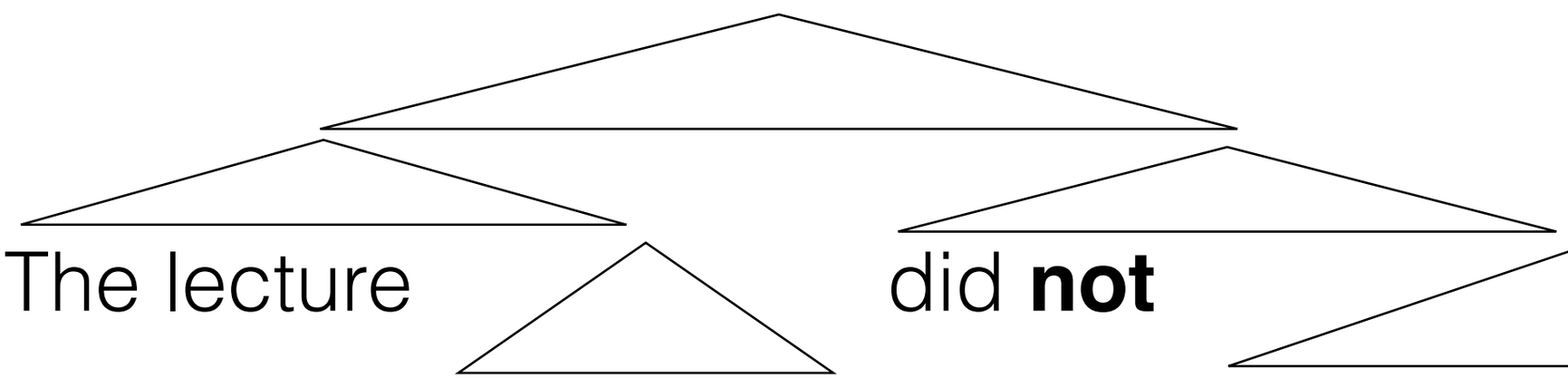
ᓯᒪᓕᒃᑐᖅᓄᑦ ᓇᒥᓐᔅᑕᓂᖅᑐᑦ ᓇᓗᒋᑦᑐᒃᑯᐊᒃᑐᑦ ᓇᓂᒃᑎᖅᑎᑦ

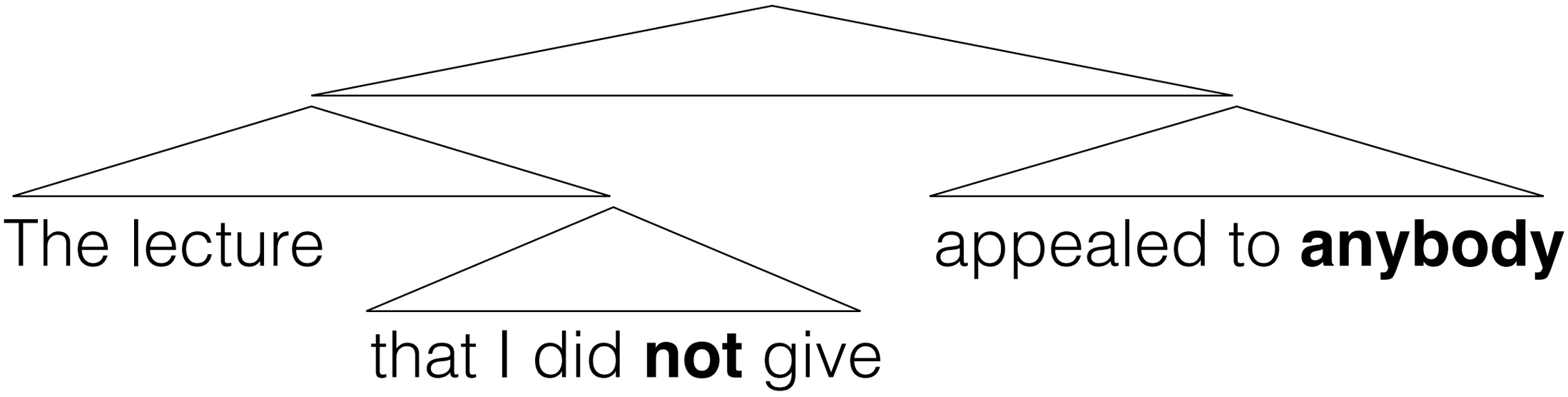
Recurrent neural network grammars

Dyer et al., 2017

Language is hierarchical

negative polarity items





One theory of hierarchy

- Generate symbols sequentially using an RNN

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- Add some “control symbols” to rewrite the history periodically
    - Periodically “compress” a sequence into a single “constituent”
    - Augment RNN with an operation to compress recent history into a single vector (-> “reduce”)
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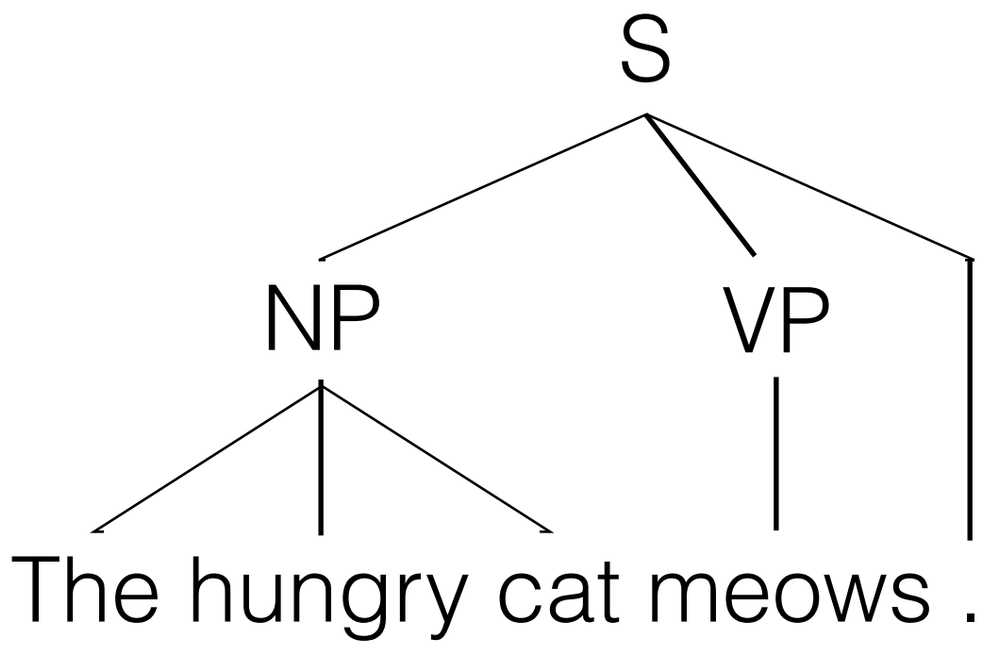
- We call such models **recurrent neural network grammars**.

Trees as sequences



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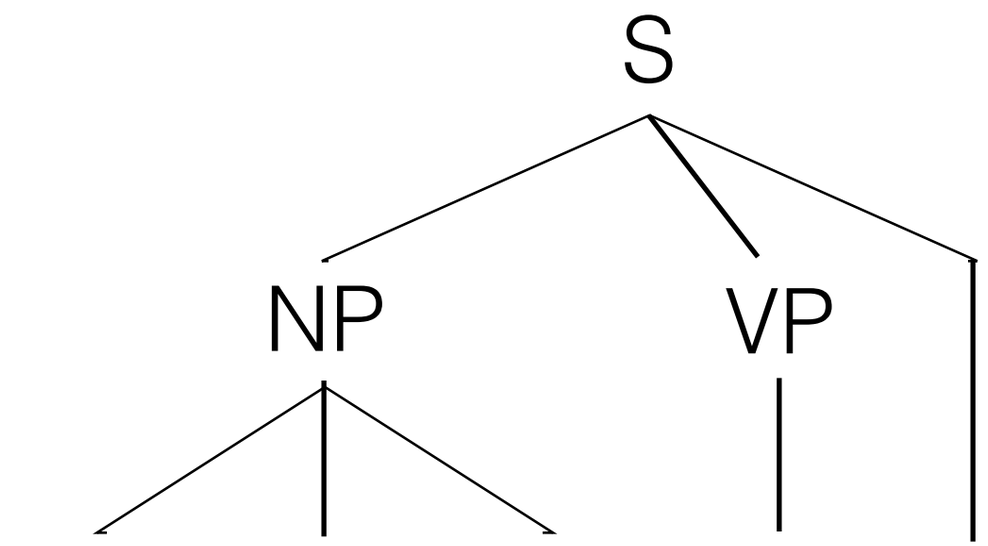
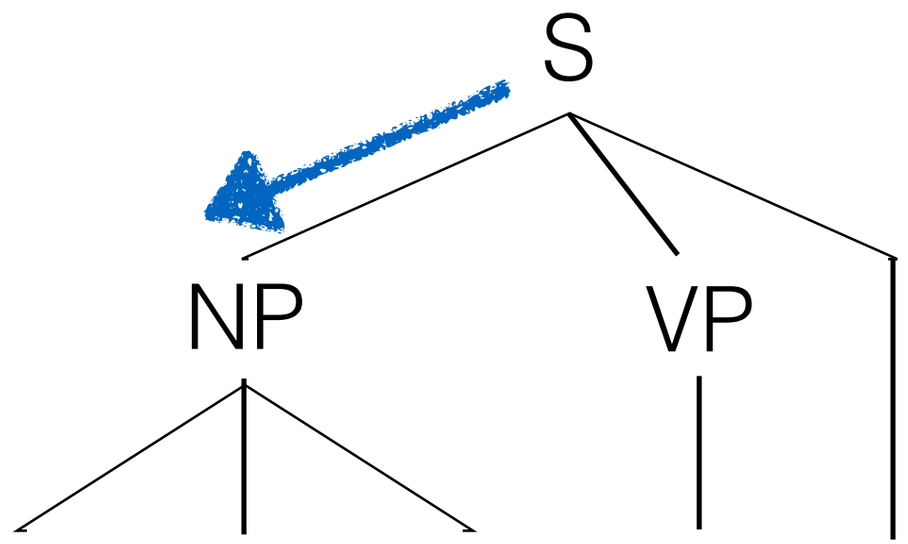


S(NP(The hungry cat) VP(meows) .)

Trees as sequences



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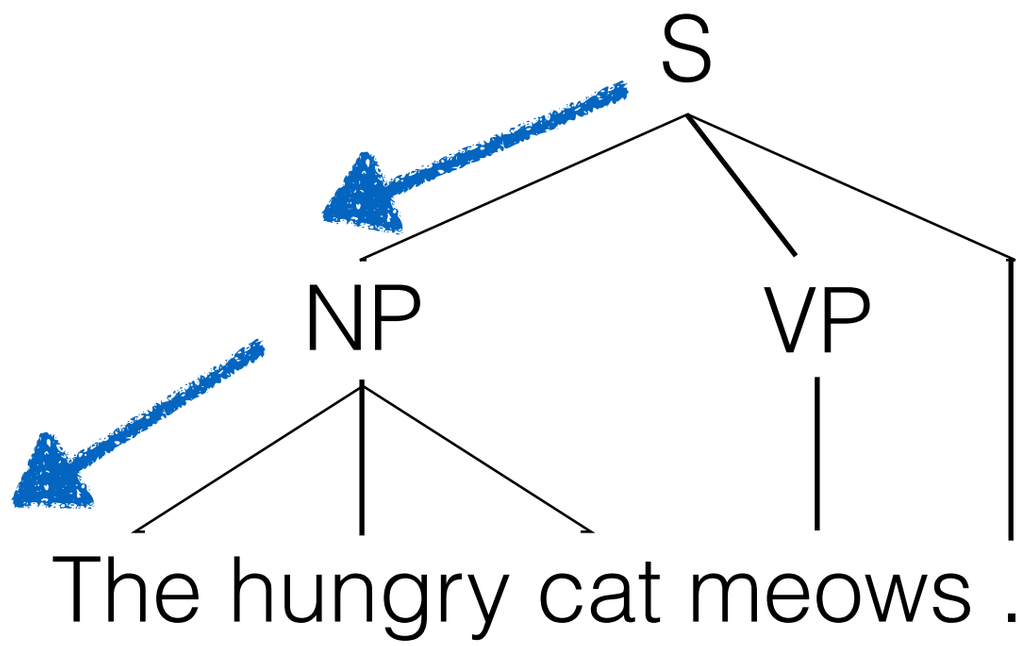
Tree traversals correspond to stack operations

