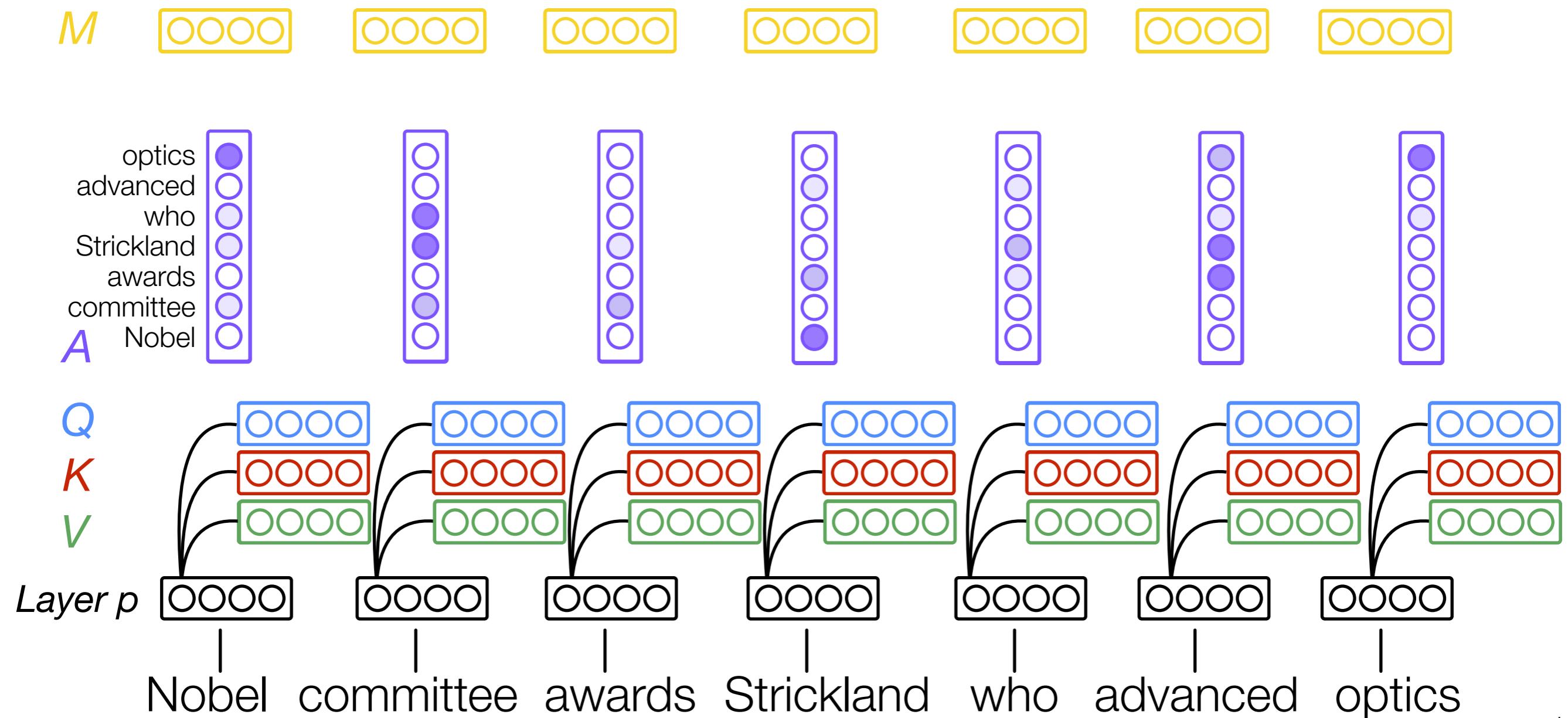
Self-attention



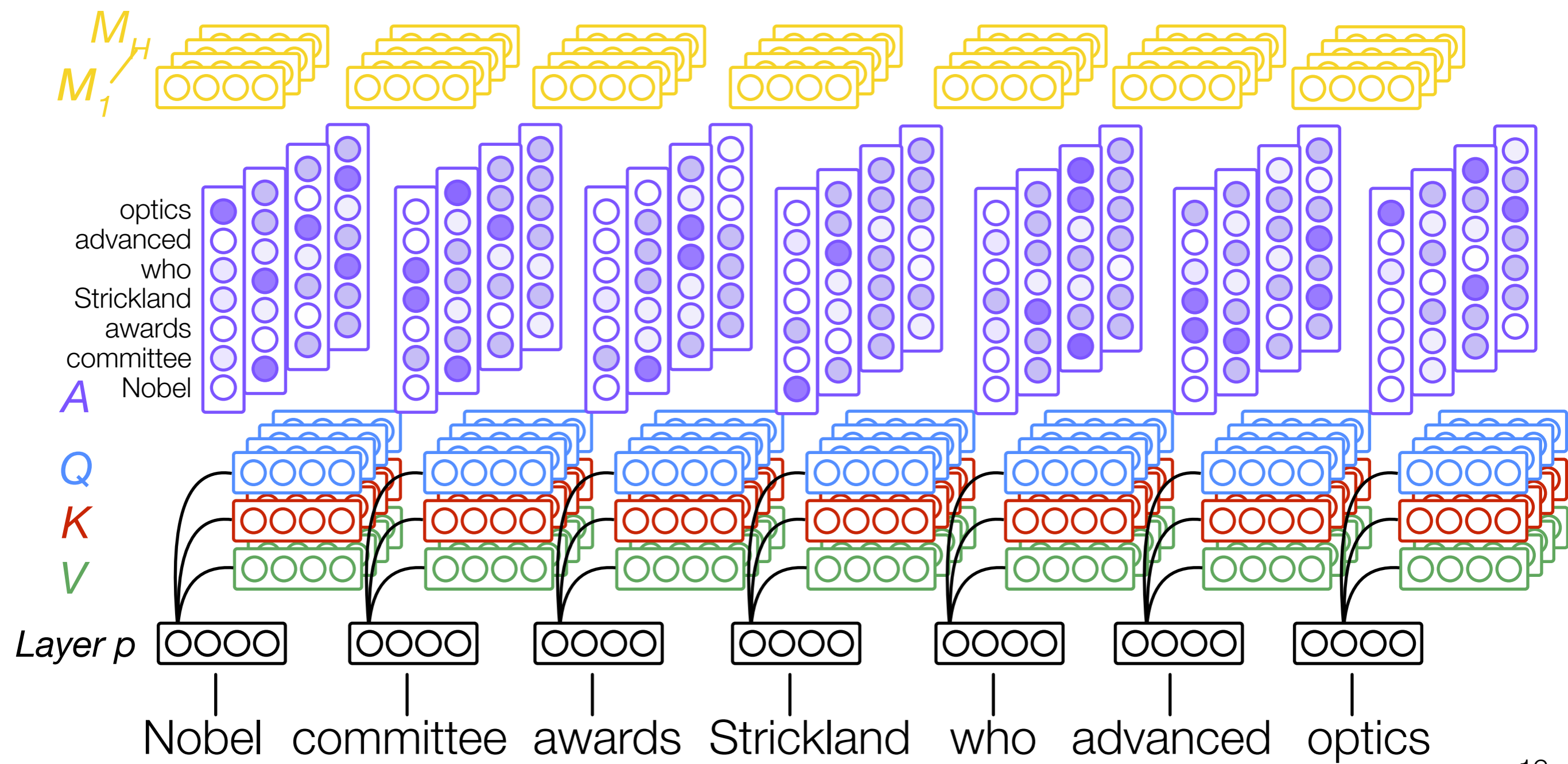
Self-attention



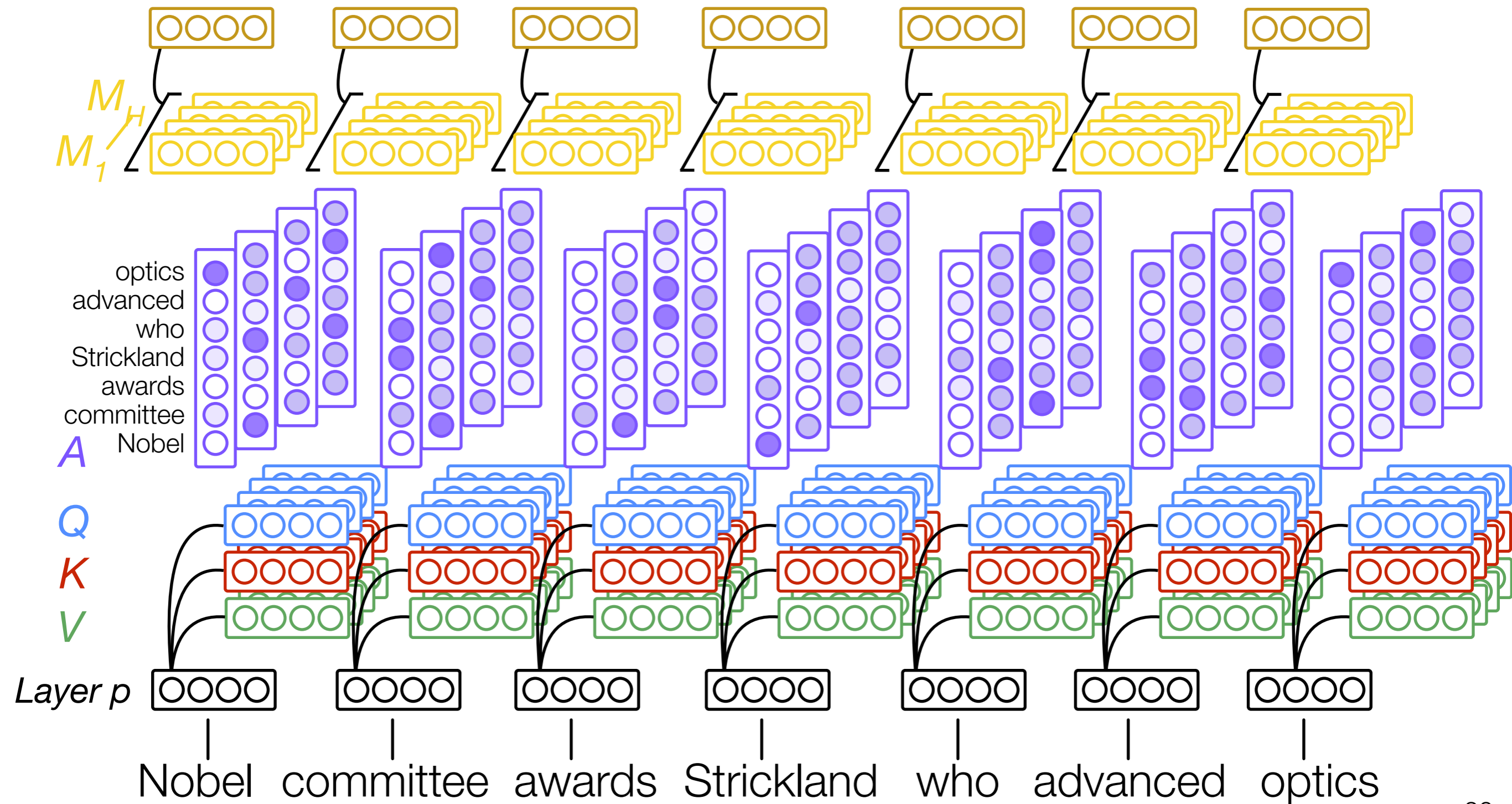
Self-attention



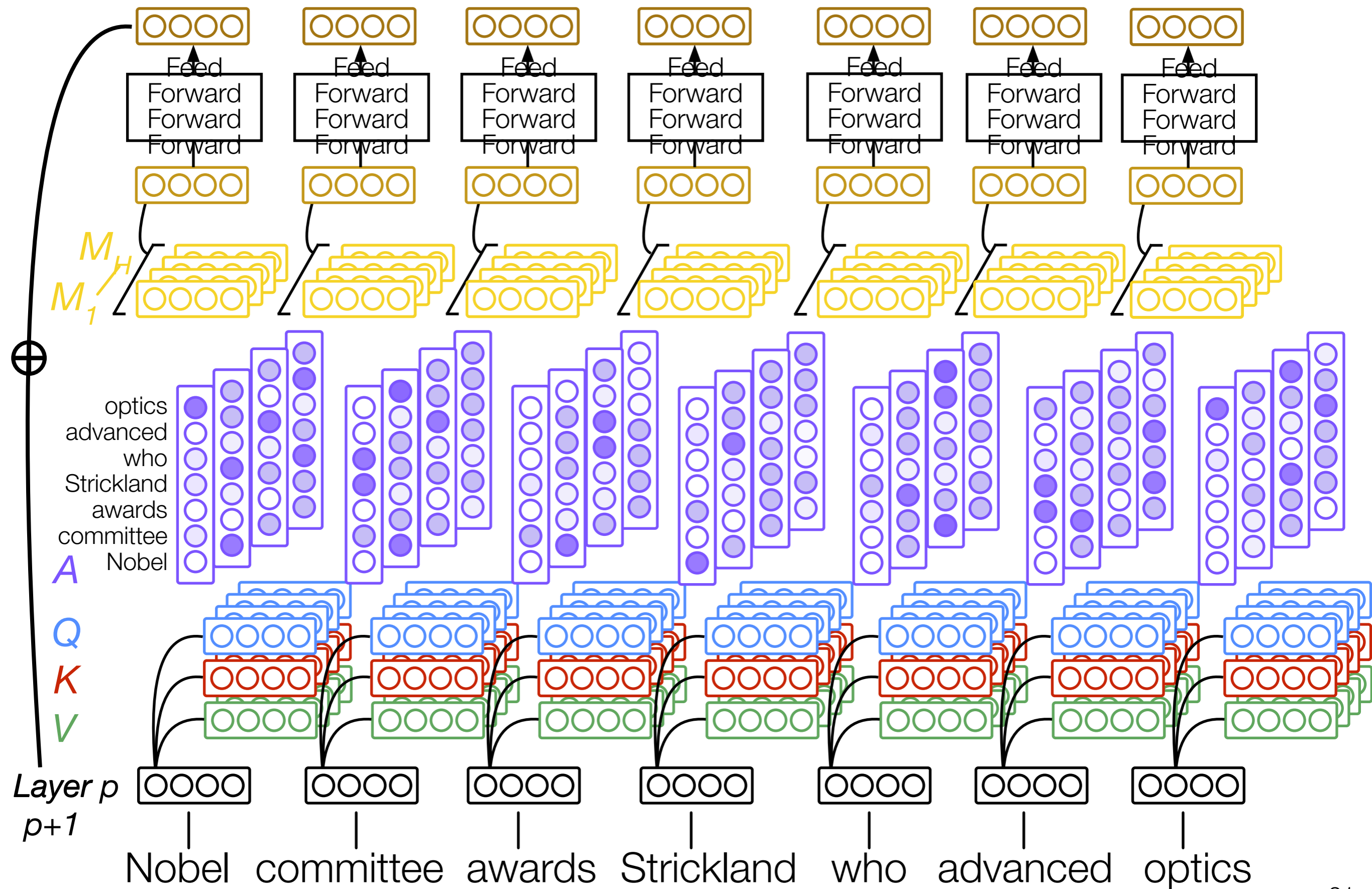
Multi-head self-attention



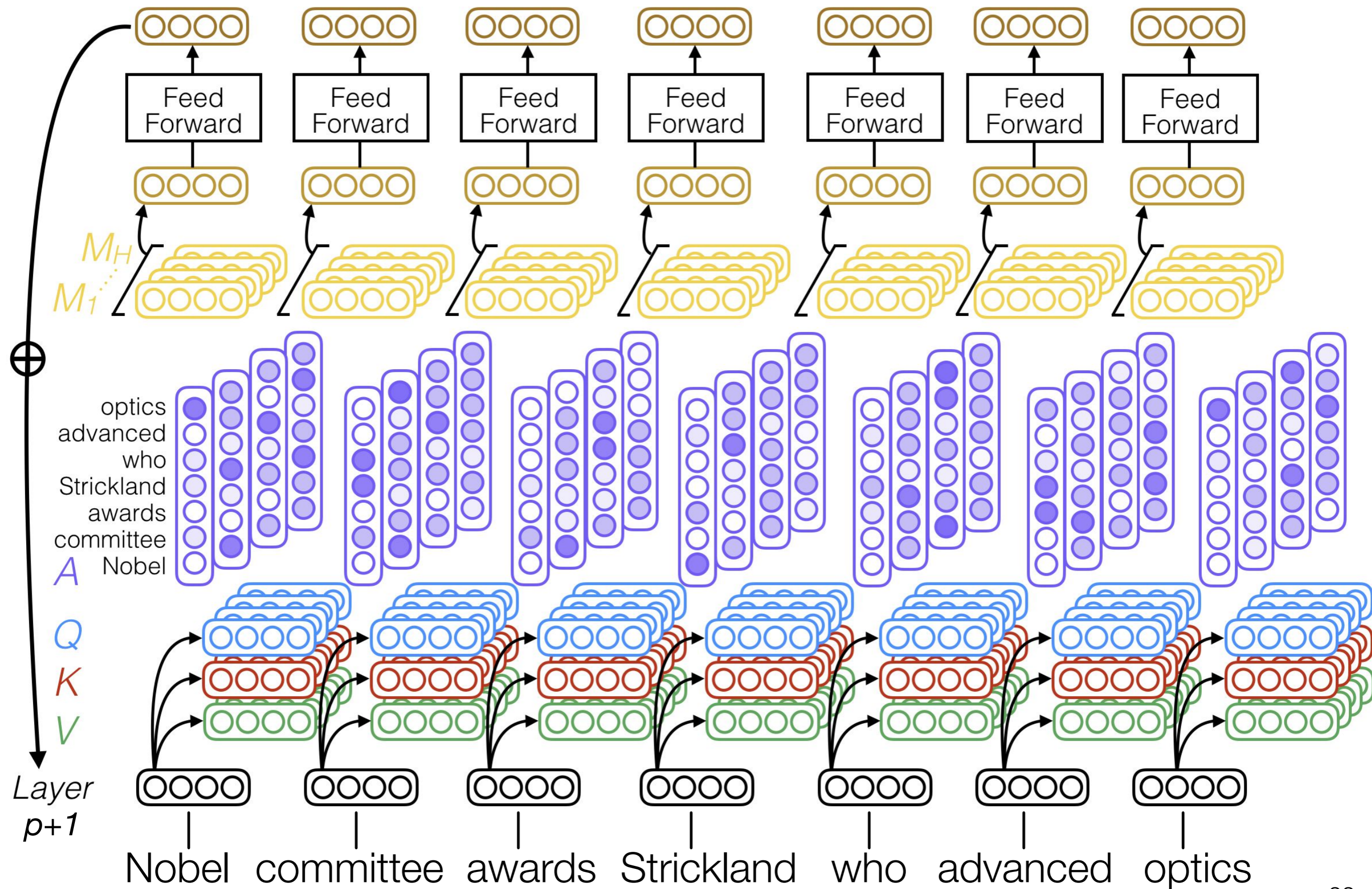
Multi-head self-attention



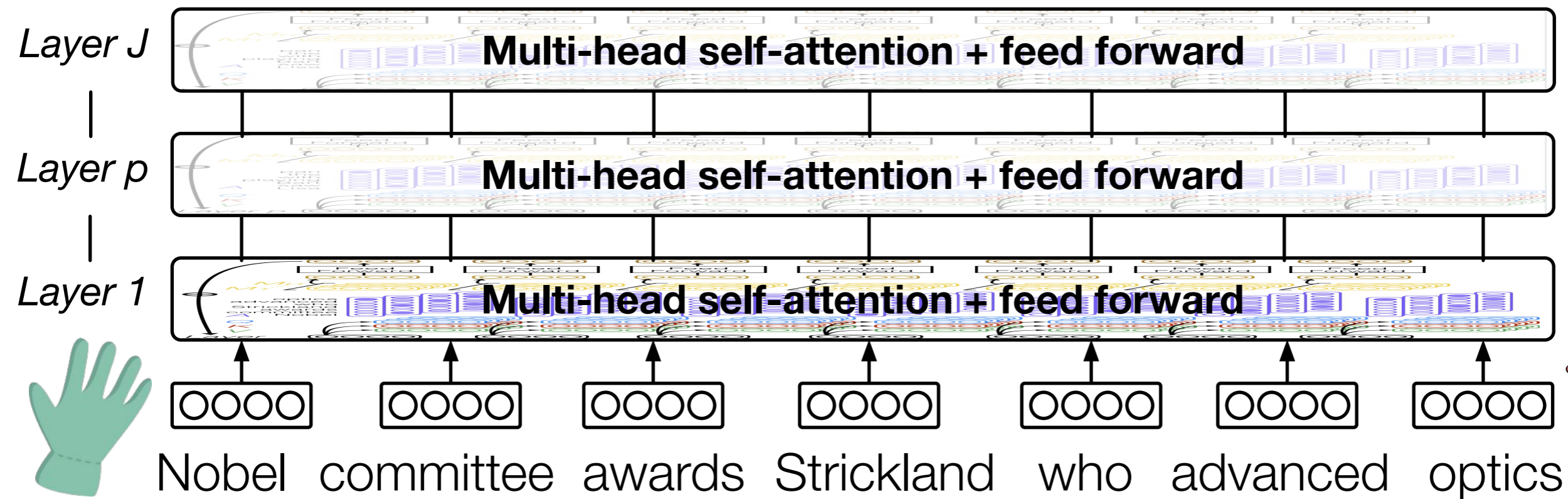
Multi-head self-attention



Multi-head self-attention



