Should Neural Network Architecture Reflect Linguistic Structure?

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Joint work with:

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Wang Ling (Google/DeepMind)
Austin Matthews (CMU)
Noah A. Smith (UW)

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Learning language

ARBITRARINESS (de Saussure, 1916)

COMPOSITIONALITY (Frege, 1892)

Learning language

ARBITRARINESS (de Saussure, 1916)

$\text{car} - \text{c} + \text{b} = \text{bar}$

COMPOSITIONALITY (Frege, 1892)

Learning language

ARBITRARINESS (de Saussure, 1916)

car − c + b = bar

cat − c + b = bat

COMPOSITIONALITY (Frege, 1892)

Learning language

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car

COMPOSITIONALITY (Frege, 1892)

Learning language

ARBITRARINESS (de Saussure, 1916)

car − c + b = bar   cat − c + b = bat




car   Auto   voiture   xe hơi

ọkọ ayọkẹlẹ   koloi   sakyanan

COMPOSITIONALITY (Frege, 1892)

Learning language

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COMPOSITIONALITY (Frege, 1892)

John dances − John + Mary = Mary dances

DANCE(JOHN)   DANCE(MARY)

Learning language

ARBITRARINESS (de Saussure, 1916)

car − c + b = bar　　　cat − c + b = bat




car　Auto　voiture　xe hơi

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COMPOSITIONALITY (Frege, 1892)

John dances − John + Mary = Mary dances

$\textsc{dance}(\textsc{John})$　　　$\textsc{dance}(\textsc{Mary})$

John sings − John + Mary = Mary sings

$\textsc{sing}(\textsc{John})$　　　$\textsc{sing}(\textsc{Mary})$

Learning language

ARBITRARINESS (de Saussure, 1916)

car − c + b = bar

cat − c + b = bat




car	Auto	voiture	xe hơi
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Learning language

ARBITRARINESS (de Saussure, 1916)

car − c + b = bar   cat − c + b = bat

Memorize

car   A   xe hơi

ọkọ ayọkẹlẹ   koloi   sakyanan

COMPOSITIONALITY (Frege, 1892)

John dances − John + Mary = Mary dances

DANCE(JO   E(MARY)

Generalize

John si   sings

SING(JOHN)   SING(MARY)

Learning language

`John    gave    the    book    to    Mary`

Learning language

`John    gave    the    book    to    Mary`

$$\boxed{0 \quad \cdots \quad \cdots \quad \cdots \quad 0\;1\;0 \cdots 0} \; \mathbf{1}_{\mathsf{John}}^{\top}$$