Trees as sequences



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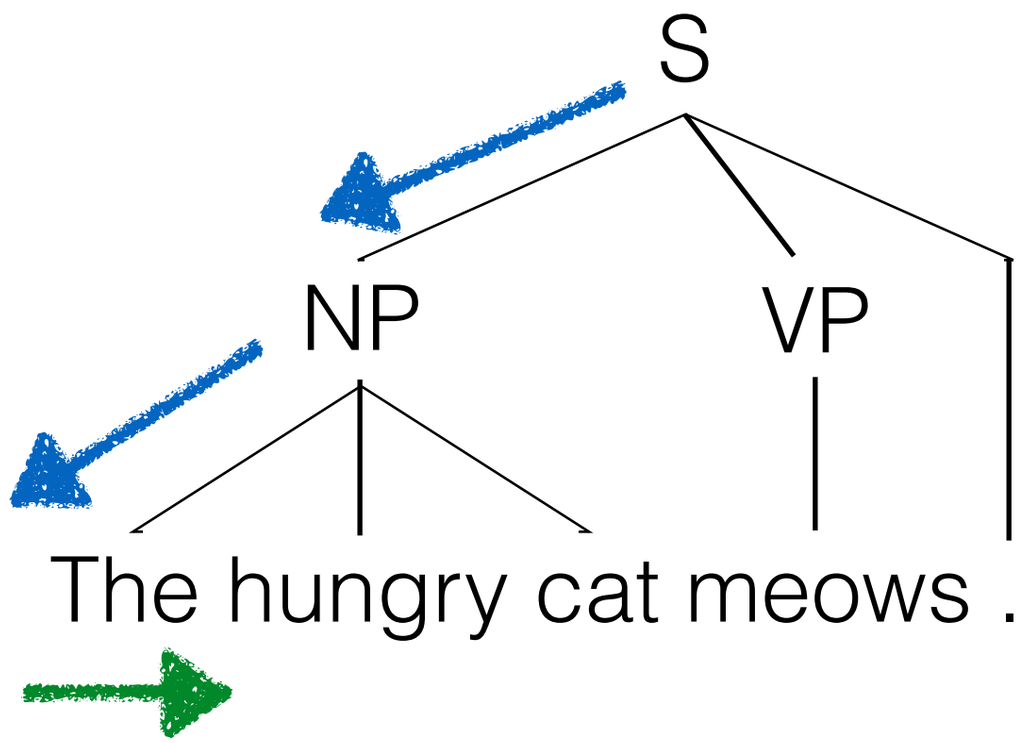

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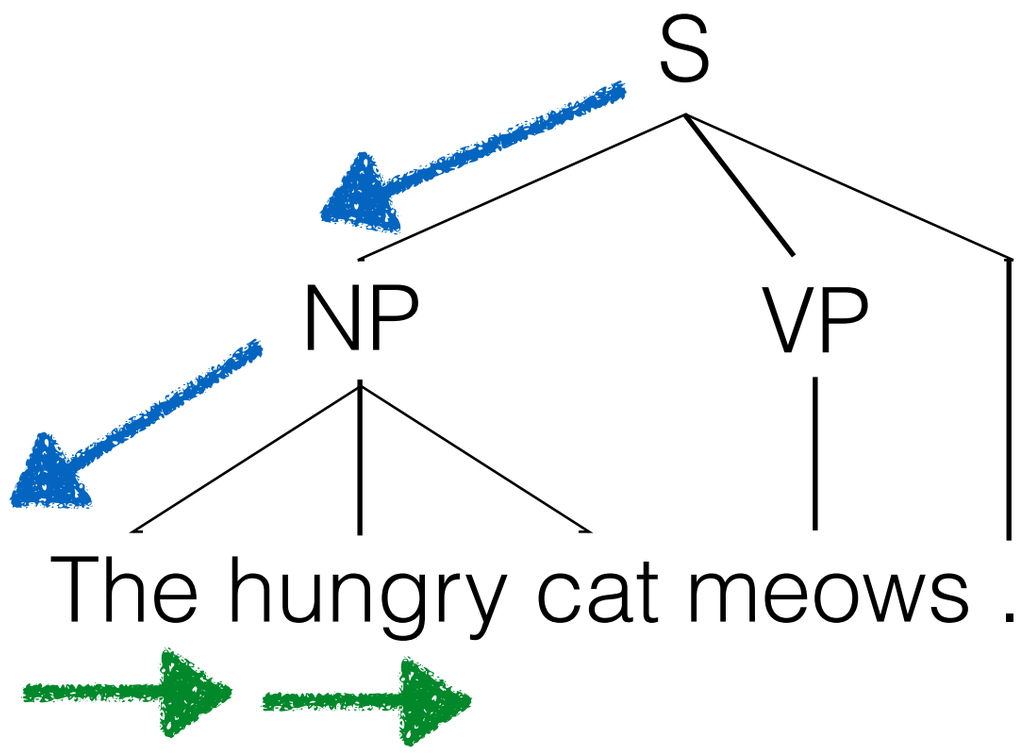

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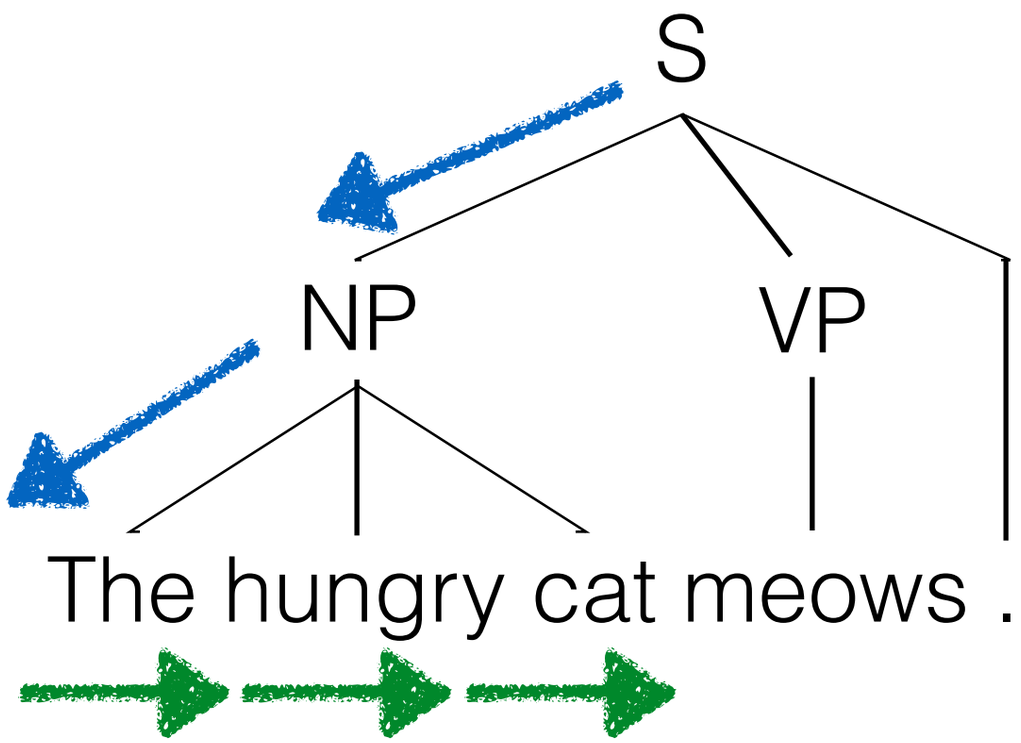

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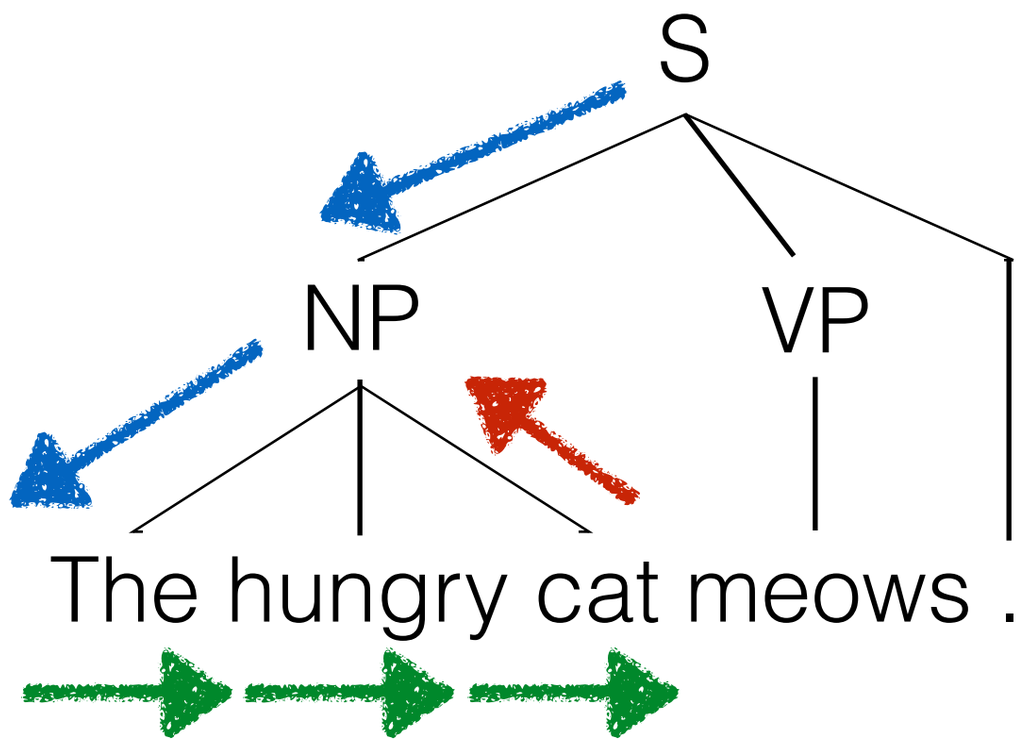

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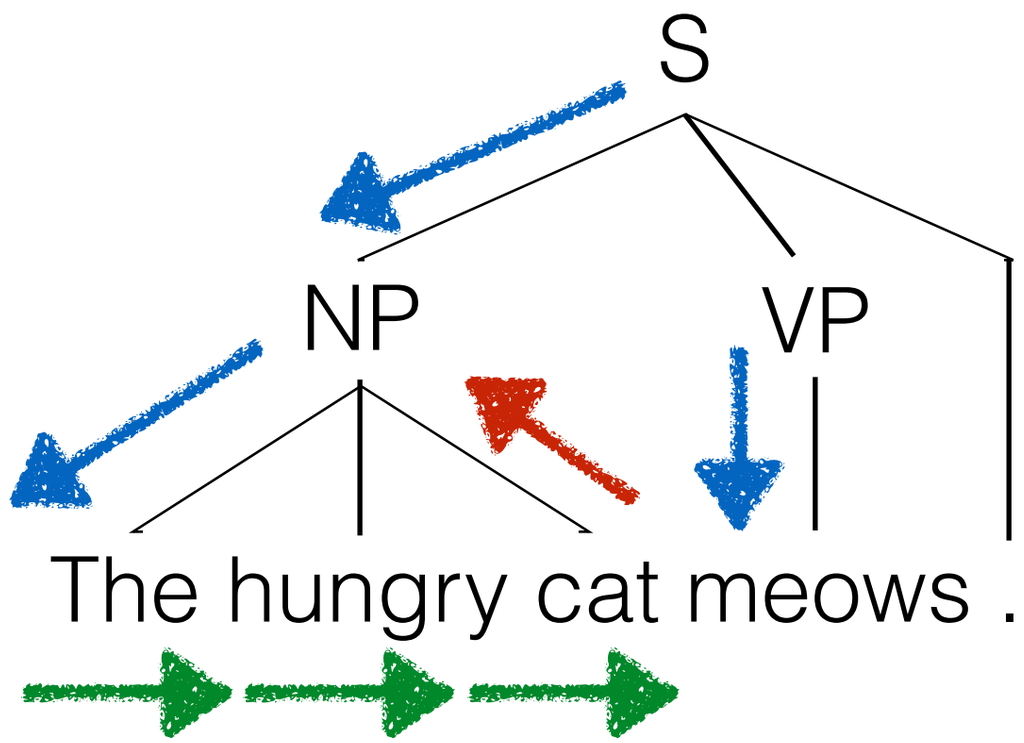