Multi-head self-attention



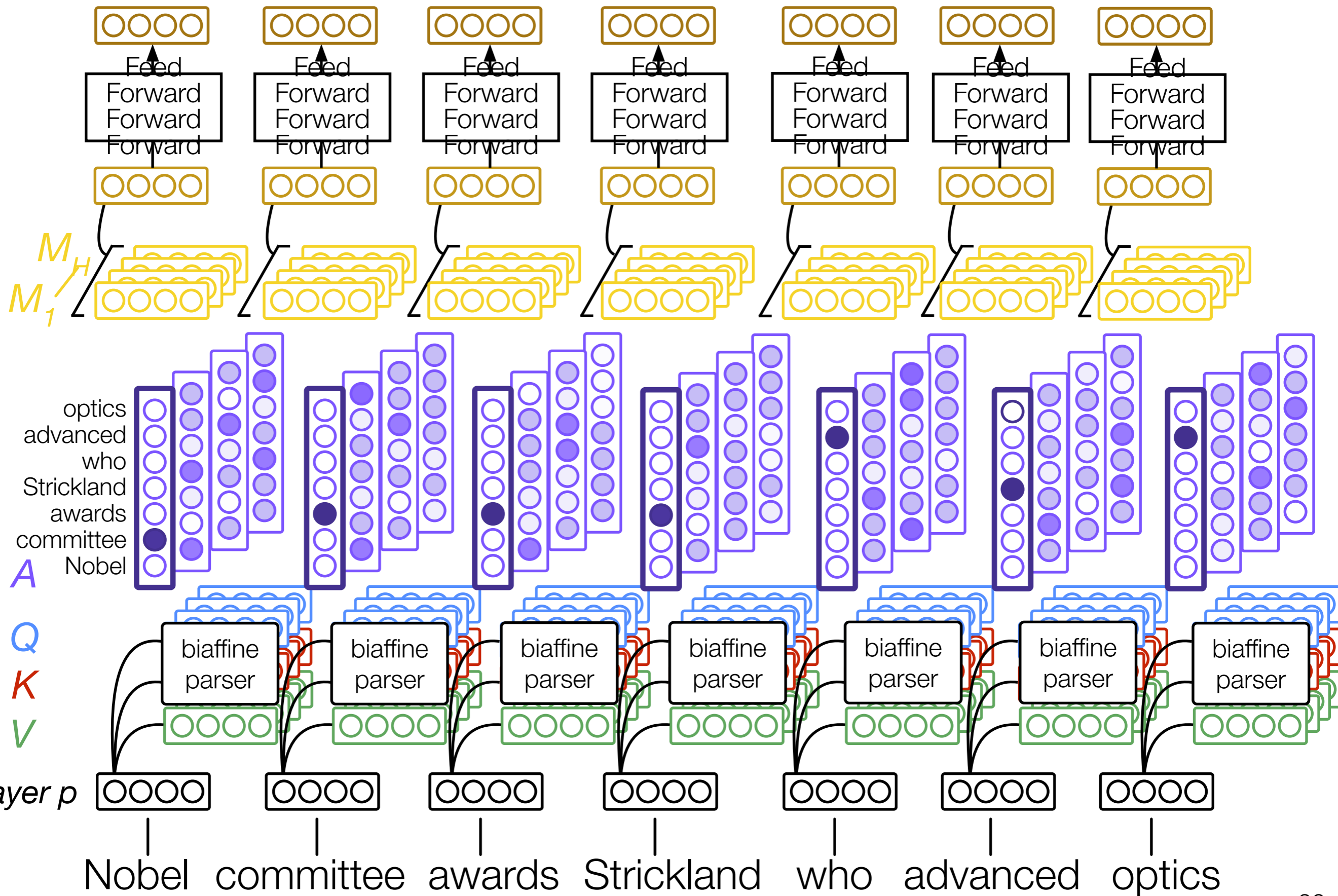
Outline

- Want fast, accurate, robust NLU
- PropBank SRL: Who did what to whom?
- 10 years of PropBank SRL
- LISA: Linguistically-informed self attention
 - Multi-head self-attention [Vaswani et al. 2017]
 - Syntactically-informed self-attention
 - Multi-task learning, single-pass inference
- Experimental results & error analysis