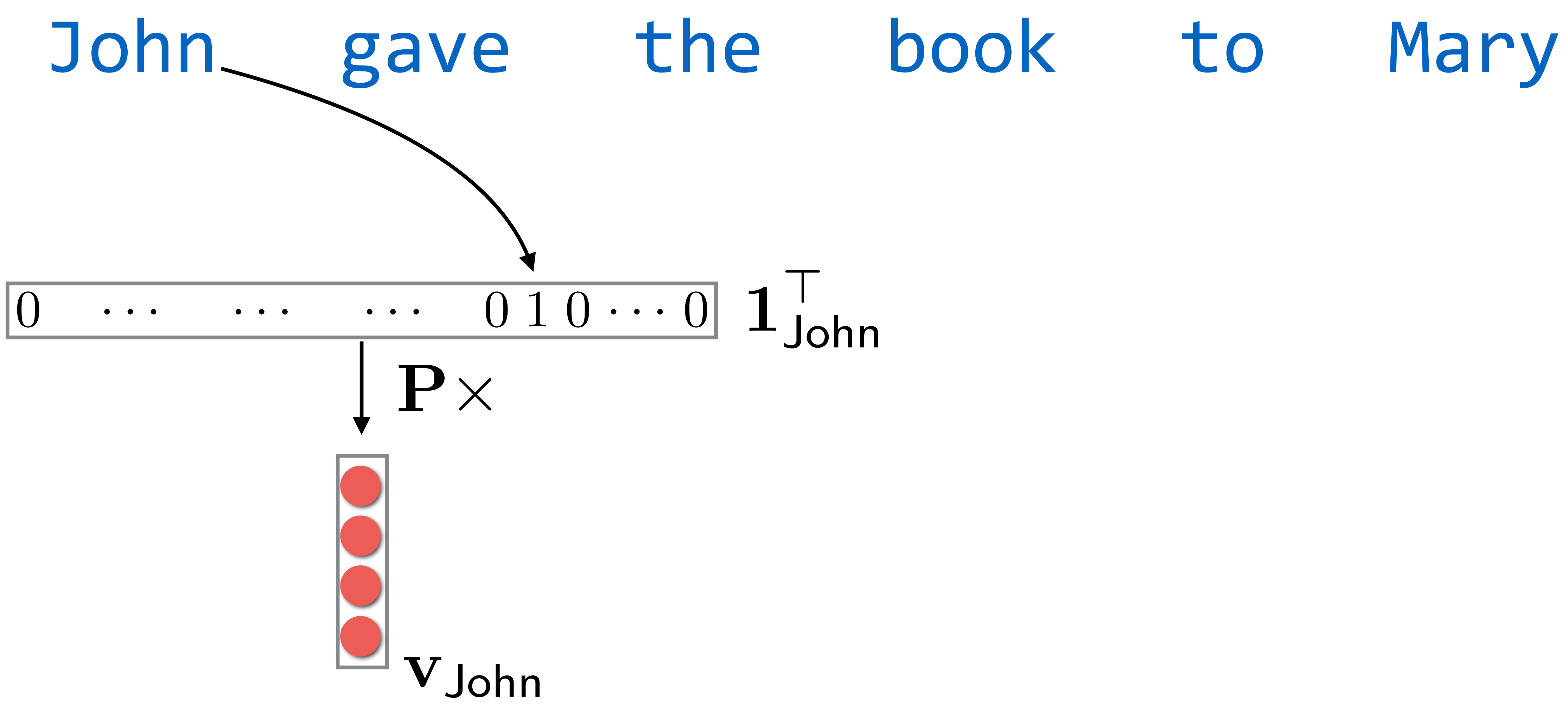
Learning language

John gave the book to Mary

$$\boxed{0 \quad \cdots \quad \cdots \quad \cdots \quad 0\;1\;0 \cdots 0} \; \mathbf{1}_{\mathsf{John}}^{\top}$$