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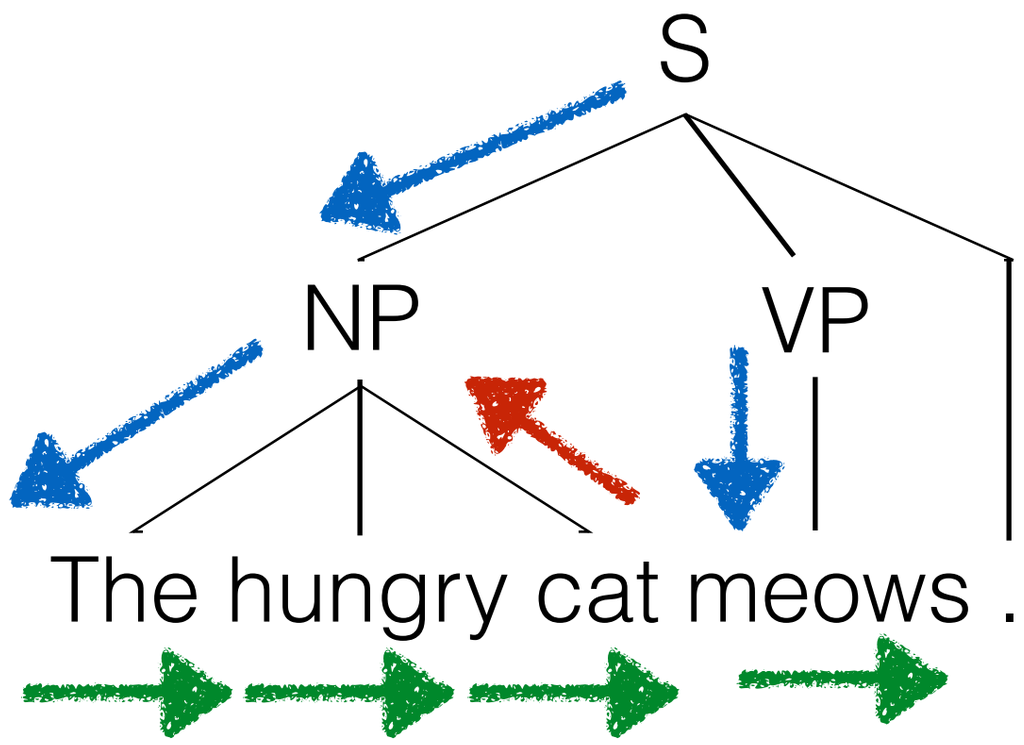

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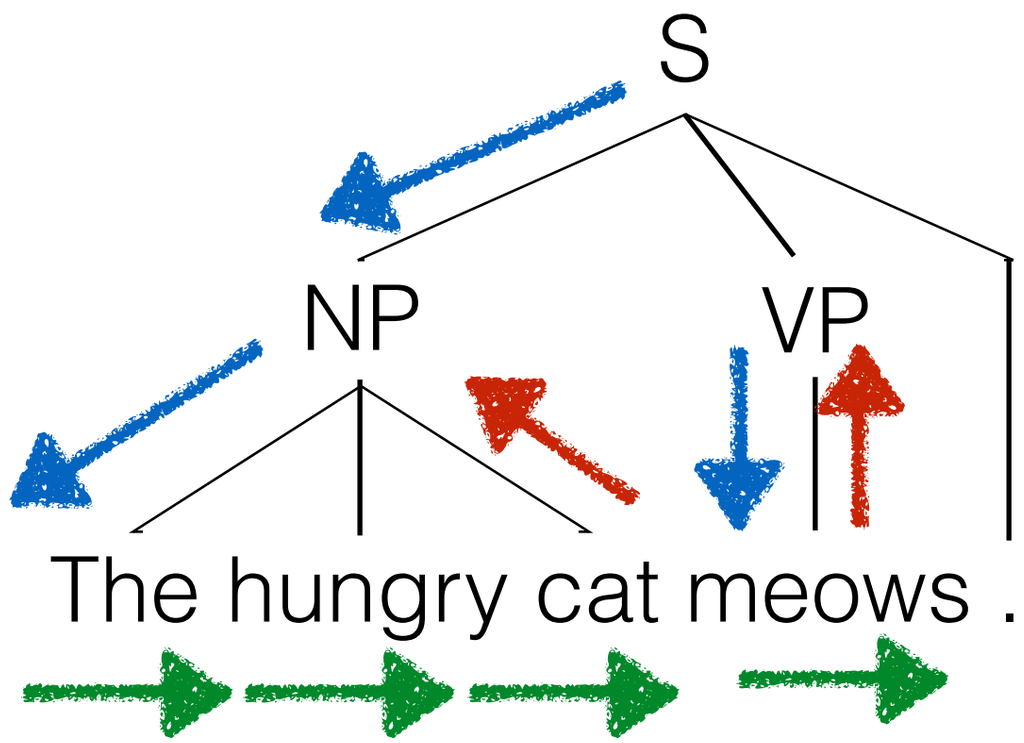

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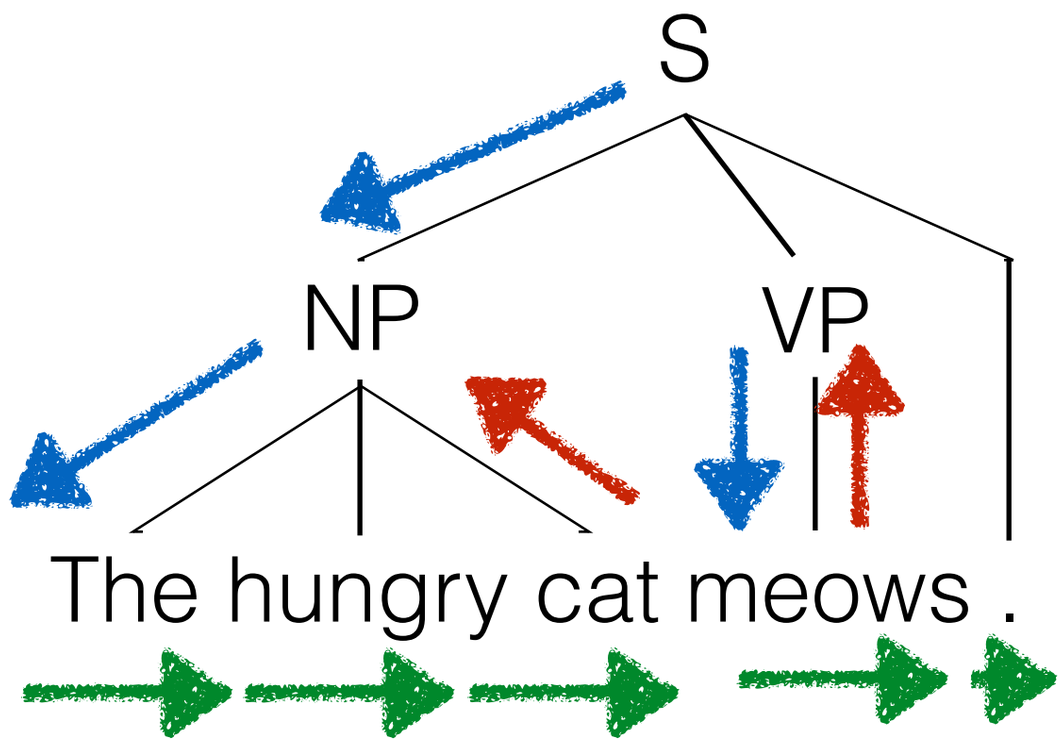

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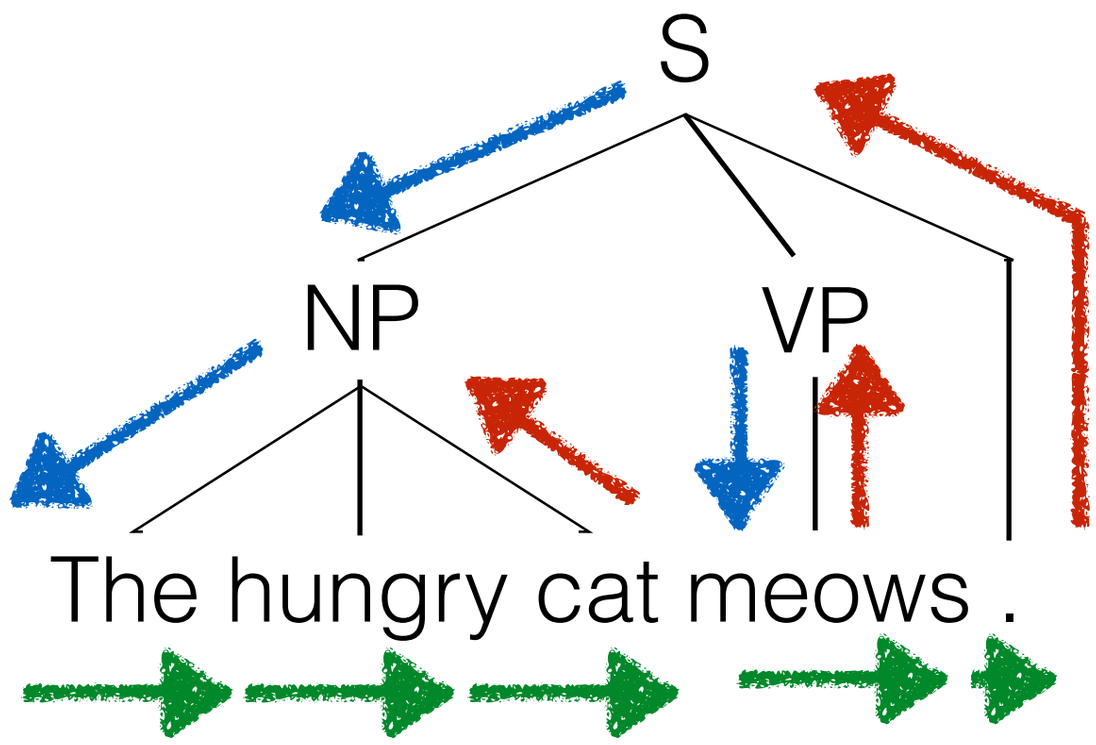

S(NP(The hungry cat) VP(meows) .)

Tree traversals correspond to stack operations

Terminals	Stack	Action

Terminals	Stack	Action
		NT(S)

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)
The hungry cat	(S (NP *The hungry cat*	

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)
The hungry cat	(S (NP *The hungry cat*	**REDUCE**

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)
The hungry cat	(S (NP *The hungry cat*	**REDUCE**
The hungry cat	(S (NP *The hungry cat*)	

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)
The hungry cat	(S (NP *The hungry cat*	**REDUCE**
The hungry cat	(S (NP *The hungry cat*)	
	(S (NP *The hungry cat*)	

Compress “The hungry cat” into a single composite symbol

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)
The hungry cat	(S (NP *The hungry cat*	**REDUCE**
The hungry cat	(S (NP *The hungry cat*)	

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)
The hungry cat	(S (NP *The hungry cat*	**REDUCE**
The hungry cat	(S (NP *The hungry cat*)	**NT**(VP)

Terminals	Stack	Action
		NT(S)
	(S	**NT**(NP)
	(S (NP	**GEN**(*The*)
The	(S (NP *The*	**GEN**(*hungry*)
The hungry	(S (NP *The hungry*	**GEN**(*cat*)
The hungry cat	(S (NP *The hungry cat*	**REDUCE**
The hungry cat	(S (NP *The hungry cat*)	**NT**(VP)
The hungry cat	(S (NP *The hungry cat*) (VP	

Terminals	Stack	Action
		NT(S**)**
	(S	**NT(**NP**)**
	(S (NP	**GEN(***The***)**
The	(S (NP *The*	**GEN(***hungry***)**
The hungry	(S (NP *The hungry*	**GEN(***cat***)**
The hungry cat	(S (NP *The hungry cat*	**REDUCE**
The hungry cat	(S (NP *The hungry cat*)	**NT(**VP**)**
The hungry cat	(S (NP *The hungry cat*) (VP	**GEN(***meows***)**

Terminals	Stack	Action
		NT(S**)**
	(S	**NT(**NP**)**
	(S (NP	**GEN(***The***)**
The	(S (NP *The*	**GEN(***hungry***)**
The hungry	(S (NP *The hungry*	**GEN(***cat***)**
The hungry cat	(S (NP *The hungry cat*	**REDUCE**
The hungry cat	(S (NP *The hungry cat*)	**NT(**VP**)**
The hungry cat	(S (NP *The hungry cat*) (VP	**GEN(***meows***)**
The hungry cat meows	(S (NP *The hungry cat*) (VP *meows*	**REDUCE**
The hungry cat meows	(S (NP *The hungry cat*) (VP *meows*)	**GEN(.)**
The hungry cat meows .	(S (NP *The hungry cat*) (VP *meows*) .	**REDUCE**
The hungry cat meows .	(S (NP *The hungry cat*) (VP *meows*) .)	

Syntactic Composition

Need representation for: (NP *The hungry cat*)

Syntactic Composition

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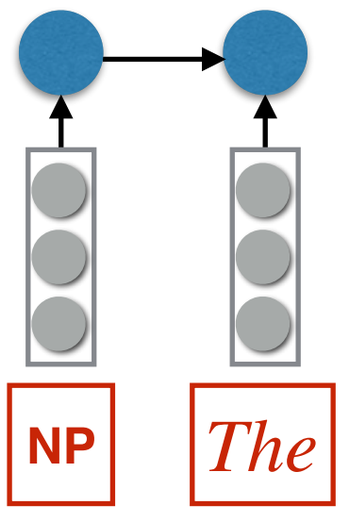

What head type?