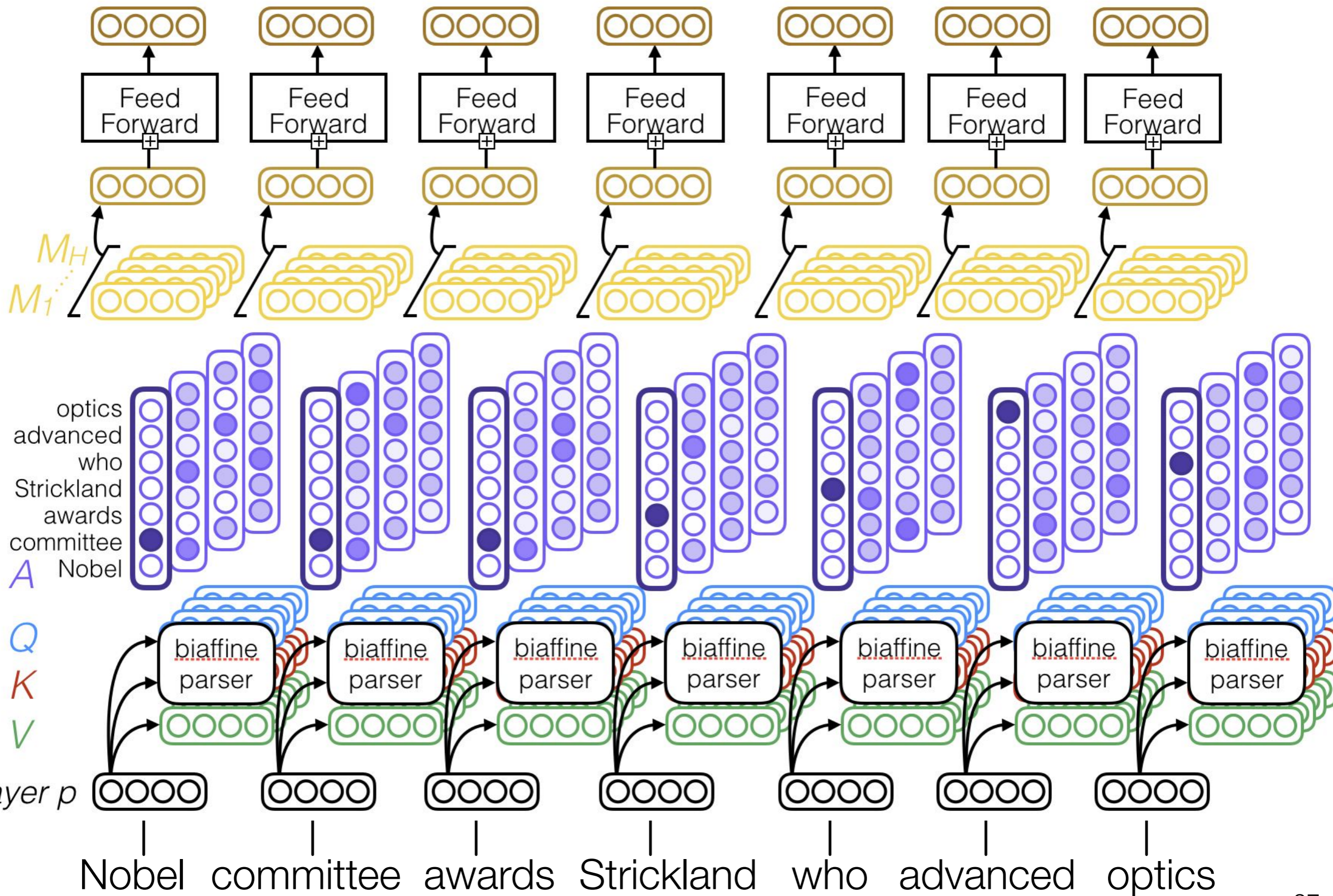
How to incorporate syntax?

- Multi-task learning [Caruana 1993; Collobert et al. 2011]:
 - Overfits to training domain like single-task end-to-end NN.
 - Must re-train SRL model to leverage new (improved) syntax.
- Dependency path embeddings [Roth & Lapata 2016]; Graph CNN over parse [Marcheggiani & Titov 2017]
 - Restricted context: path to predicate or fixed-width window.
- Syntactically-informed self-attention
 - In one head, token attends to its likely syntactic parent(s).
 - Global context: In next layer, tokens observe all other parents.
 - At test time: can use own predicted parse, **OR** supply syntax to improve SRL model without re-training.

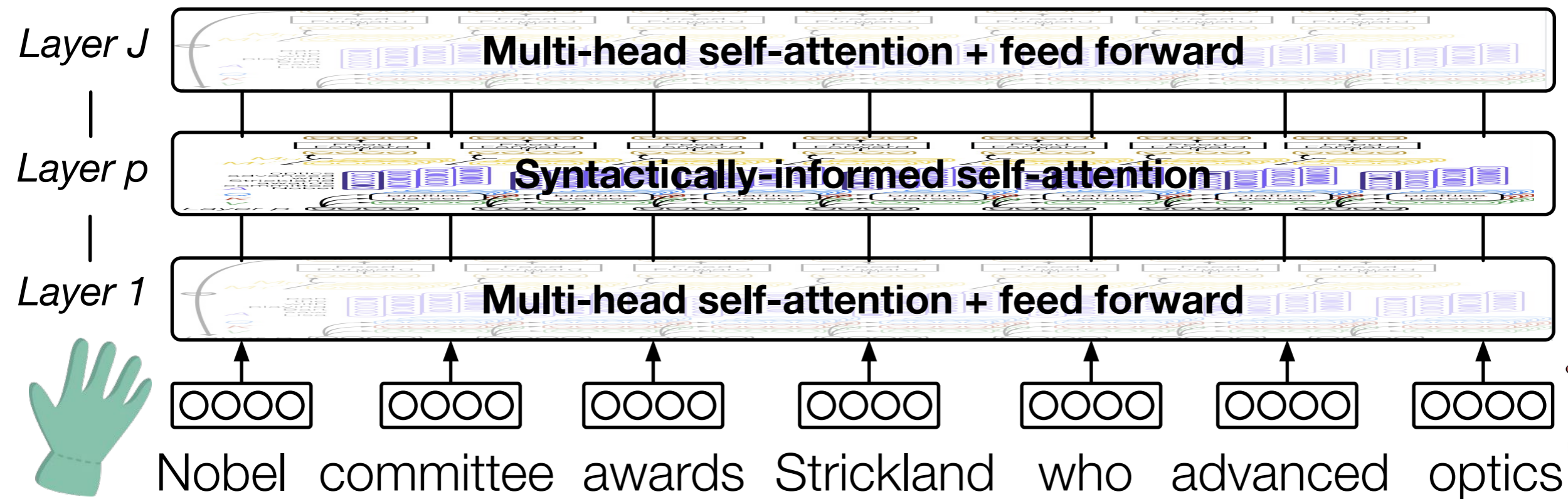
Syntactically-informed self-attention



Syntactically-informed self-attention



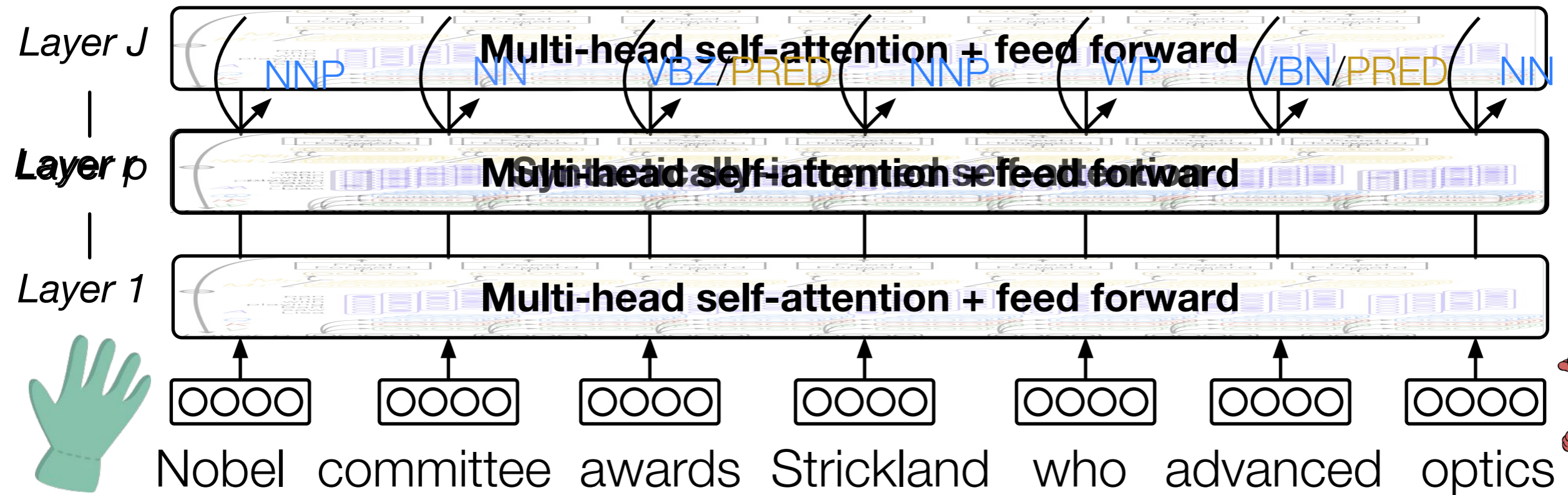
Syntactically-informed self-attention



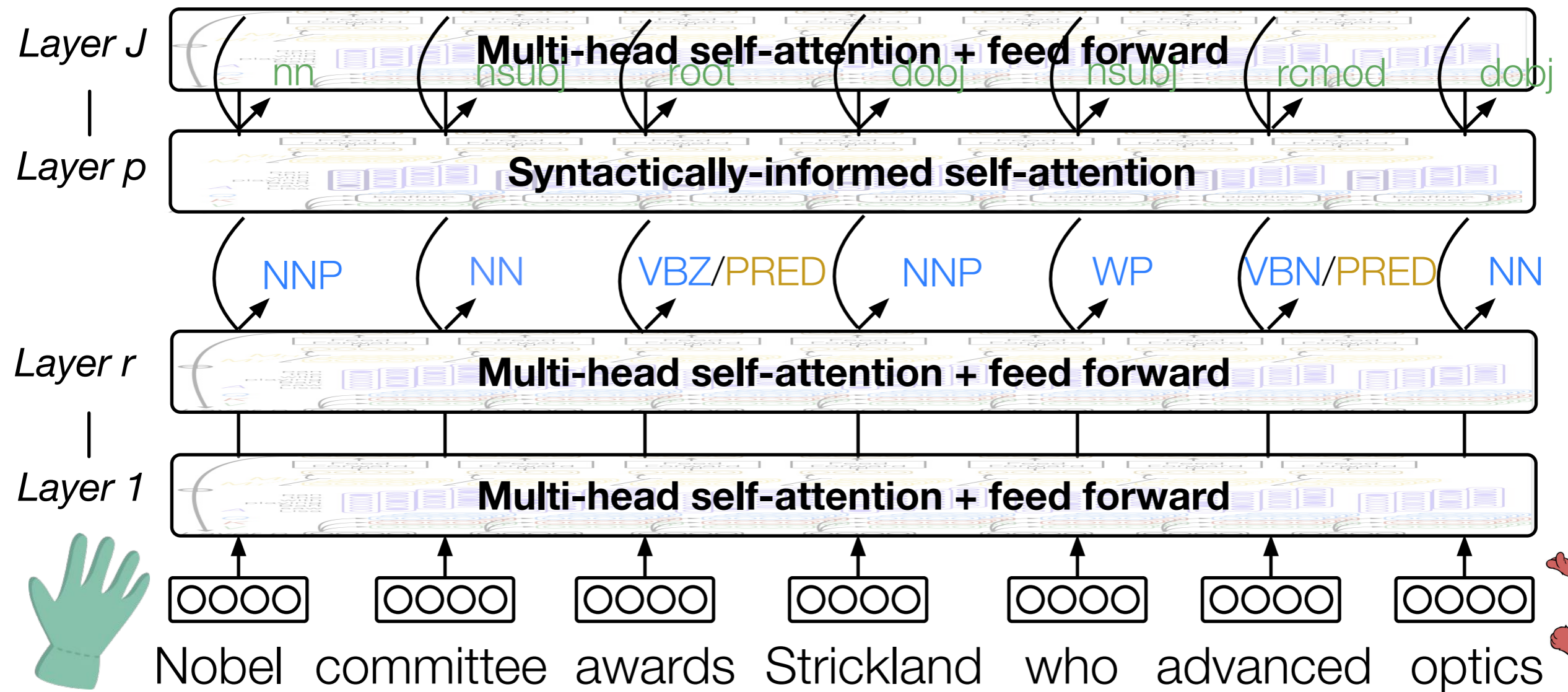
Outline

- Want fast, accurate, robust NLU
- PropBank SRL: Who did what to whom?
- 10 years of PropBank SRL
- LISA: Linguistically-informed self attention
 - Multi-head self-attention
 - Syntactically-informed self-attention
 - Multi-task learning, single-pass inference
- Experimental results & error analysis

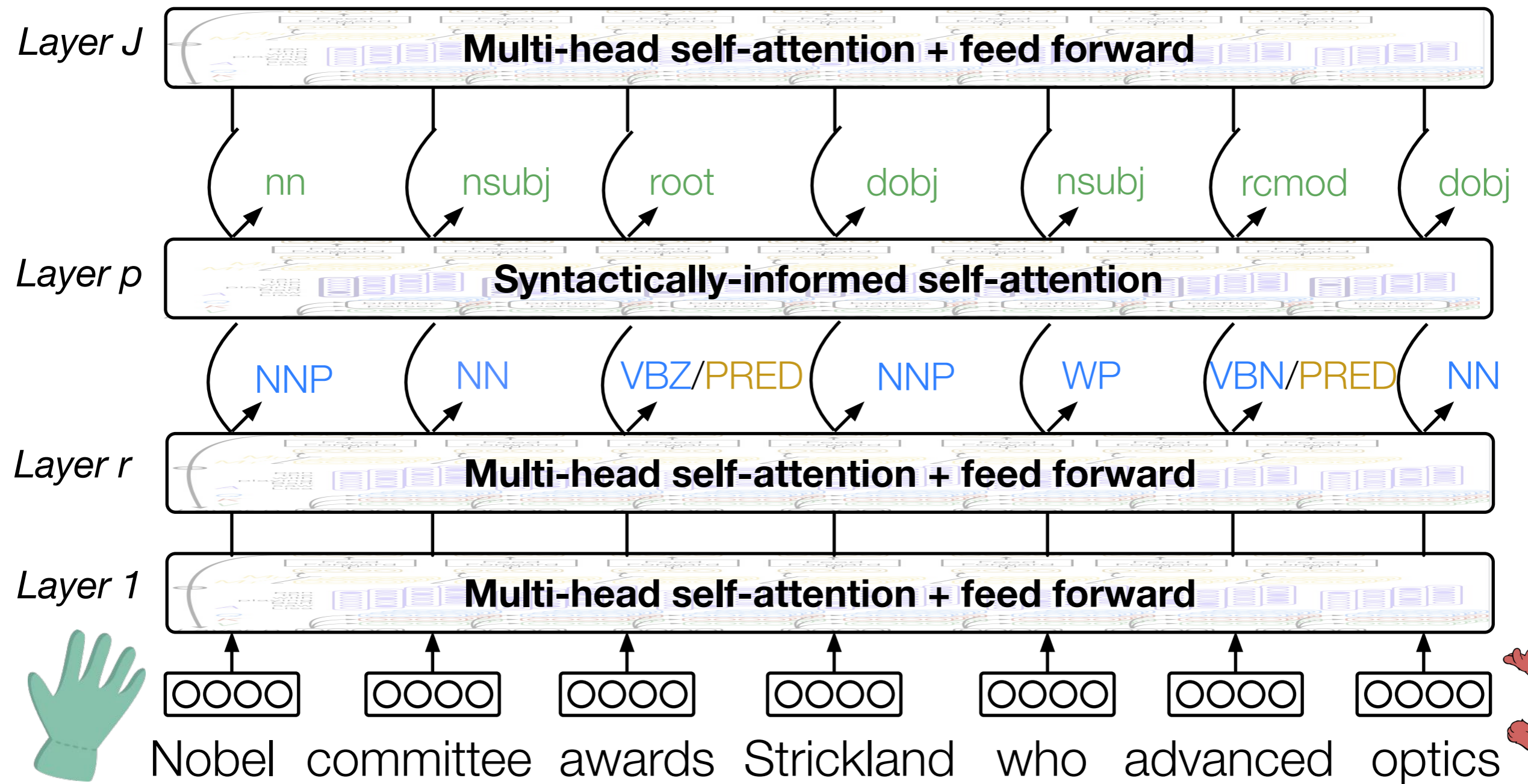
LISA: Linguistically-Informed Self-Attention



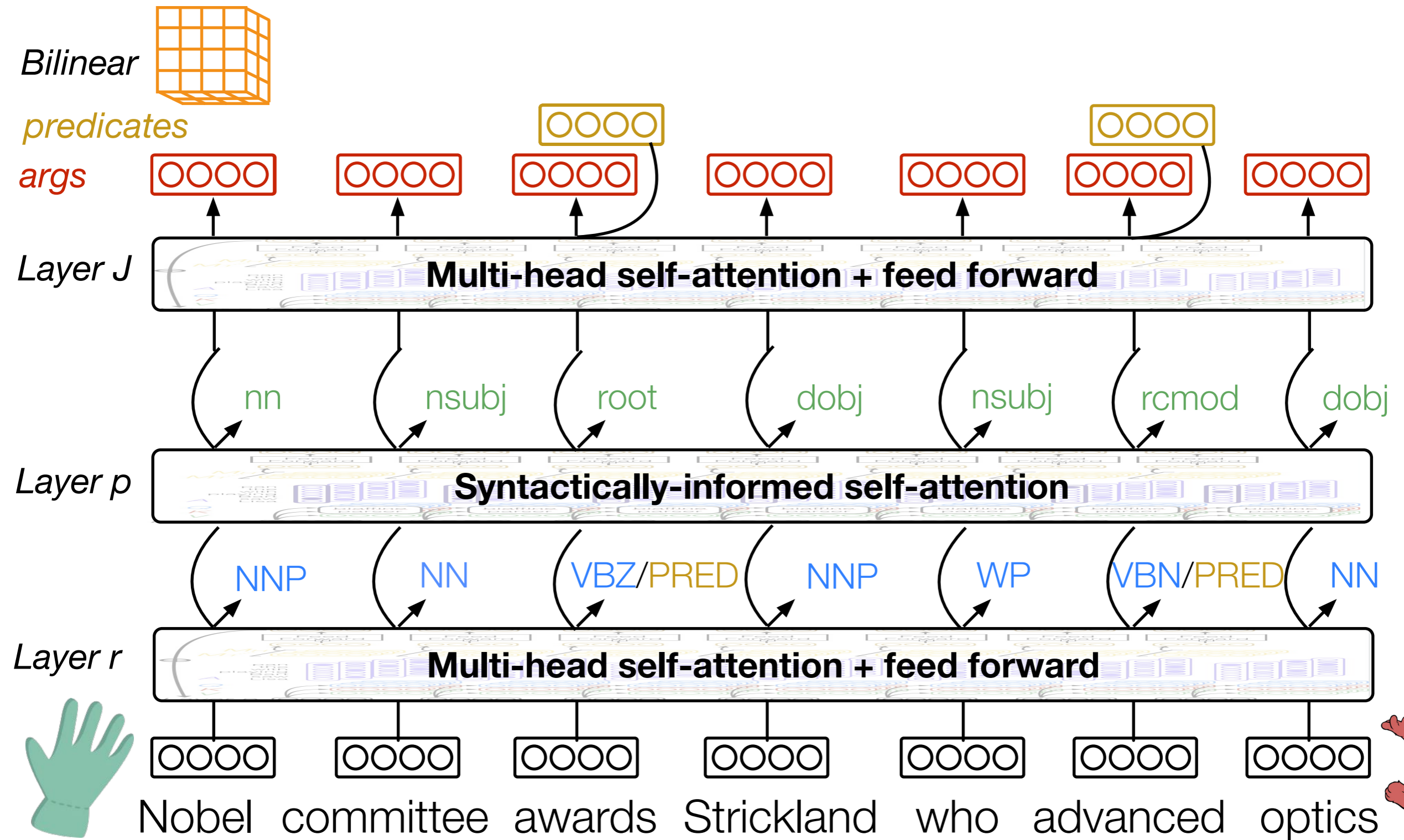
LISA: Linguistically-Informed Self-Attention



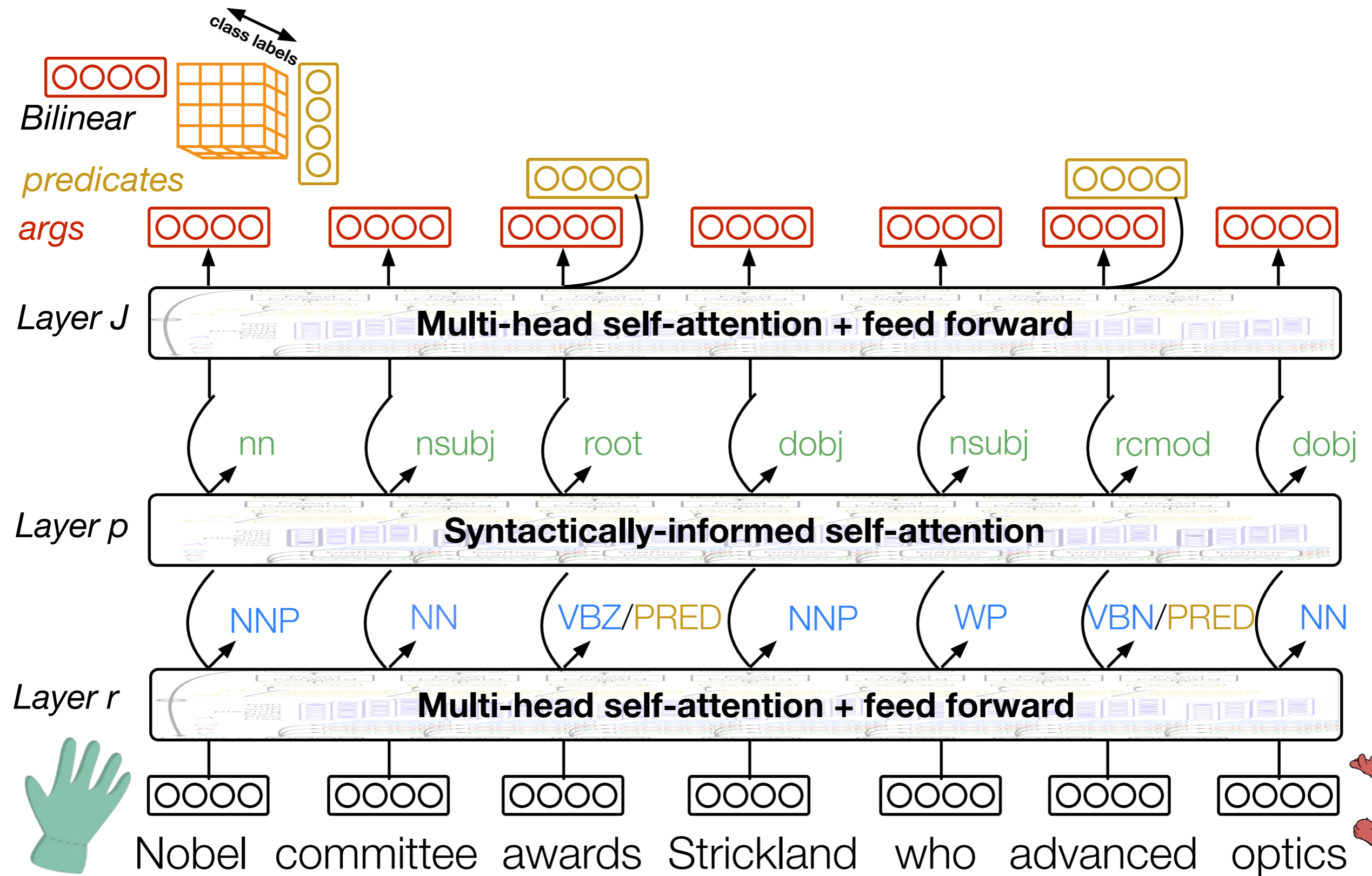
LISA: Linguistically-Informed Self-Attention



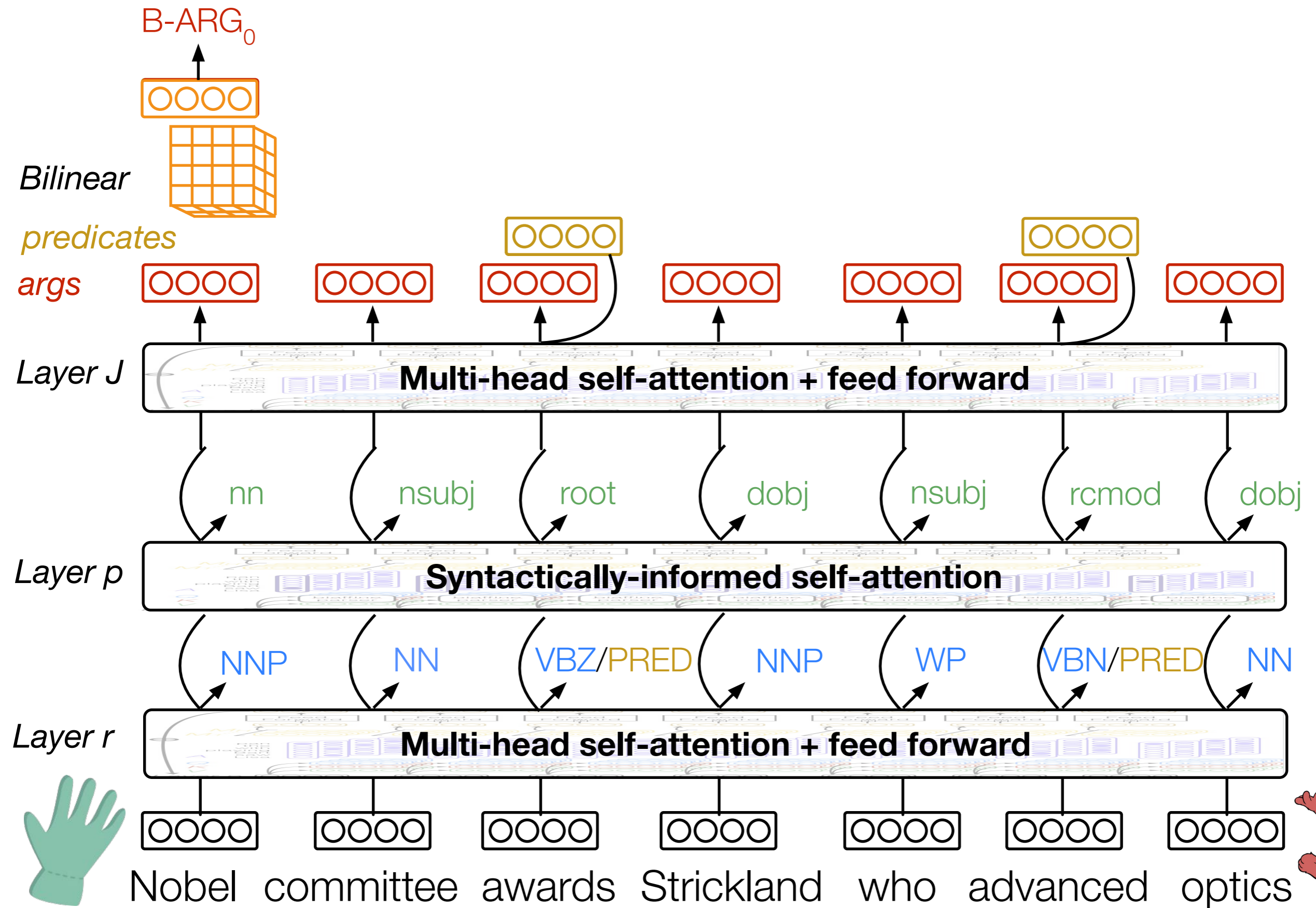
LISA: Linguistically-Informed Self-Attention