Syntactic Composition

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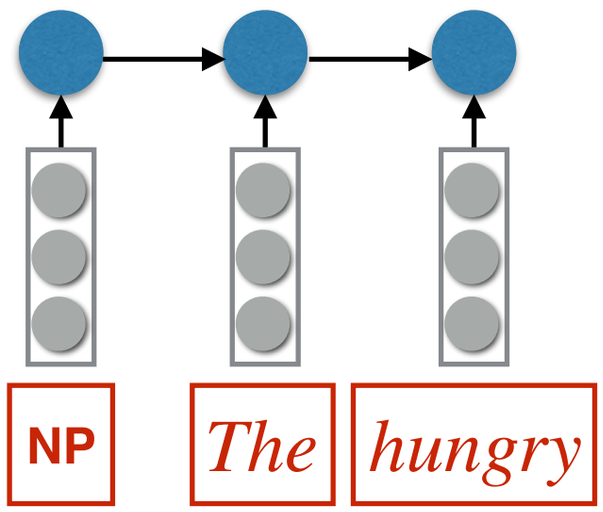

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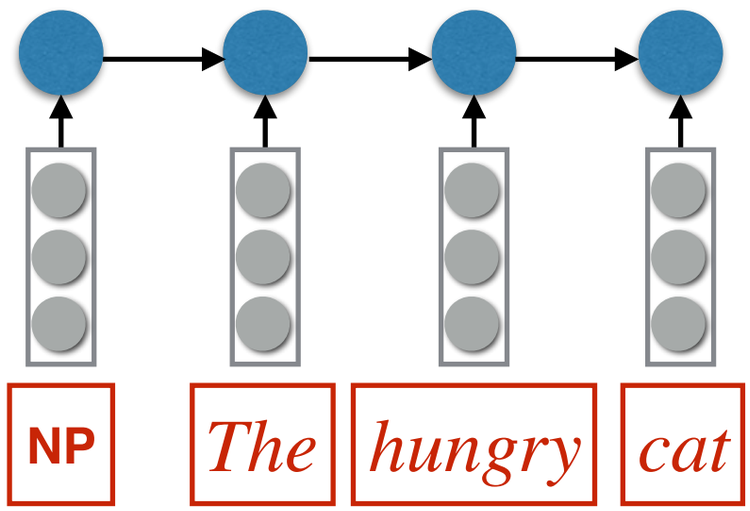

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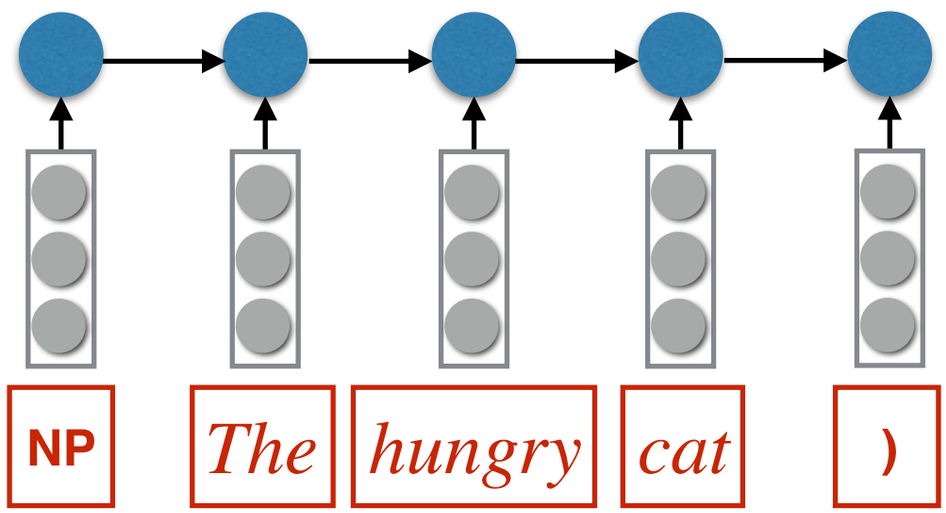

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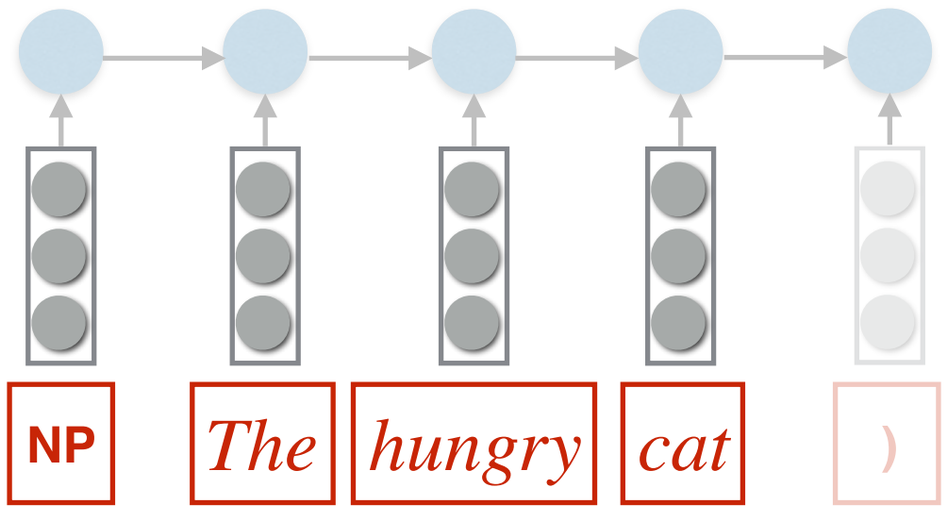

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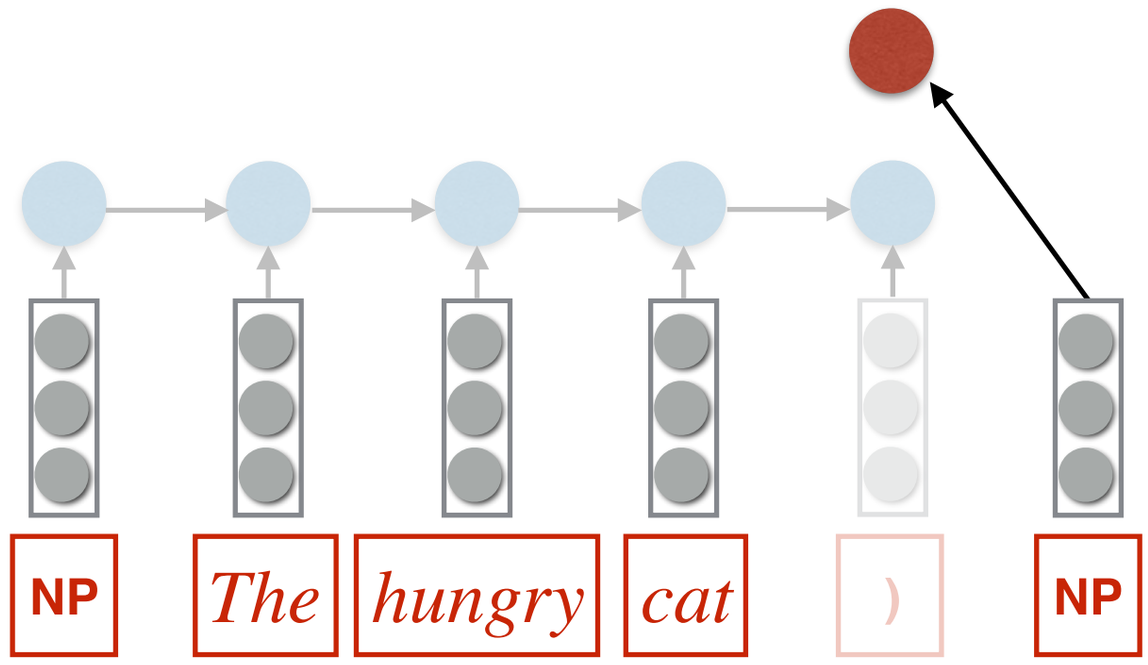

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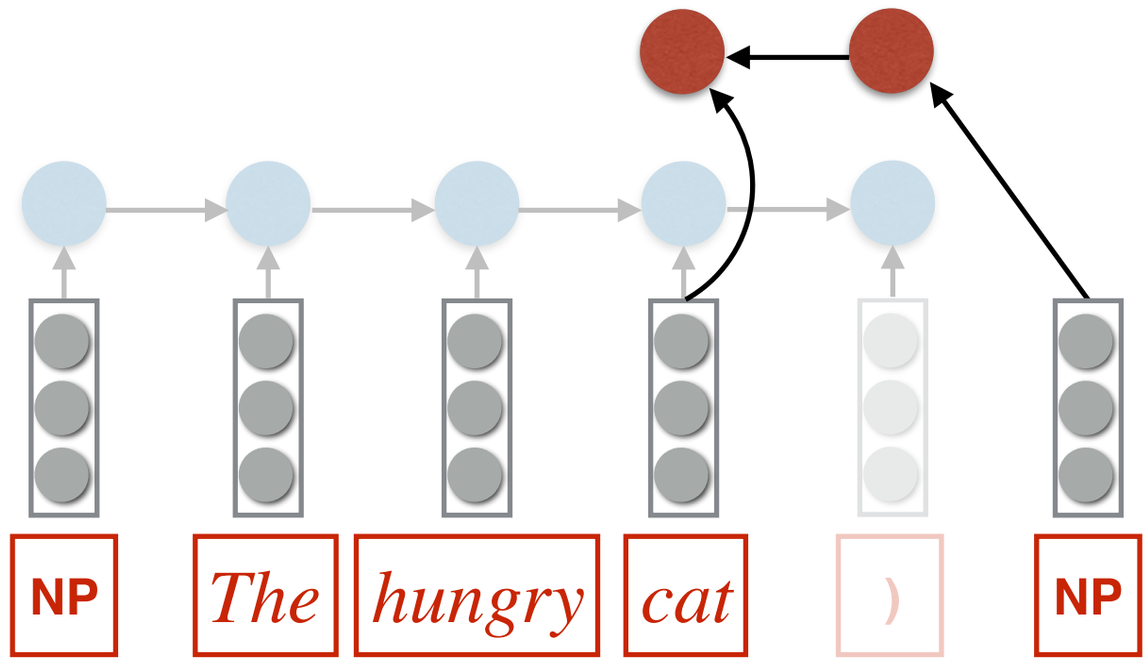

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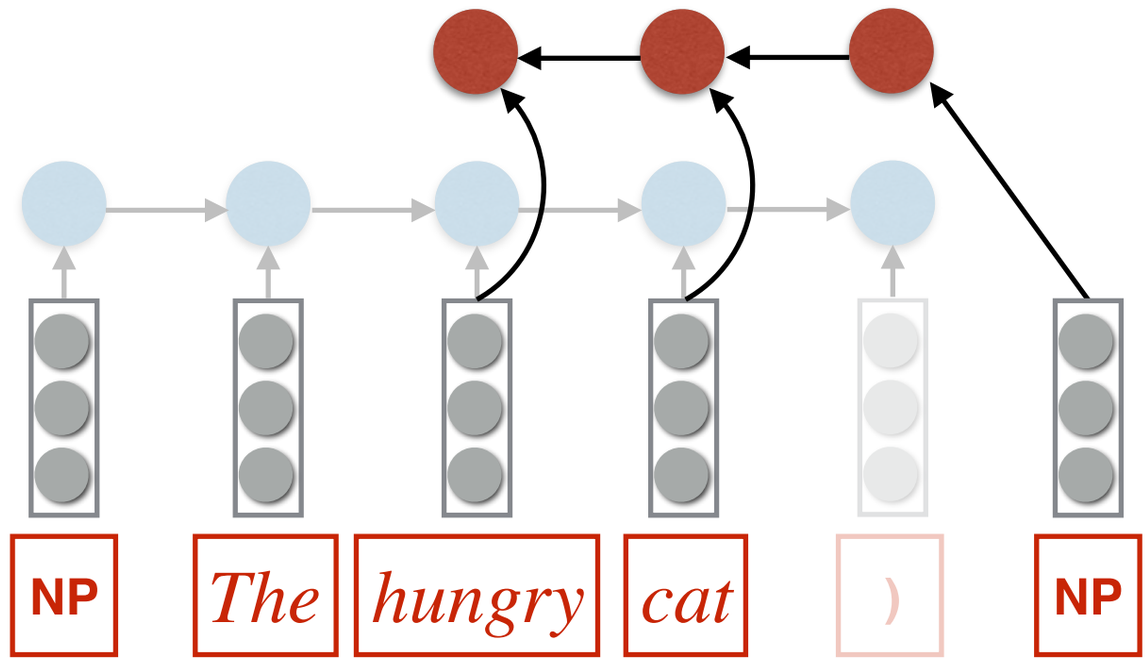