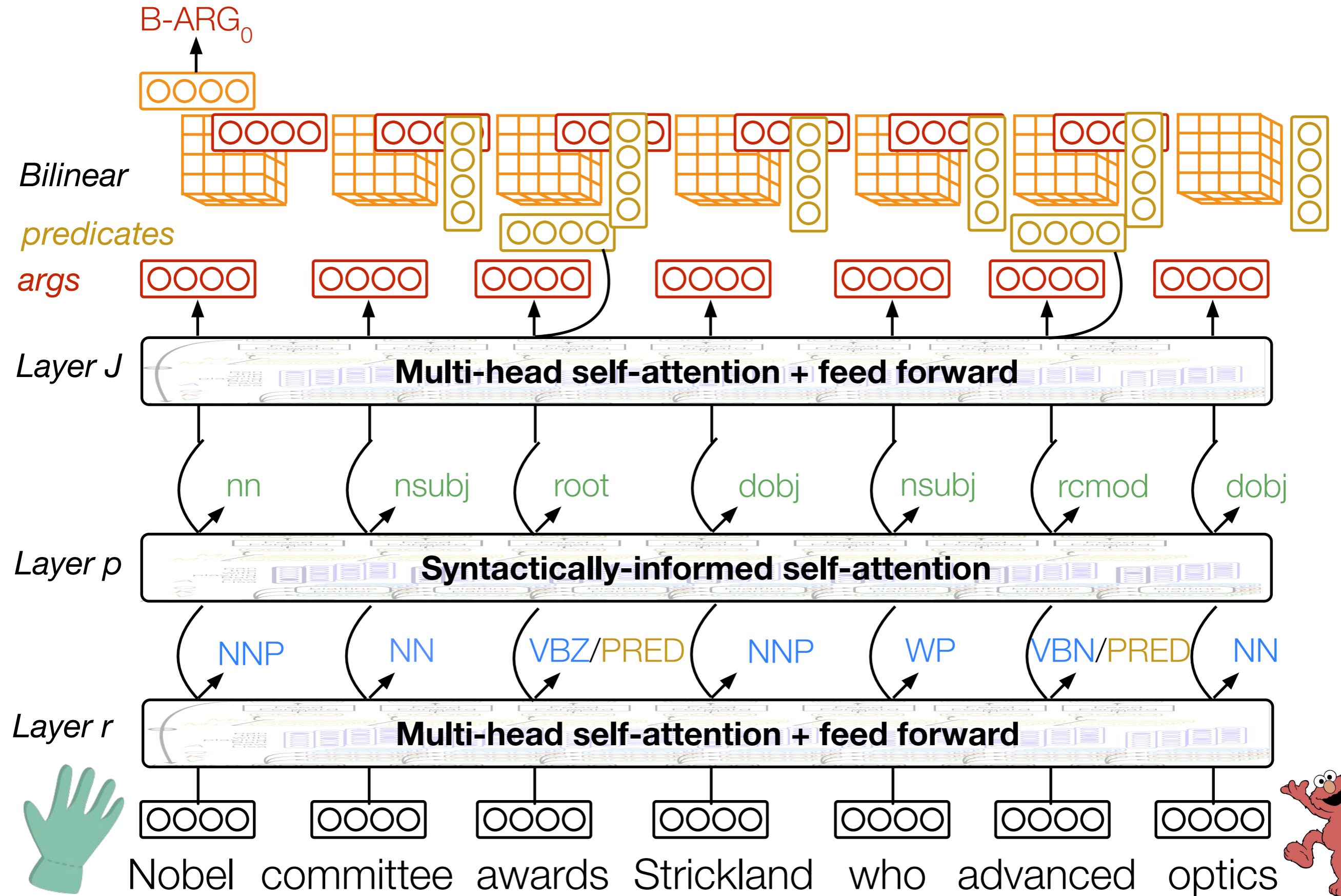
LISA: Linguistically-Informed Self-Attention



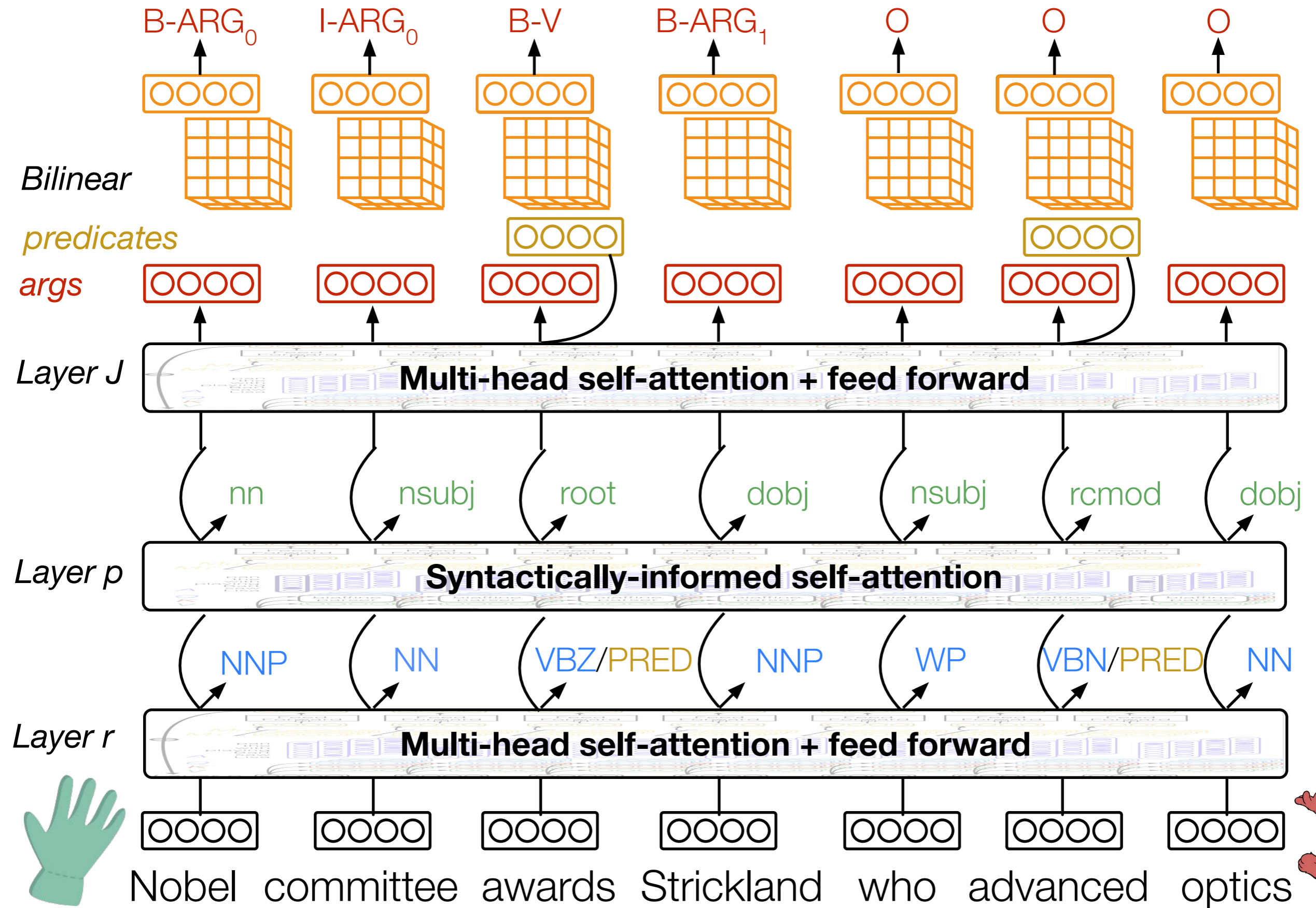
LISA: Linguistically-Informed Self-Attention



LISA: Linguistically-Informed Self-Attention

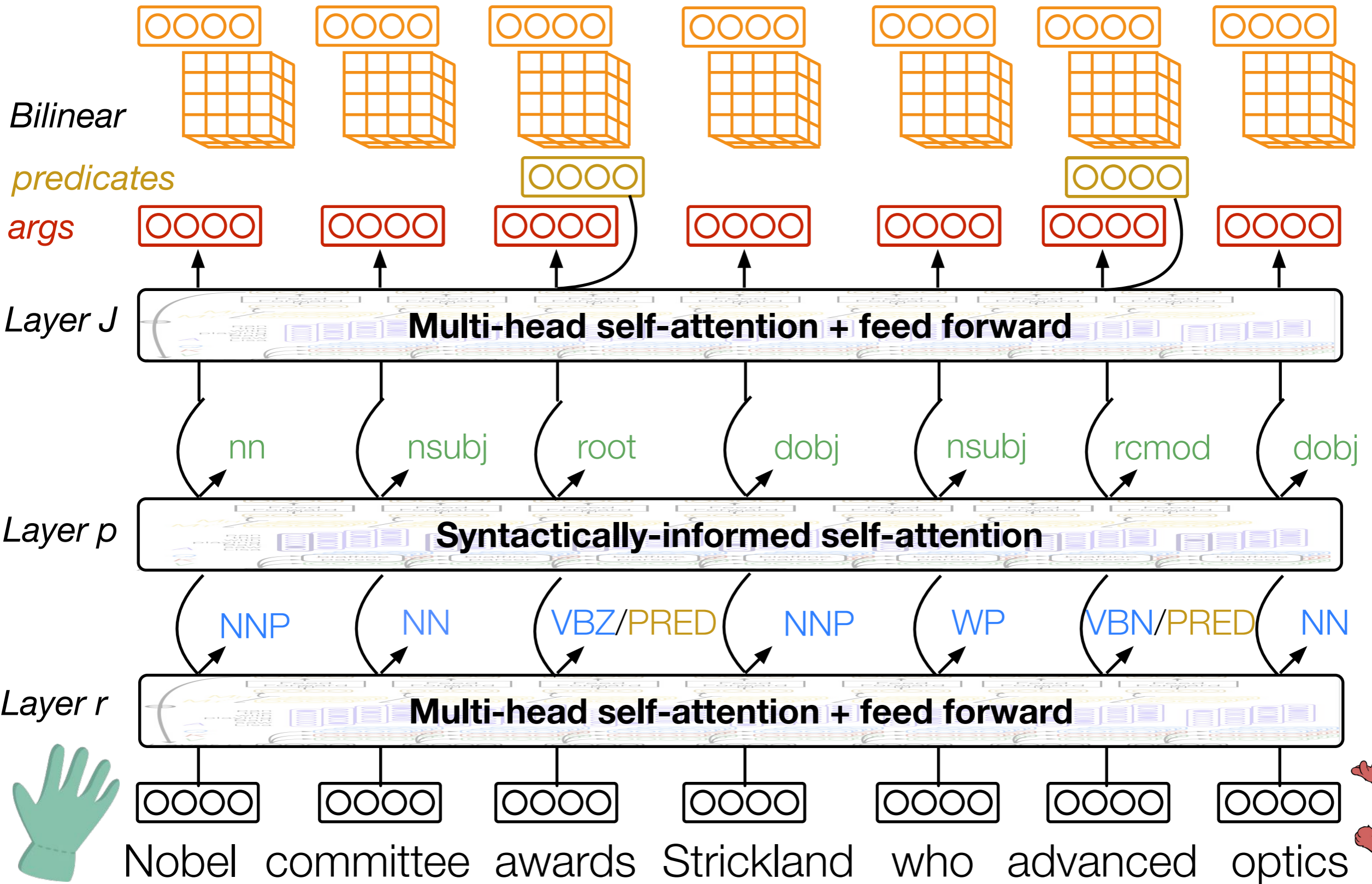


LISA: Linguistically-Informed Self-Attention



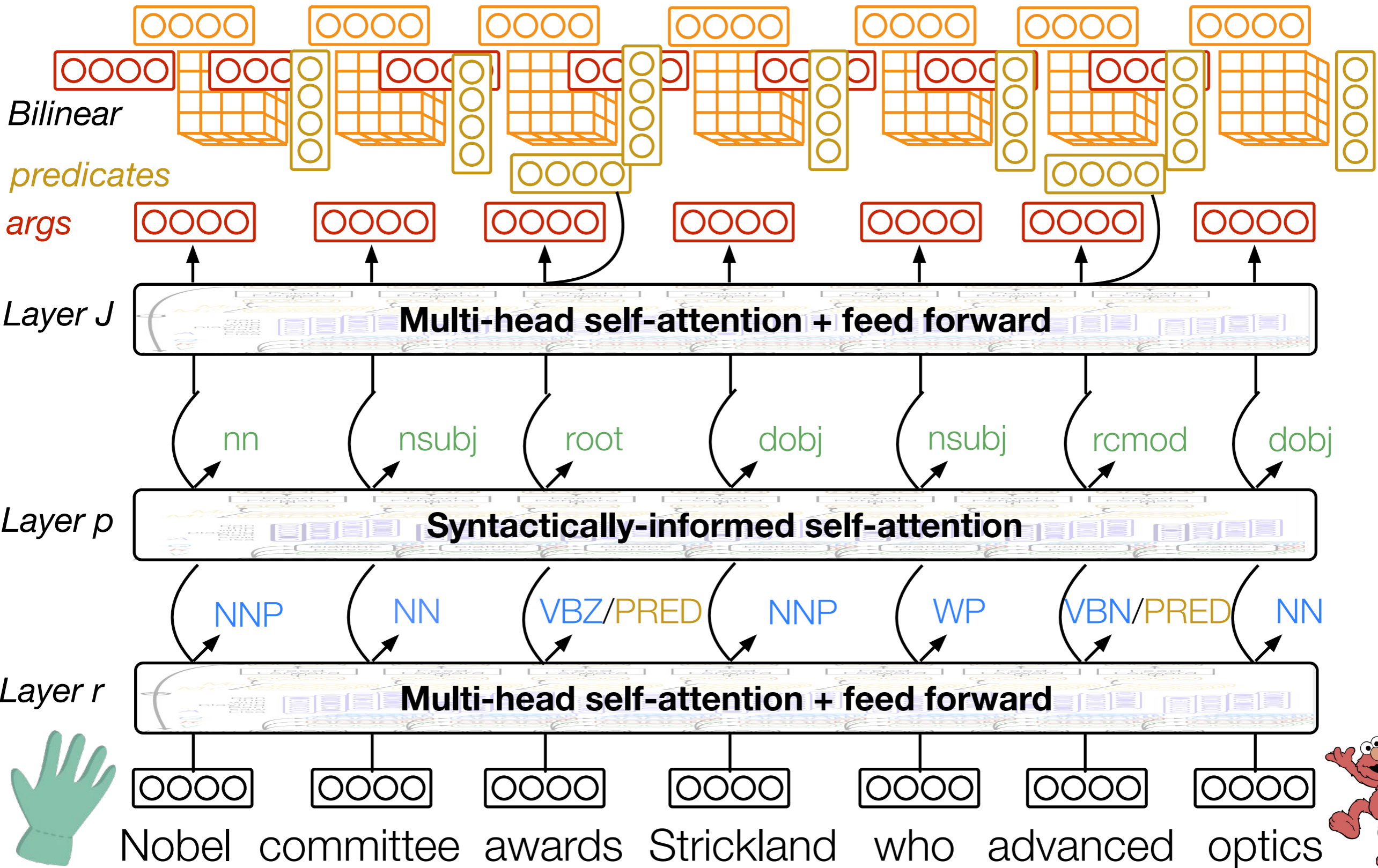
LISA: Linguistically-Informed Self-Attention

B-ARG₀ I-ARG₀ B-V B-ARG₁ O O O



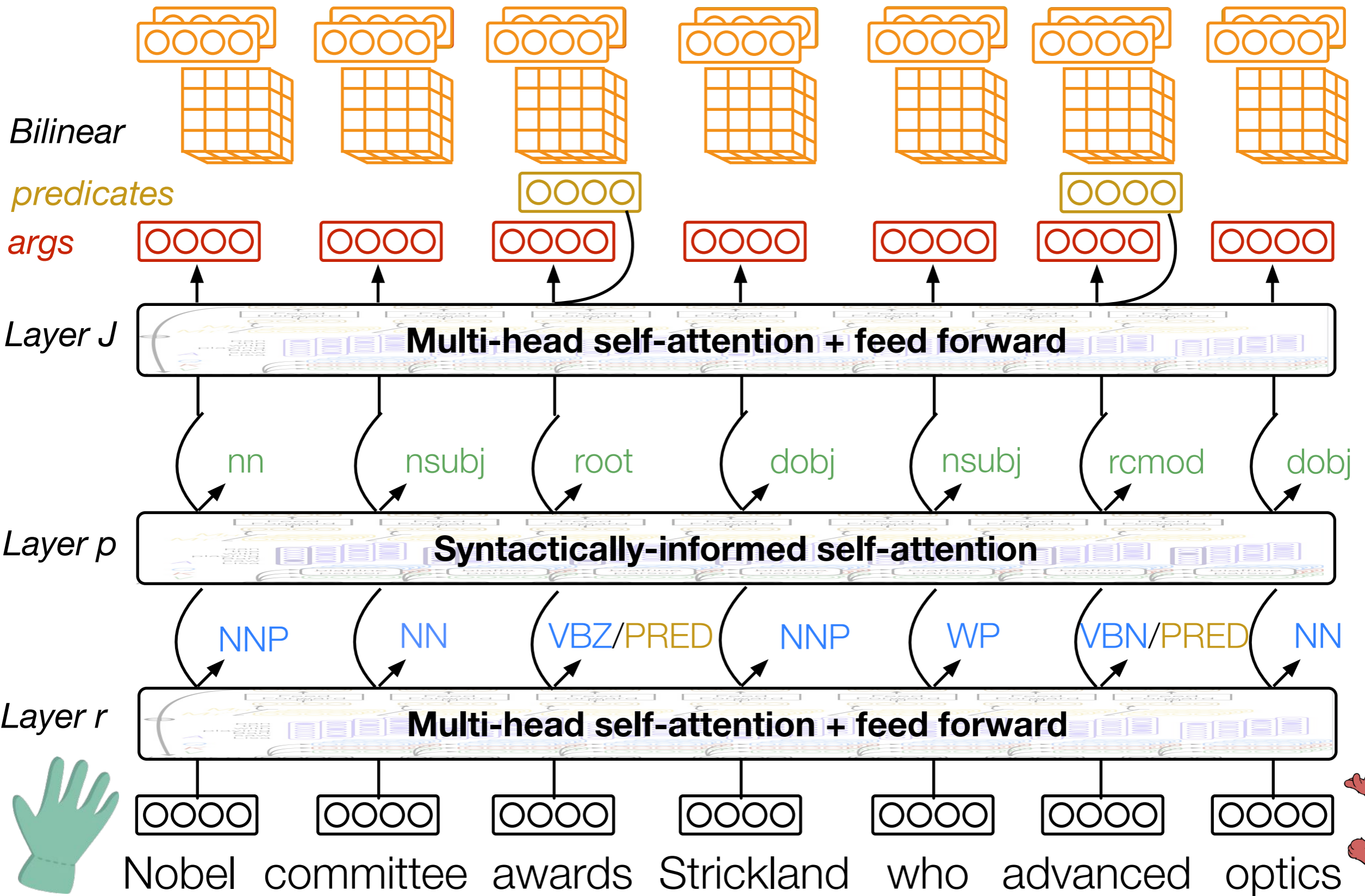
LISA: Linguistically-Informed Self-Attention