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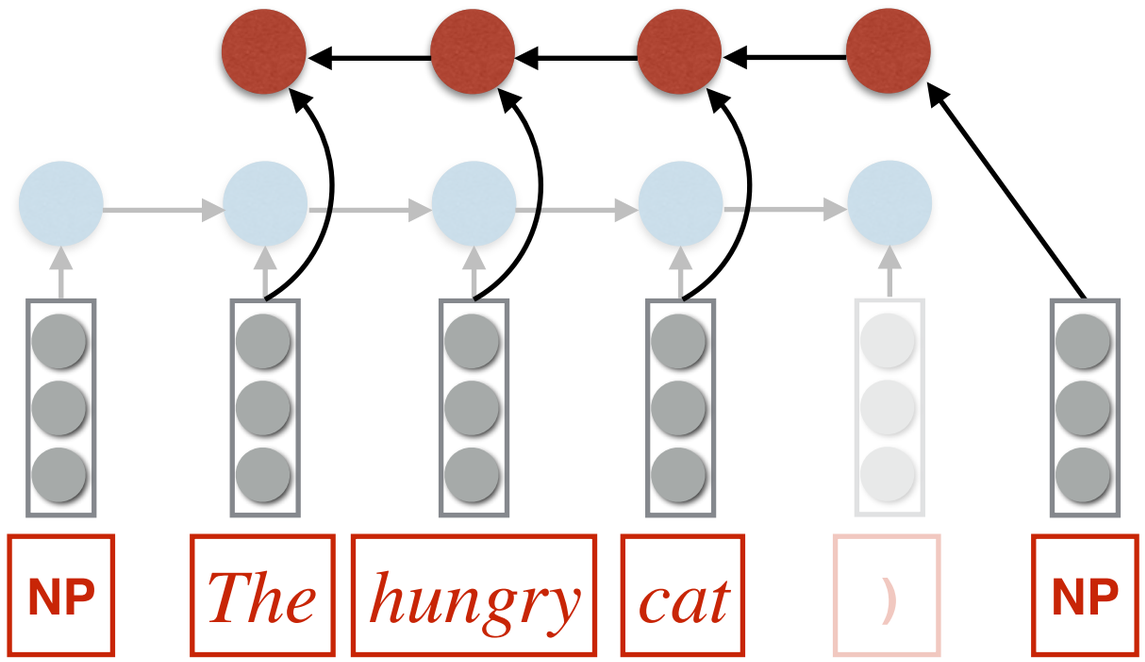

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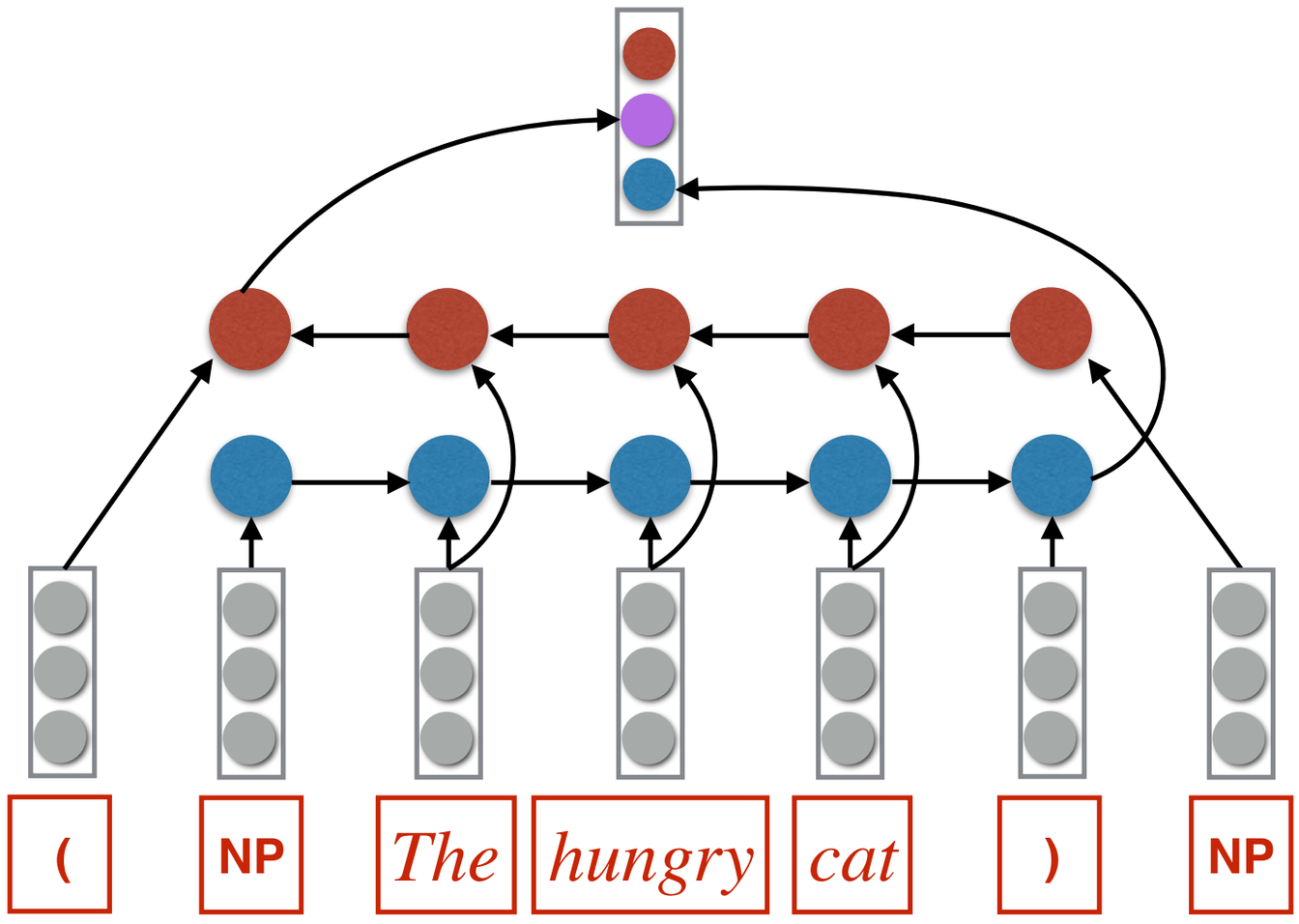
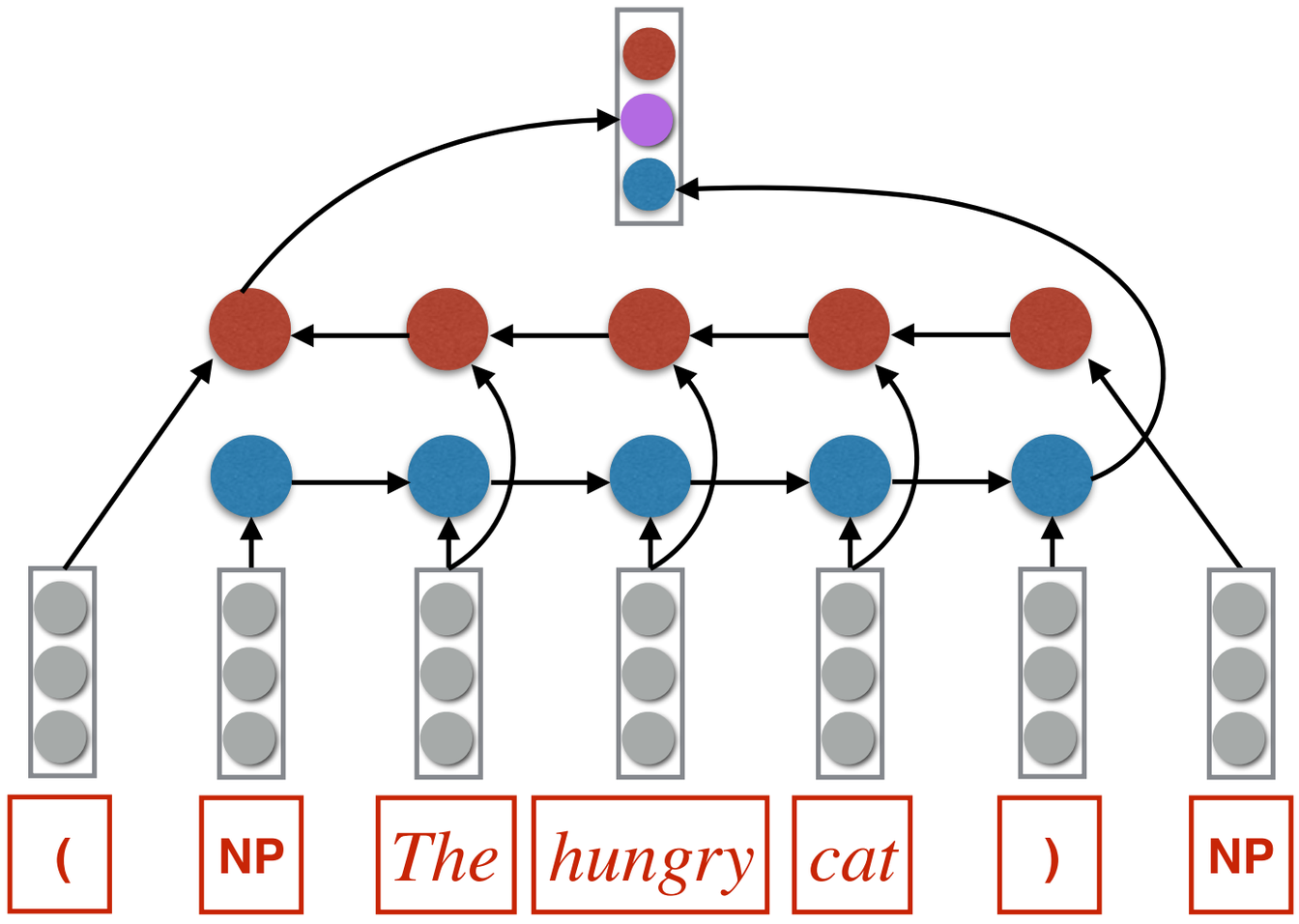


Recursion

Need representation for: (NP *The hungry cat*)

(NP *The* (ADJP *very hungry*) *cat*)



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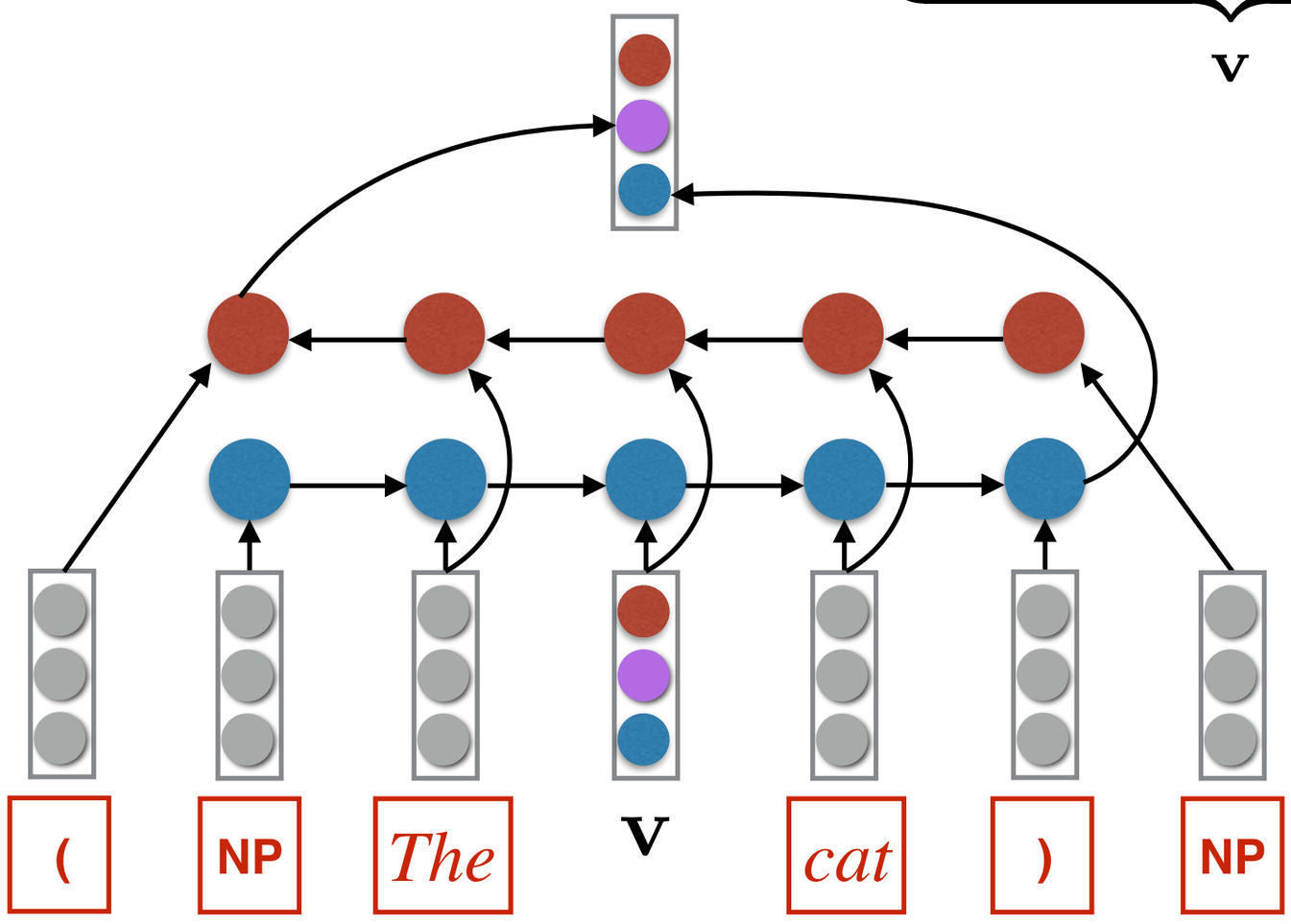