B-ARG₀ I-ARG₀ B-V B-ARG₁ O O O

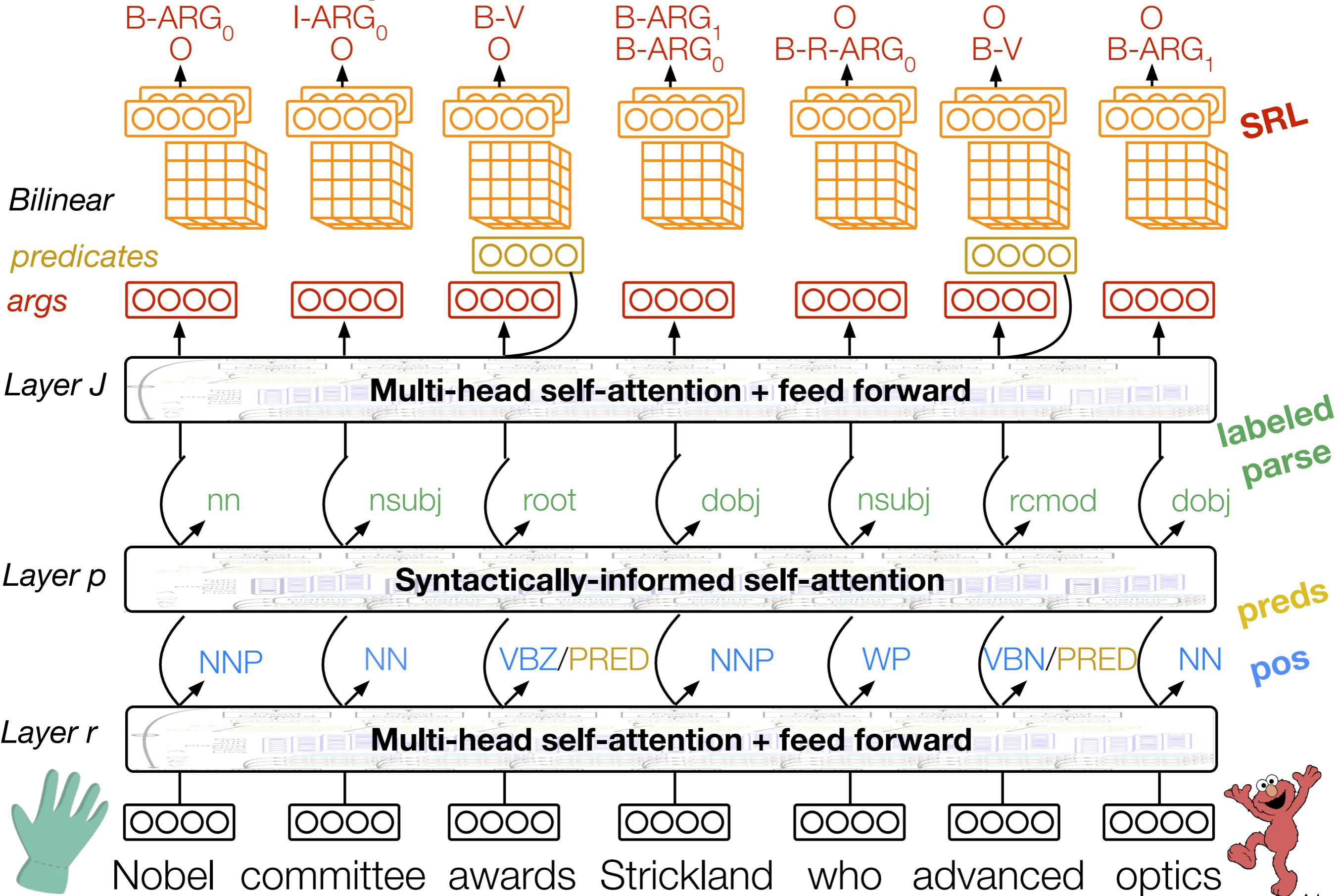


LISA: Linguistically-Informed Self-Attention

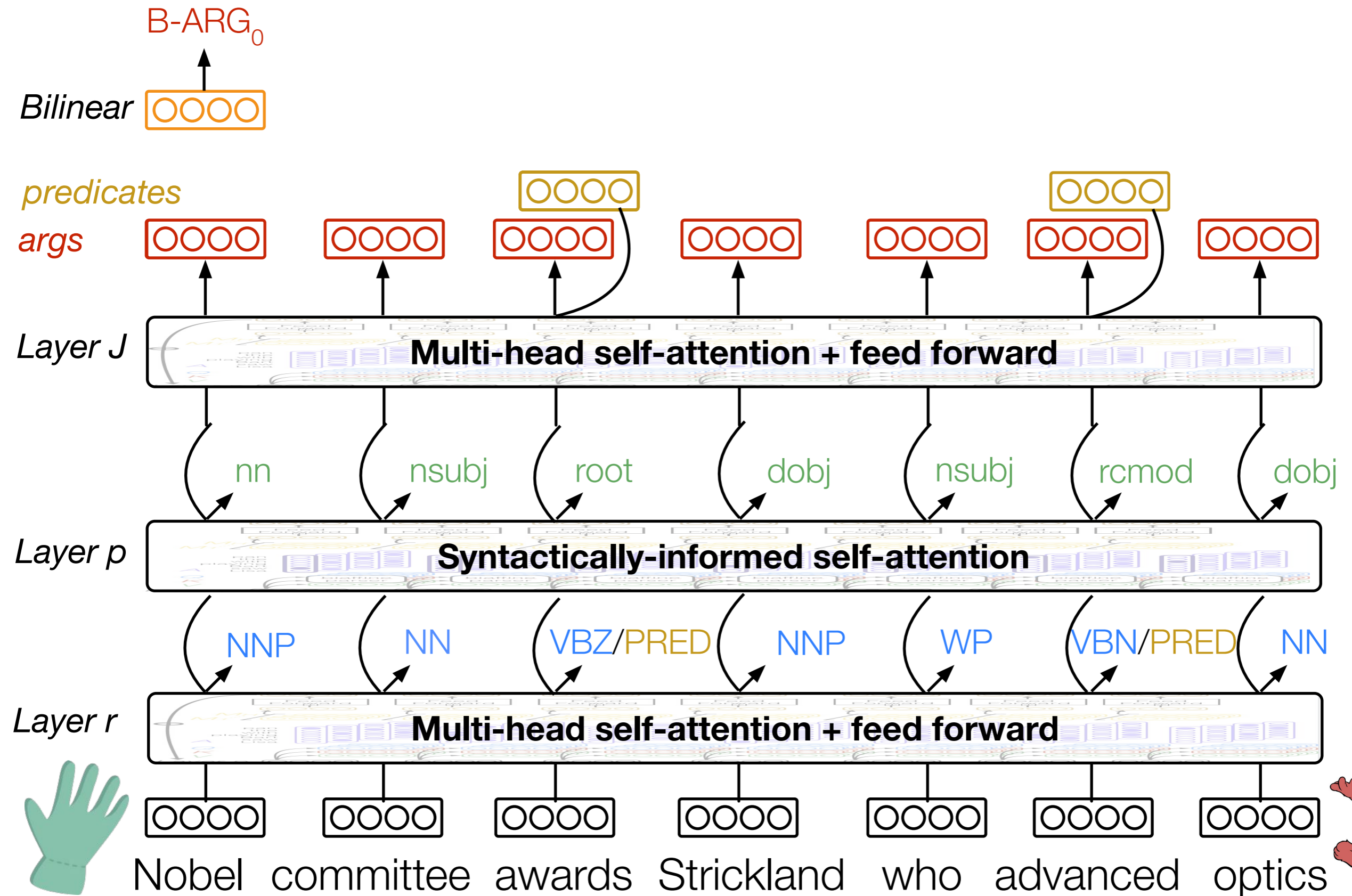
B-ARG₀ I-ARG₀ B-V B-ARG₁ O O O



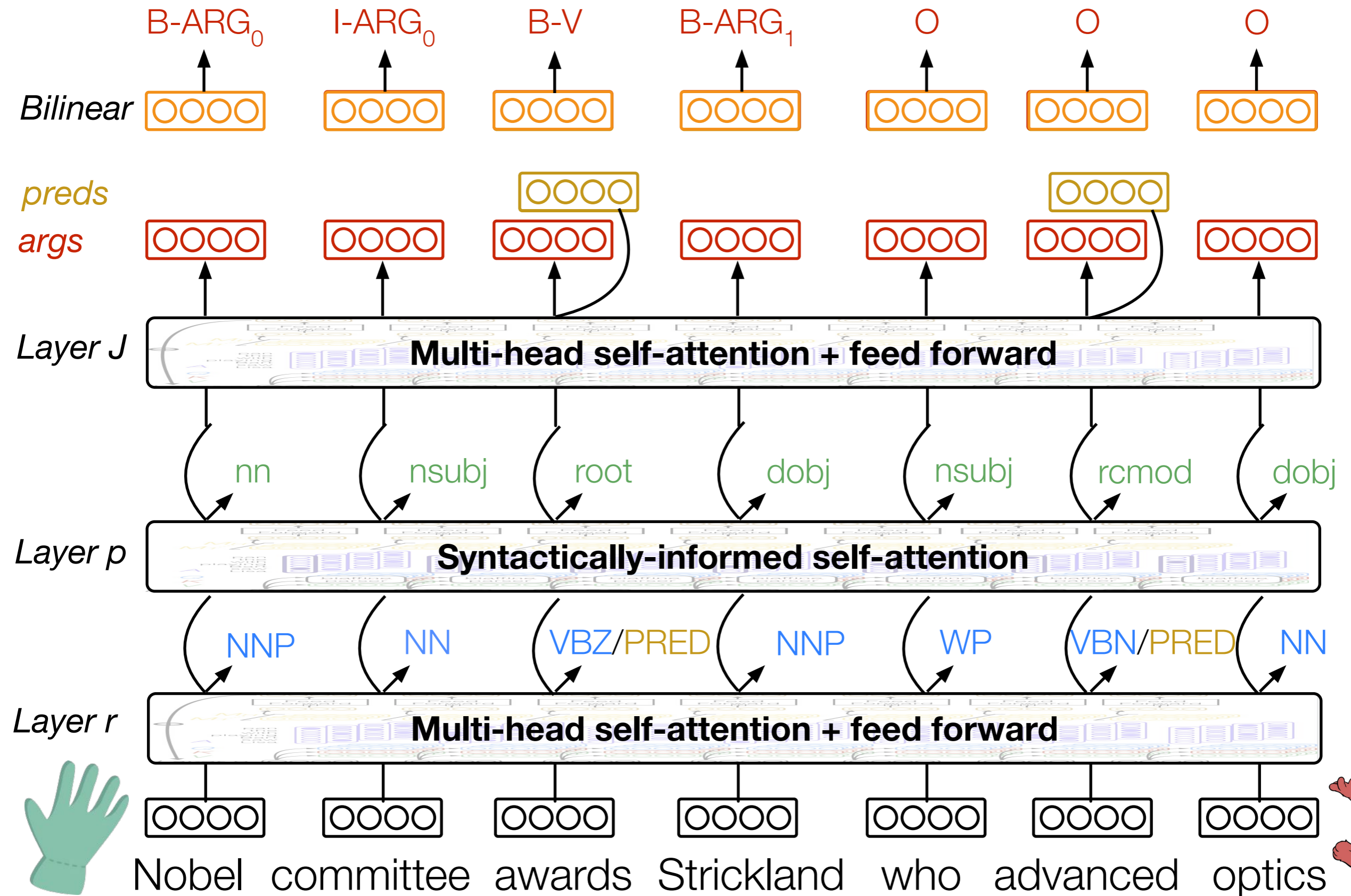
LISA: Linguistically-Informed Self-Attention



LISA: Linguistically-Informed Self-Attention

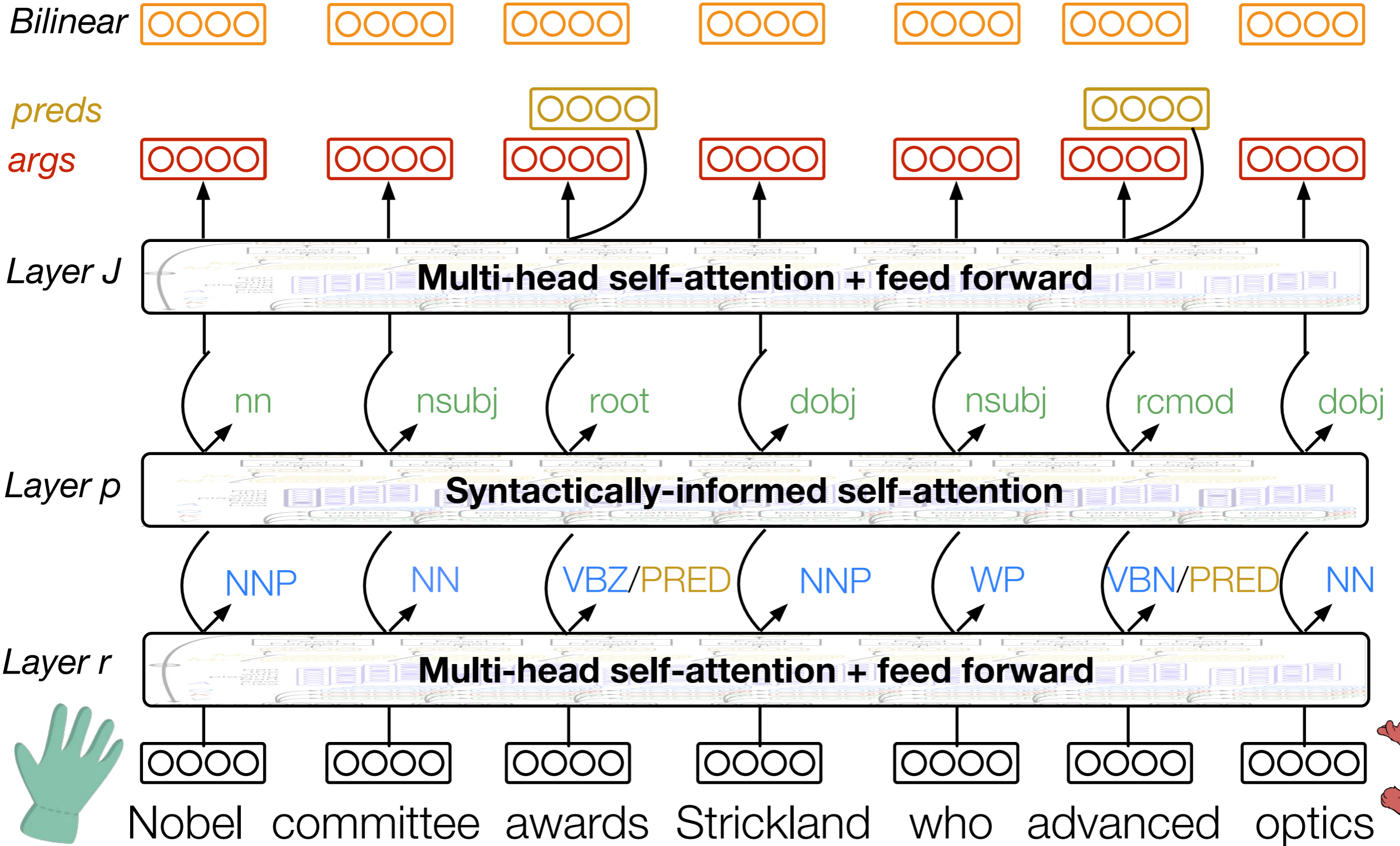


LISA: Linguistically-Informed Self-Attention

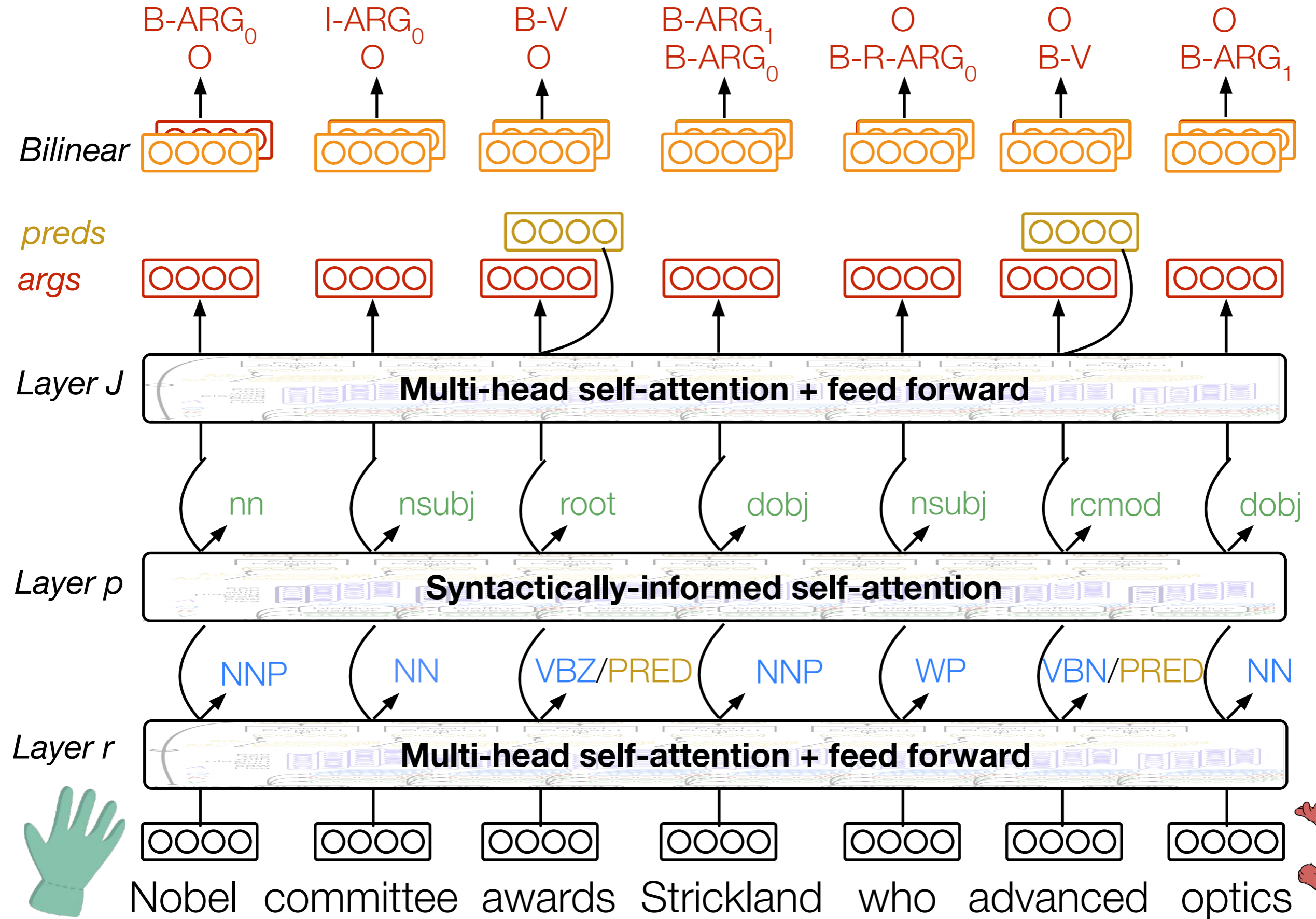


LISA: Linguistically-Informed Self-Attention

B-ARG₀ I-ARG₀ B-V B-ARG₁ O O O



LISA: Linguistically-Informed Self-Attention





Outline

- Want fast, accurate, robust NLU
- PropBank SRL: Who did what to whom?
- 10 years of PropBank SRL
- LISA: Linguistically-informed self attention
 - Multi-head self-attention
 - Syntactically-informed self-attention
 - Multi-task learning, single-pass inference
- Experimental results & error analysis

Experimental results

	CoNLL-2005	CoNLL-2012
domains	Train, dev: news Test: news, novels	Train, dev, test: 7 domains (news, telephone, bible, ...)
word embeddings	GloVe [Pennington et al. 2014] ELMo [Peters et al. 2018]	GloVe [Pennington et al. 2014] ELMo [Peters et al. 2018]
predicates	predicted; gold	predicted
baselines	He et al. 2017 He et al. 2018 Tan et al. 2018	He et al. 2018
our models	SA LISA LISA+D&M, +Gold Lisa_Gold	SA LISA LISA+D&M, +Gold Lisa_Gold

Experimental results: CoNLL-2005

	 GloVe		 ELMo	
	in-domain	out-of-domain	in-domain	out-of-domain
He et al. 2017	82.7	70.1	---	---
He et al. 2018	82.5	70.8	86.0	76.1
SA	83.72	71.51	86.09	76.35
LISA	83.61	71.91	86.55	78.05
+D&M	89.99 94.9 UAS	74.66 90.3 UAS	86.90 96.8 UAS	78.25 93.4 UAS
	+2.49 F1	+3.86 F1	+0.9 F1 ?	+2.15 F1

Experimental results: CoNLL-2005



GloVe

ELMo



in-domain (dev)

in-domain (dev)

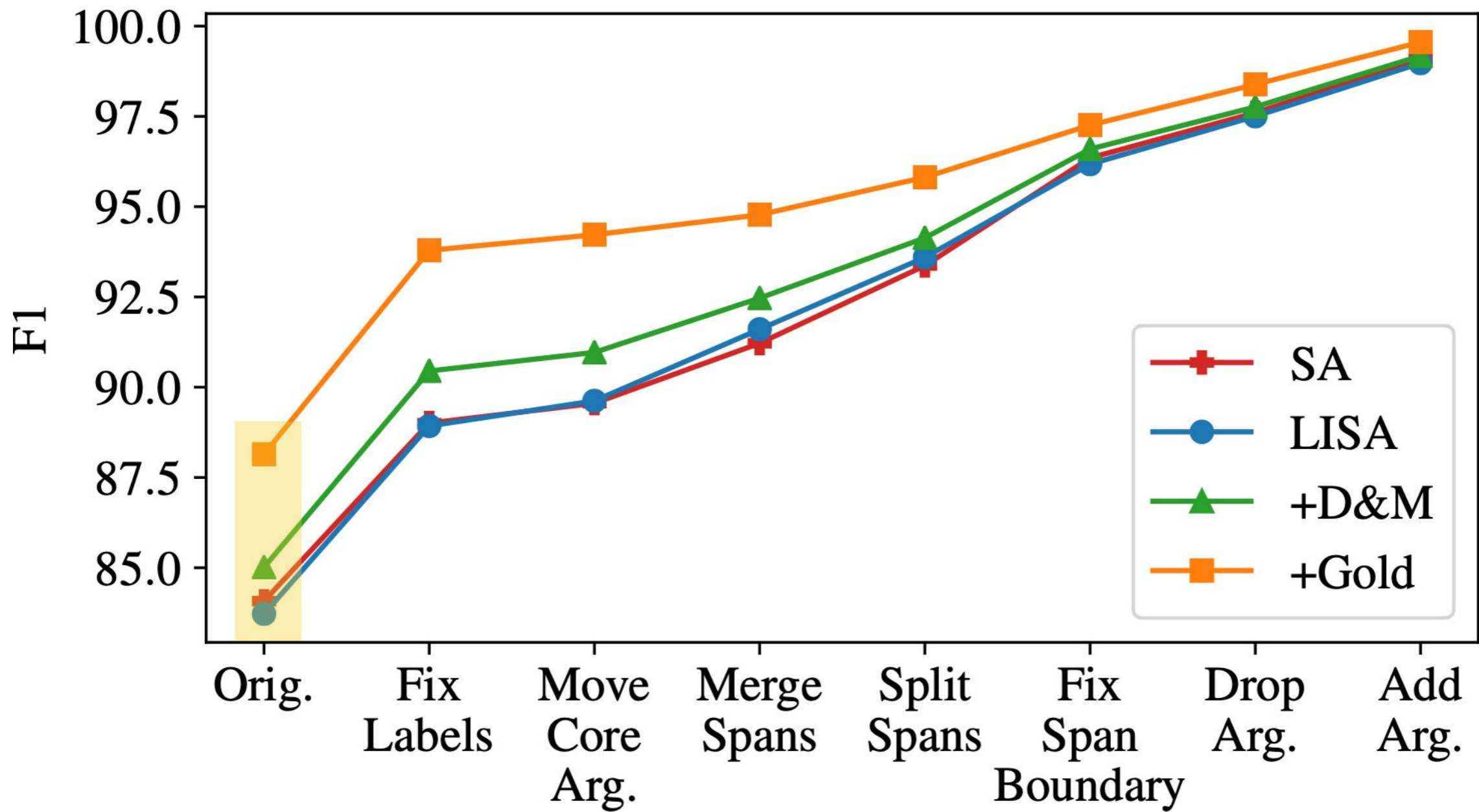
96.5 UAS!

Experimental results: Validation

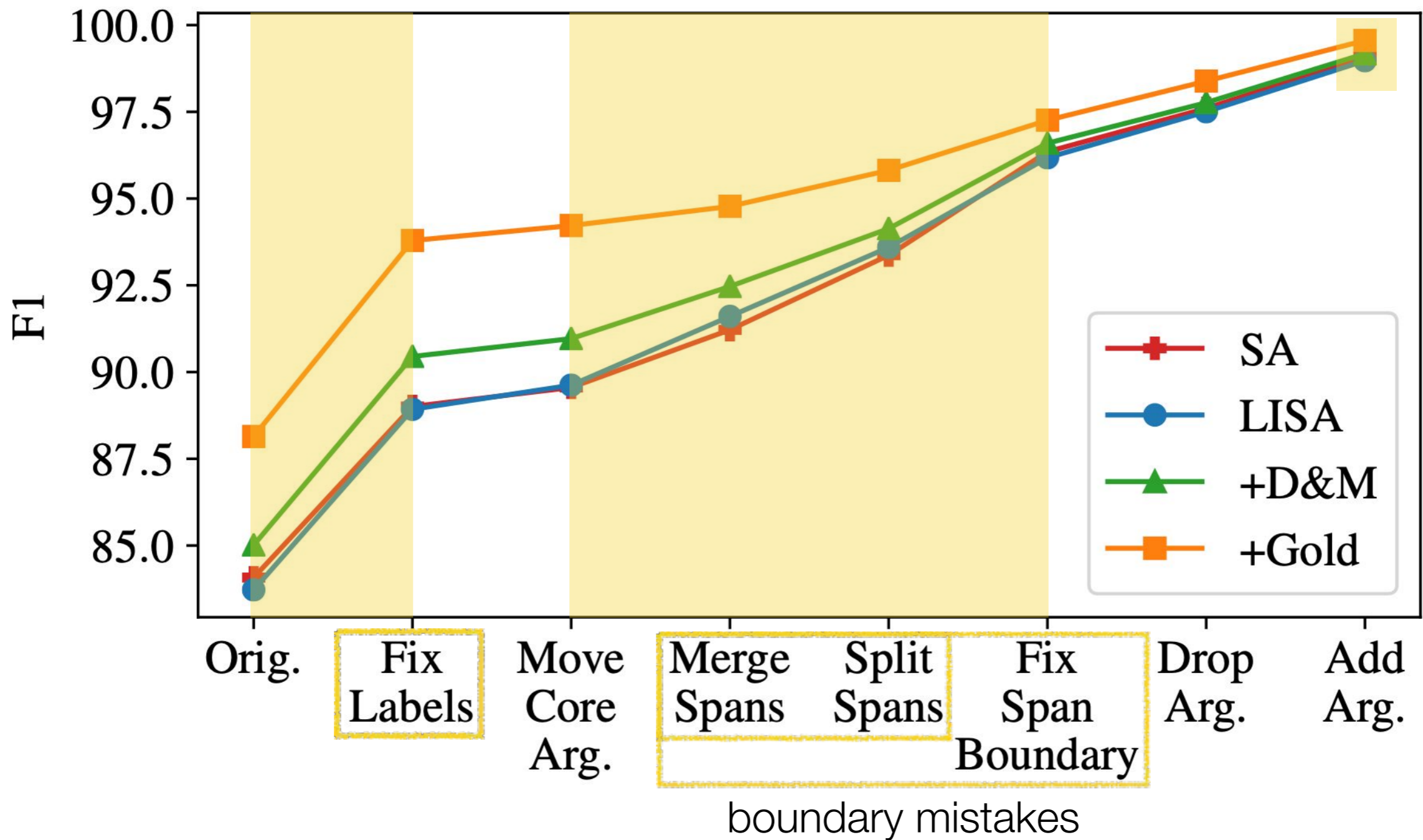
	GloVe		ELMo	
	CoNLL-05	CoNLL-12	CoNLL-05	CoNLL-12
<i>+Gold $\Delta F1$</i>	<i>5.21</i>	<i>7.03</i>	<i>2.33</i>	<i>4.36</i>
<i>+D&M $\Delta F1$</i>	1.98	2.65	-0.13	0.36

	GloVe		ELMo	
	CoNLL-05	CoNLL-12	CoNLL-05	CoNLL-12
LISA UAS	94.92	93.35	96.48	94.84
D&M UAS	---	---	96.28	94.99

Experimental results: Analysis



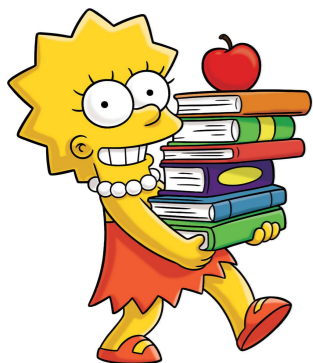
Experimental results: Analysis



Summary

Thank you!

- **LISA**: Multi-task learning + multi-head self attention trained to attend to syntactic parents
 - Achieves state-of-the-art F1 on PropBank SRL
 - Linguistic structure improves generalization
 - Fast: encodes sequence *only once* to predict predicates, parts-of-speech, labeled dependency parse, SRL
- Everyone wants to run NLP on the entire web:
 - **accuracy**, **robustness**, **computational efficiency**.



Models & Code:

<https://github.com/strubell/LISA>

I am on the academic job market this spring!

Experimental results: CoNLL-2005

Gold predicates; GloVe embeddings 

WSJ Test (in-domain):

	Precision	Recall	F1
He et al. 2018	84.2	83.7	83.9
Tan et al. 2018	81.2	83.9	84.8
SA	84.7	84.24	84.47
LISA	84.72	84.57	84.64
+D&M	86.02	86.05	86.04

Brown Test (out-of-domain):

	Precision	Recall	F1
He et al. 2018	74.2	73.1	73.7
Tan et al. 2018	73.5	74.6	74.1
SA	73.89	72.39	73.13
LISA	74.77	74.32	74.55
+D&M	76.65	76.44	76.54

Experimental results: CoNLL-2012

Predicted predicates

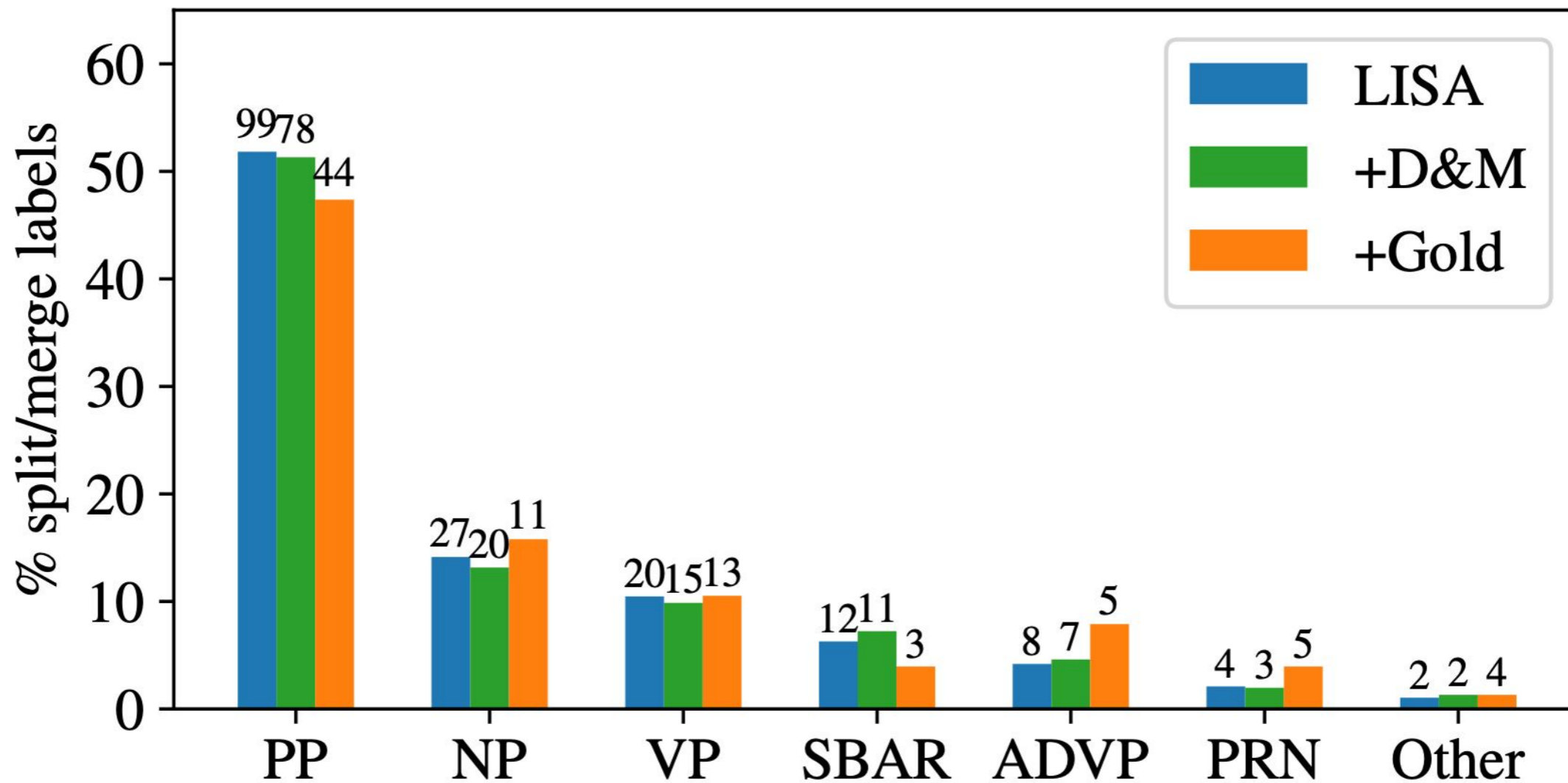


	Precision	Recall	F1
He et al. 2018	79.4	80.1	79.8
SA	82.55	80.02	81.26
LISA	81.86	79.56	80.70
+D&M	83.3	81.38	82.33



	Precision	Recall	F1
He et al. 2018	81.9	84.0	82.9
SA	84.39	82.21	83.28
LISA	83.97	82.29	83.12
+D&M	84.14	82.64	83.38

Experimental results: Analysis



Experimental results: Analysis

	L+/D+	L-/D+	L+/D-	L-/D-
Proportion	26%	12%	4%	56%
SA	79.29	75.14	75.97	75.08
LISA	79.51	74.33	79.69	75.00
+D&M	79.03	76.96	77.73	76.52
<i>+Gold</i>	<i>79.61</i>	<i>78.38</i>	<i>81.41</i>	<i>80.47</i>

Experimental results: Analysis