Syntactic Composition

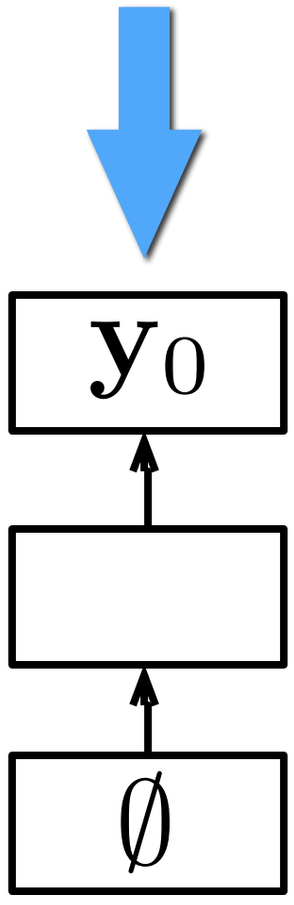
- Inspired by Socher et al (2011, 2012 …)
  - words and constituents embedded in same space
- Composition functions designed to
  - capture linguistic notion of **headedness**
    (LSTMs know what type of head they are looking for while they traverse children)
  - support any number of children
  - are learned via backpropagation through structure

Implementing RNNGs
Stack RNNs

- Augment a sequential RNN with a **stack pointer**
- Two constant-time operations
  - **push** - read input, add to top of stack, connect to current location of the stack pointer
  - **pop** - move stack pointer to its parent
- A **summary** of stack contents is obtained by accessing the output of the RNN at location of the stack pointer
- Note: **push** and **pop** are discrete actions here (*cf.* Grefenstette et al., 2015)

Implementing RNNGs

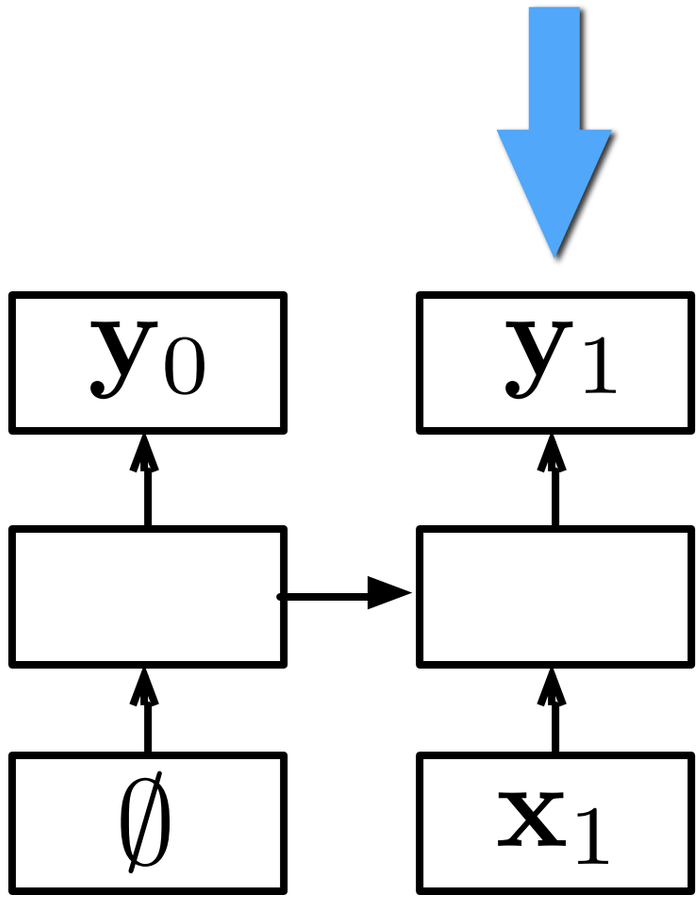
Stack RNNs



PUSH

Implementing RNNGs

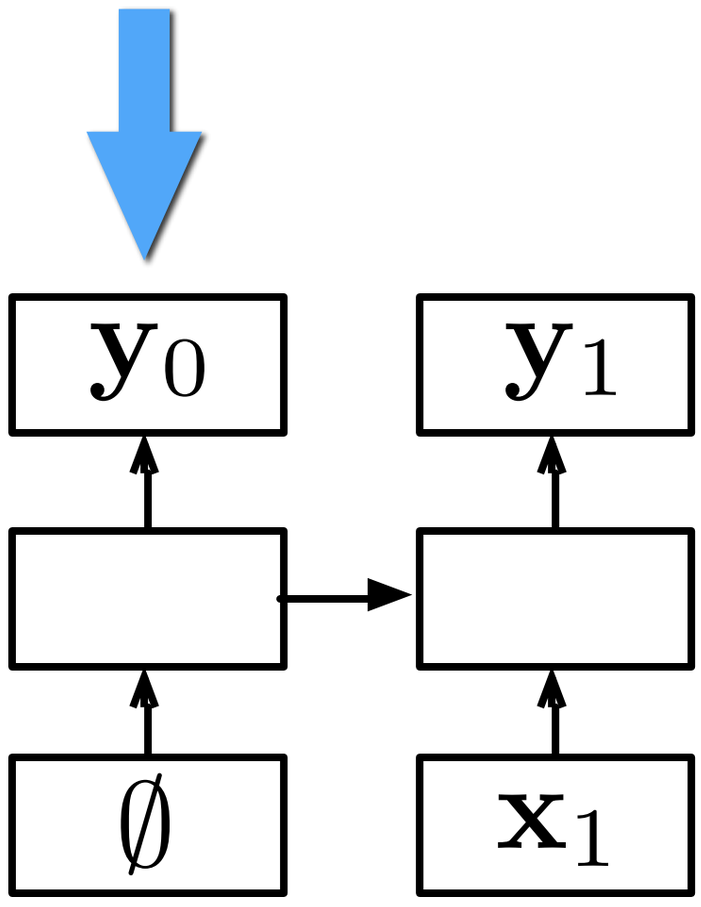
Stack RNNs



POP

Implementing RNNGs

Stack RNNs



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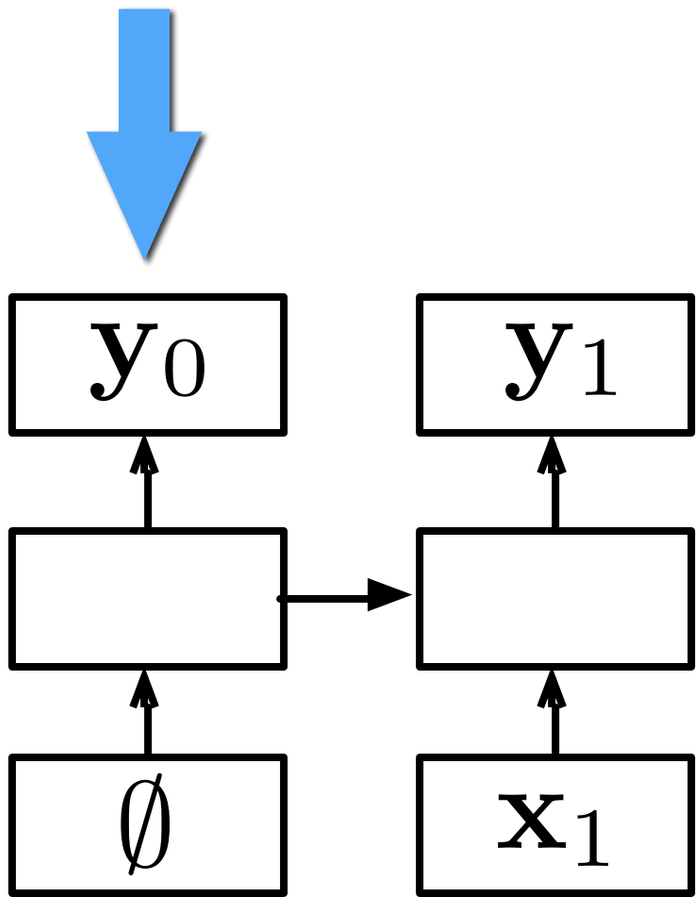

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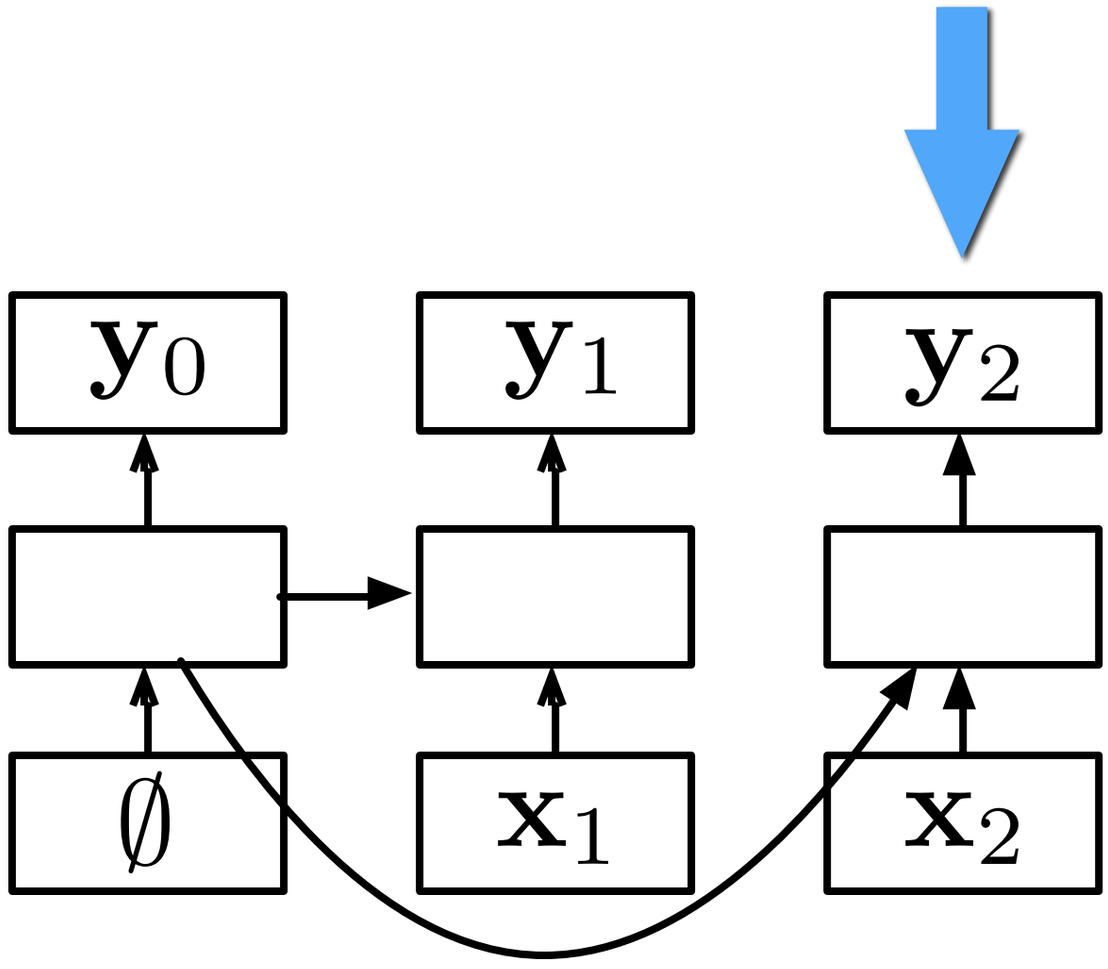

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Implementing RNNGs

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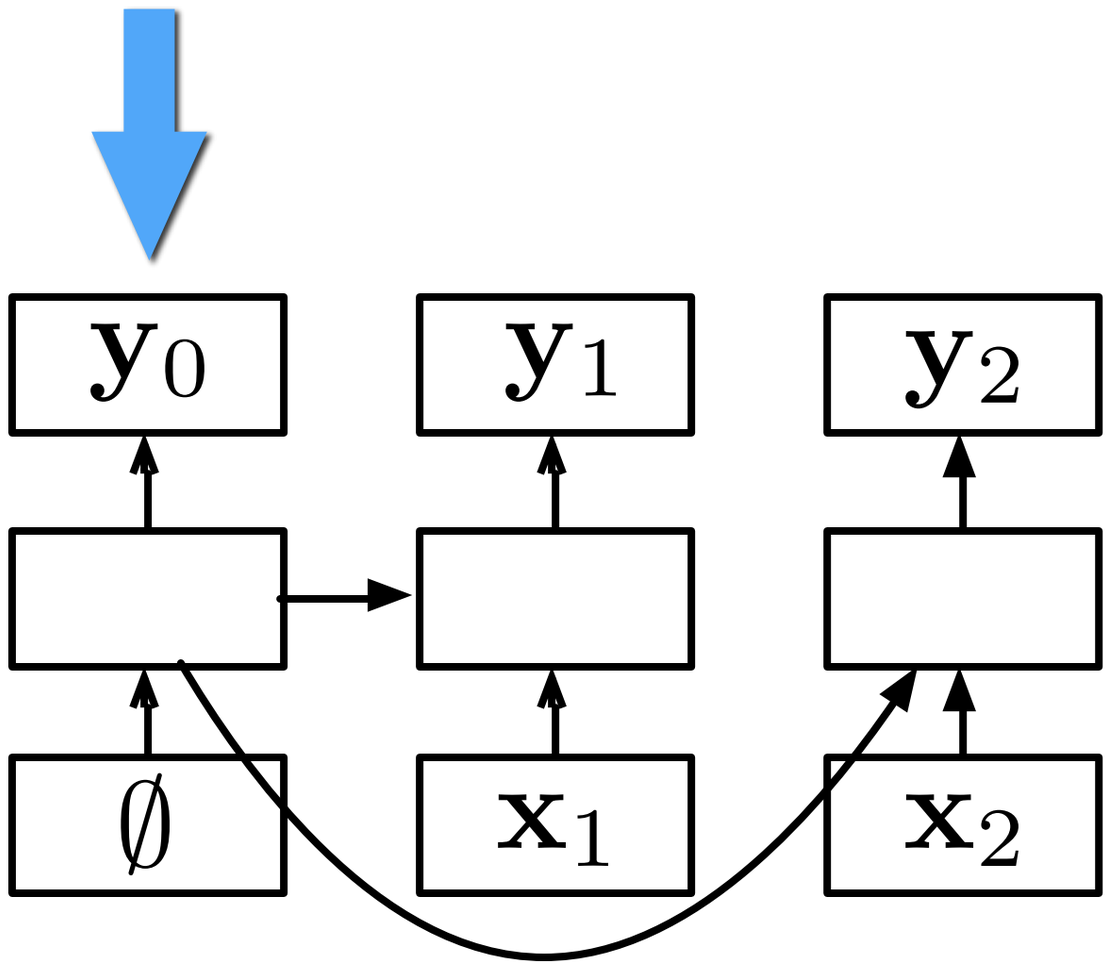
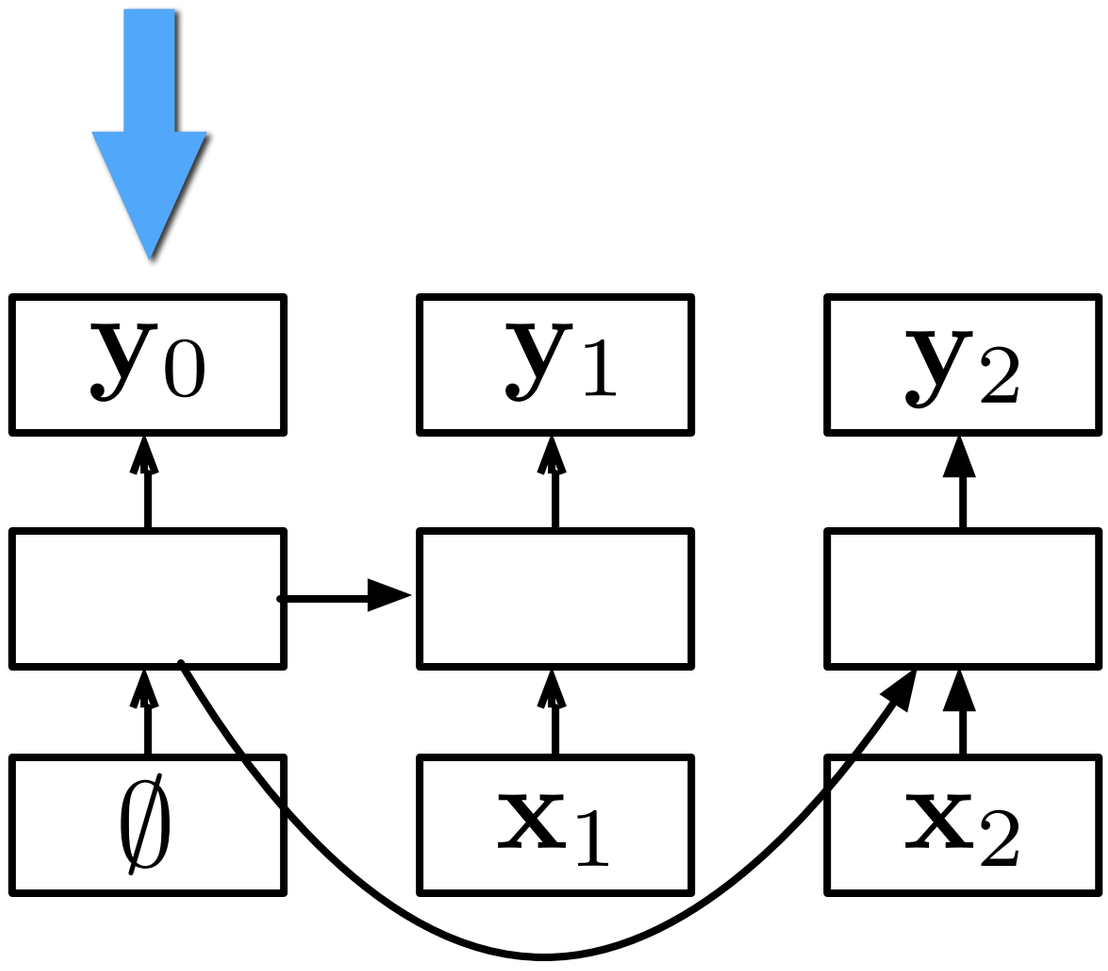


Implementing RNNGs

Stack RNNs



PUSH

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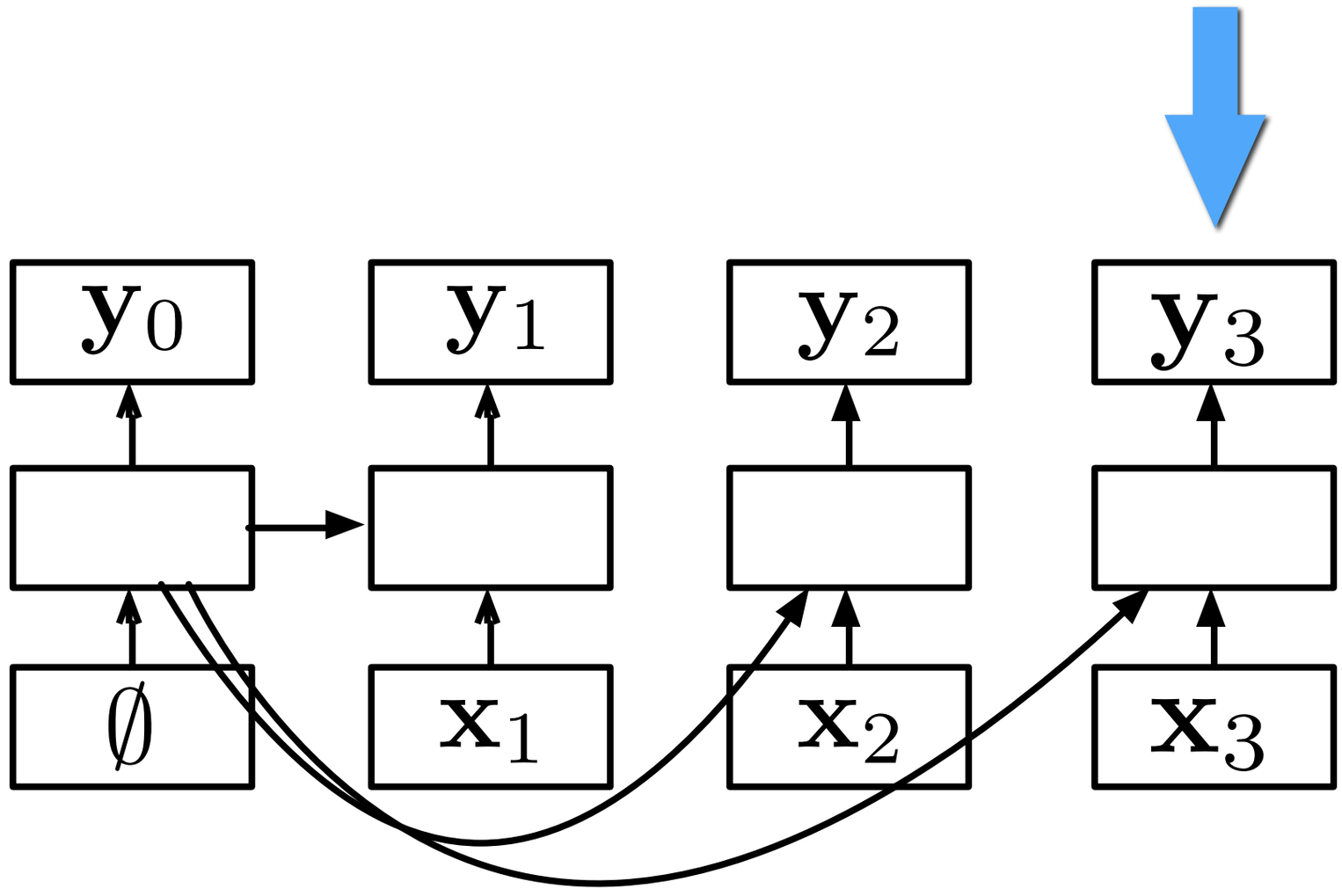

Complete model

Sequence of actions (completely defines *x* and *y*)

sentence

$$p(\boldsymbol{x}, \boldsymbol{y}) = \prod_{t=1}^{|\boldsymbol{a}(\boldsymbol{x},\boldsymbol{y})|} p(a_t \mid \boldsymbol{a}_{<t})$$

Actions up to time *t*

tree $= \prod_{t=1}^{|\boldsymbol{a}(\boldsymbol{x},\boldsymbol{y})|} \frac{\exp \mathbf{r}_{a_t}^\top \mathbf{u}_t + b_{a_t}}{\sum_{a' \in \mathcal{A}_G(T_t,S_t,n_t)} \exp \mathbf{r}_{a'}^\top \mathbf{u}_t + b_{a'}}$

bias

allowable actions at this step

action embedding

history embedding

Complete model

sentence

Sequence of actions (completely defines *x* and *y*)

$$p(\boldsymbol{x}, \boldsymbol{y}) = \prod_{t=1}^{|\boldsymbol{a}(\boldsymbol{x},\boldsymbol{y})|} p(a_t \mid \boldsymbol{a}_{<t}) \quad \text{tree} = \prod_{t=1}^{|\boldsymbol{a}(\boldsymbol{x},\boldsymbol{y})|} \frac{\exp \mathbf{r}_{a_t}^\top \mathbf{u}_t + b_{a_t}}{\sum_{a' \in \mathcal{A}_G(T_t,S_t,n_t)} \exp \mathbf{r}_{a'}^\top \mathbf{u}_t + b_{a'}}$$

Actions up to time *t*

bias

Model is **dynamic**: variable number of context-dependent actions at each step

allowable actions at this step

action embedding

history embedding

Complete model

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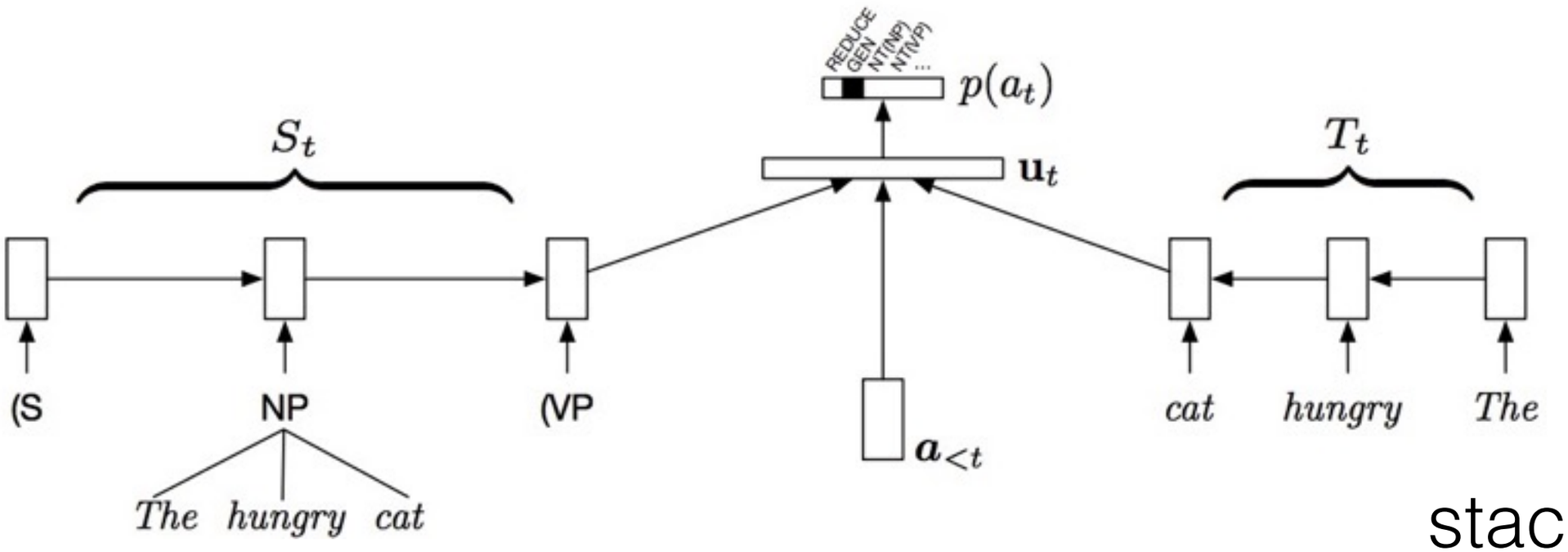
$$\mathbf{u}_t = \tanh\left(\mathbf{W}[\mathbf{o}_t; \mathbf{s}_t; \mathbf{h}_t] + \mathbf{c}\right)$$

stack

output (buffer)

action history

Complete model



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Implementing RNNGs
Parameter Estimation

- RNNGs jointly model sequences of words together with a "tree structure", $p_{\boldsymbol{\theta}}(\boldsymbol{x}, \boldsymbol{y})$

- Any parse tree can be converted to a sequence of actions (depth first traversal) and vice versa (subject to wellformedness constraints)

  - We use trees from the Penn Treebank

- We could treat the non-generation actions as latent variables or learn them with RL, effectively making this a problem of *grammar induction*. Future work…

Implementing RNNGs
Inference

- An RNNG is a joint distribution $p(\mathbf{x},\mathbf{y})$ over strings ($\mathbf{x}$) and parse trees ($\mathbf{y}$)

- We are interested in two inference questions:
  - What is $p(\mathbf{x})$ for a given $\mathbf{x}$? [**language modeling**]
  - What is $\max_{\mathbf{y}} p(\mathbf{y} \mid \mathbf{x})$ for a given $\mathbf{x}$? [**parsing**]
- Unfortunately, the dynamic programming algorithms we often rely on are of no help here

- We can use importance sampling to do both by sampling from a discriminatively trained model

English PTB (Parsing)

	Type	F1
Petrov and Klein (2007)	G	90.1
Shindo et al (2012) Single model	G	91.1
Shindo et al (2012) Ensemble	~G	92.4
Vinyals et al (2015) PTB only	D	90.5
Vinyals et al (2015) Ensemble	S	**92.8**
Discriminative	D	89.8
Generative (IS)	G	**92.4**

Importance Sampling

Assume we've got a conditional distribution $q(\boldsymbol{y} \mid \boldsymbol{x})$

s.t. (i) $p(\boldsymbol{x}, \boldsymbol{y}) > 0 \implies q(\boldsymbol{y} \mid \boldsymbol{x}) > 0$

(ii) $\boldsymbol{y} \sim q(\boldsymbol{y} \mid \boldsymbol{x})$ is tractable and

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$$p(\boldsymbol{x}) = \sum_{\boldsymbol{y} \in \mathcal{Y}(\boldsymbol{x})} p(\boldsymbol{x}, \boldsymbol{y}) = \sum_{\boldsymbol{y} \in \mathcal{Y}(\boldsymbol{x})} w(\boldsymbol{x}, \boldsymbol{y}) q(\boldsymbol{y} \mid \boldsymbol{x})$$

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Replace this expectation with its Monte Carlo estimate.

$$\boldsymbol{y}^{(i)} \sim q(\boldsymbol{y} \mid \boldsymbol{x}) \quad \text{for } i \in \{1, 2, \ldots, N\}$$

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$$\boldsymbol{y}^{(i)} \sim q(\boldsymbol{y} \mid \boldsymbol{x}) \quad \text{for } i \in \{1, 2, \ldots, N\}$$

$$\mathbb{E}_{q(\boldsymbol{y} \mid \boldsymbol{x})} w(\boldsymbol{x}, \boldsymbol{y}) \overset{\text{MC}}{\approx} \frac{1}{N} \sum_{i=1}^{N} w(\boldsymbol{x}, \boldsymbol{y}^{(i)})$$

English PTB (LM)

	Perplexity
5-gram IKN	169.3
LSTM + Dropout	113.4
Generative (IS)	**102.4**

Chinese CTB (LM)

	Perplexity
5-gram IKN	255.2
LSTM + Dropout	207.3
Generative (IS)	**171.9**

Do we need a stack?

Kuncoro et al., Oct 2017

- Both stack and action history encode the same information, but expose it to the classifier in different ways.

Model	F_1
Vinyals et al. (2015)†	92.1
Choe and Charniak (2016)	92.6
Choe and Charniak (2016)†	**93.8**
Baseline RNNG	93.3
Ablated RNNG (no history)	93.2
Ablated RNNG (no buffer)	93.3
Ablated RNNG (no stack)	92.5
Stack-only RNNG	**93.6**
GA-RNNG	93.5

Leaving out stack is harmful; using it on its own works slightly better than complete model!

RNNG as a mini-linguist

- Replace composition with one that computes attention over objects in the composed sequence, using embedding of NT for similarity.
- What does this learn?

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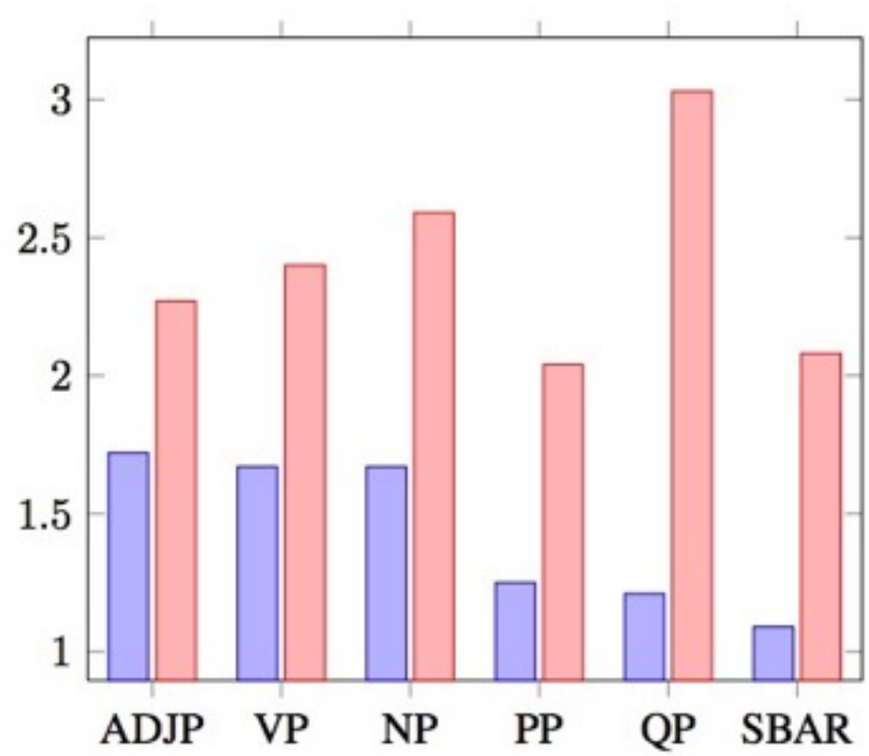

Figure 3: Average perplexity of the learned attention vectors on the test set (blue), as opposed to the average perplexity of the uniform distribution (red), computed for each major phrase type.

RNNG as a mini-linguist

- Replace composition with one that computes attention over objects in the composed sequence, using embedding of NT for similarity.
- What does this learn?

Noun phrases
Canadian (0.09) **Auto (0.31)** Workers (0.2) union (0.22) president (0.18)
no (0.29) major (0.05) **Eurobond (0.32)** or (0.01) foreign (0.01) bond (0.1) offerings (0.22)
Saatchi (0.12) client (0.14) Philips (0.21) Lighting (0.24) **Co. (0.29)**
nonperforming (0.18) commercial (0.23) **real (0.25)** estate (0.1) **assets (0.25)**
the (0.1) Jamaica (0.1) Tourist (0.03) Board (0.17) ad (0.20) **account (0.40)**
the (0.0) final (0.18) **hour (0.81)**
their (0.0) first (0.23) **test (0.77)**
Apple (0.62) , (0.02) Compaq (0.1) and (0.01) IBM (0.25)
both (0.02) stocks (0.03) and (0.06) **futures (0.88)**
NP (0.01) , (0.0) **and (0.98)** NP (0.01)

RNNG as a mini-linguist

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Verb phrases
buying (0.31) and (0.25) selling (0.21) NP (0.23)
ADVP (0.27) **show (0.29)** PRT (0.23) PP (0.21)
pleaded (0.48) ADJP (0.23) PP (0.15) PP (0.08) PP (0.06)
received (0.33) PP (0.18) NP (0.32) PP (0.17)
cut (0.27) **NP (0.37)** PP (0.22) PP (0.14)
to (0.99) VP (0.01)
were (0.77) n't (0.22) VP (0.01)
did (0.39) **n't (0.60)** VP (0.01)
handle (0.09) **NP (0.91)**
VP (0.15) **and (0.83)** VP 0.02)

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Prepositional phrases
ADVP (0.14) **on (0.72)** NP (0.14)
ADVP (0.05) **for (0.54)** NP (0.40)
ADVP (0.02) **because (0.73)** of (0.18) NP (0.07)
such (0.31) **as (0.65)** NP (0.04)
from (0.39) **NP (0.49)** PP (0.12)
of (0.97) NP (0.03)
in (0.93) NP (0.07)
by (0.96) S (0.04)
at (0.99) NP (0.01)
NP (0.1) **after (0.83)** NP (0.06)

RNNGs in MT

Eriguchi et al., Feb 2017

- Basic idea: learn decoder-encoder MT model and RNNG on parallel data with parsed target side, sharing target word embedding parameters. (multi-task learning). To translate, just use MT model.

	De-En	Ru-En	Cs-En	Jp-En
BLEU				
NMT	16.61	12.03	11.22	17.88
NMT+RG	16.41	**12.46**†	**12.06**†	**18.84**†
RIBES				
NMT	73.75	69.56	69.59	71.27
NMT+RG	**75.03**†	**71.04**†	**70.39**†	**72.25**†

Table 2: BLEU and RIBES scores by the baseline and proposed models on the test set. We use the bootstrap resampling method from Koehn (2004) to compute the statistical significance. We use † to mark those significant cases with $p < 0.005$.

Jp-En (Dev)	BLEU
NMT+RG	18.60
w/o Buffer	18.02
w/o Action	17.94
w/o Stack	17.58
NMT	17.75

Table 3: Effect of each component in RNNG.