$$\downarrow \mathbf{P}\times$$

Learning language



Learning language

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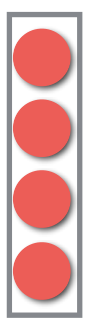
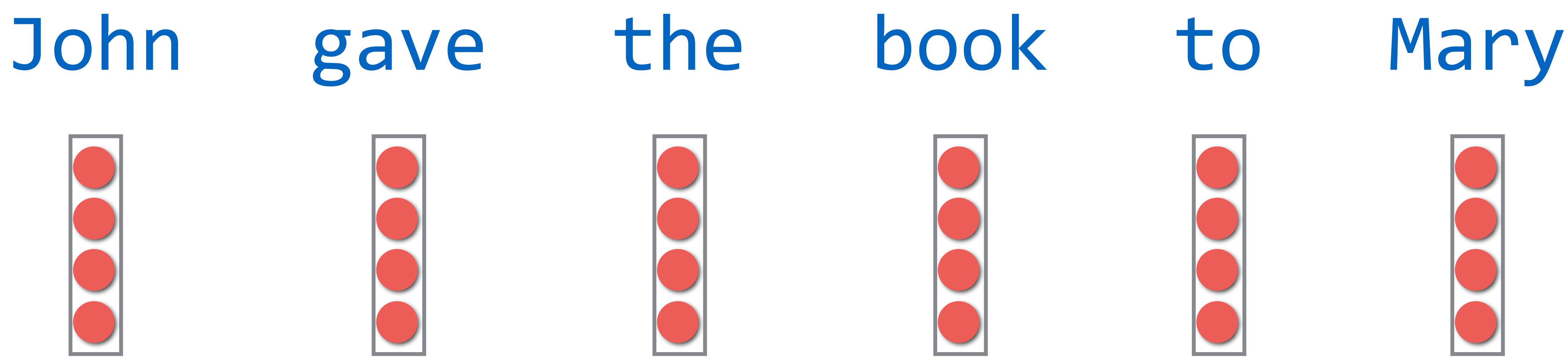
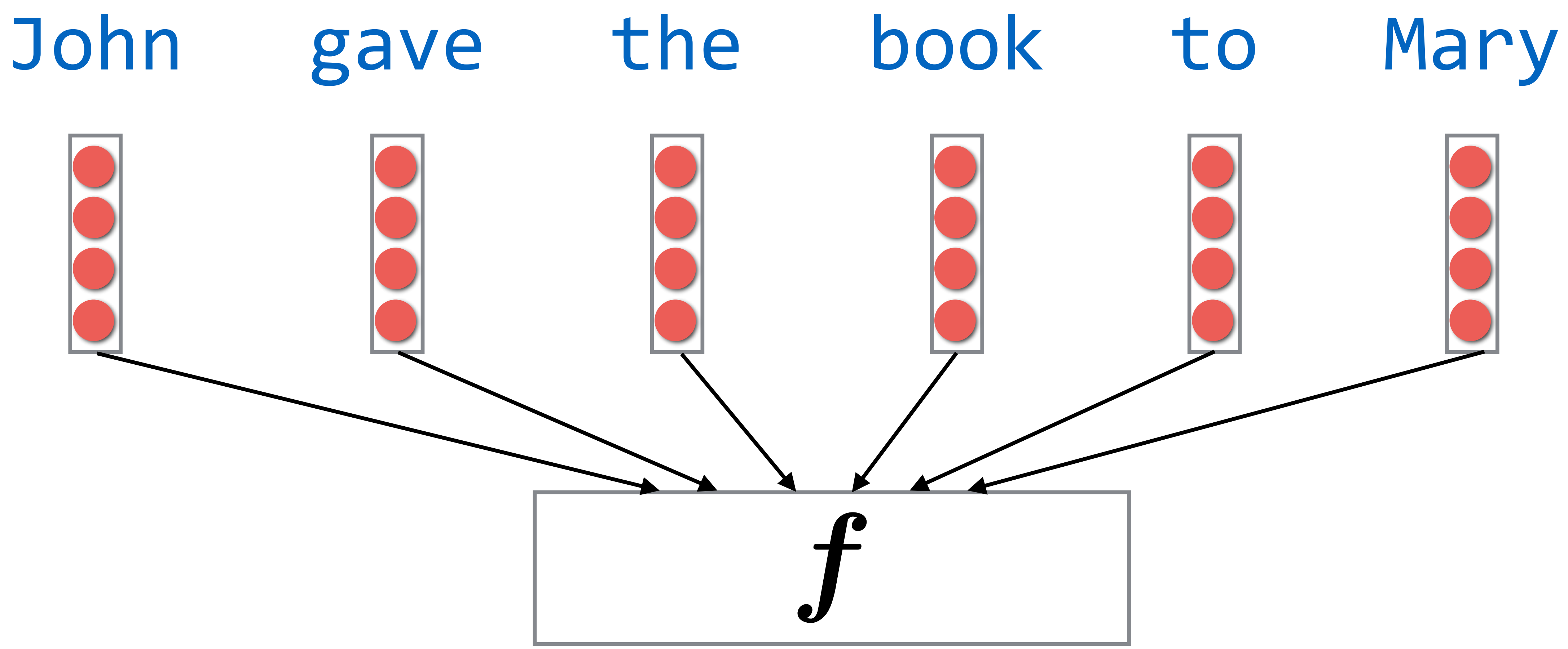


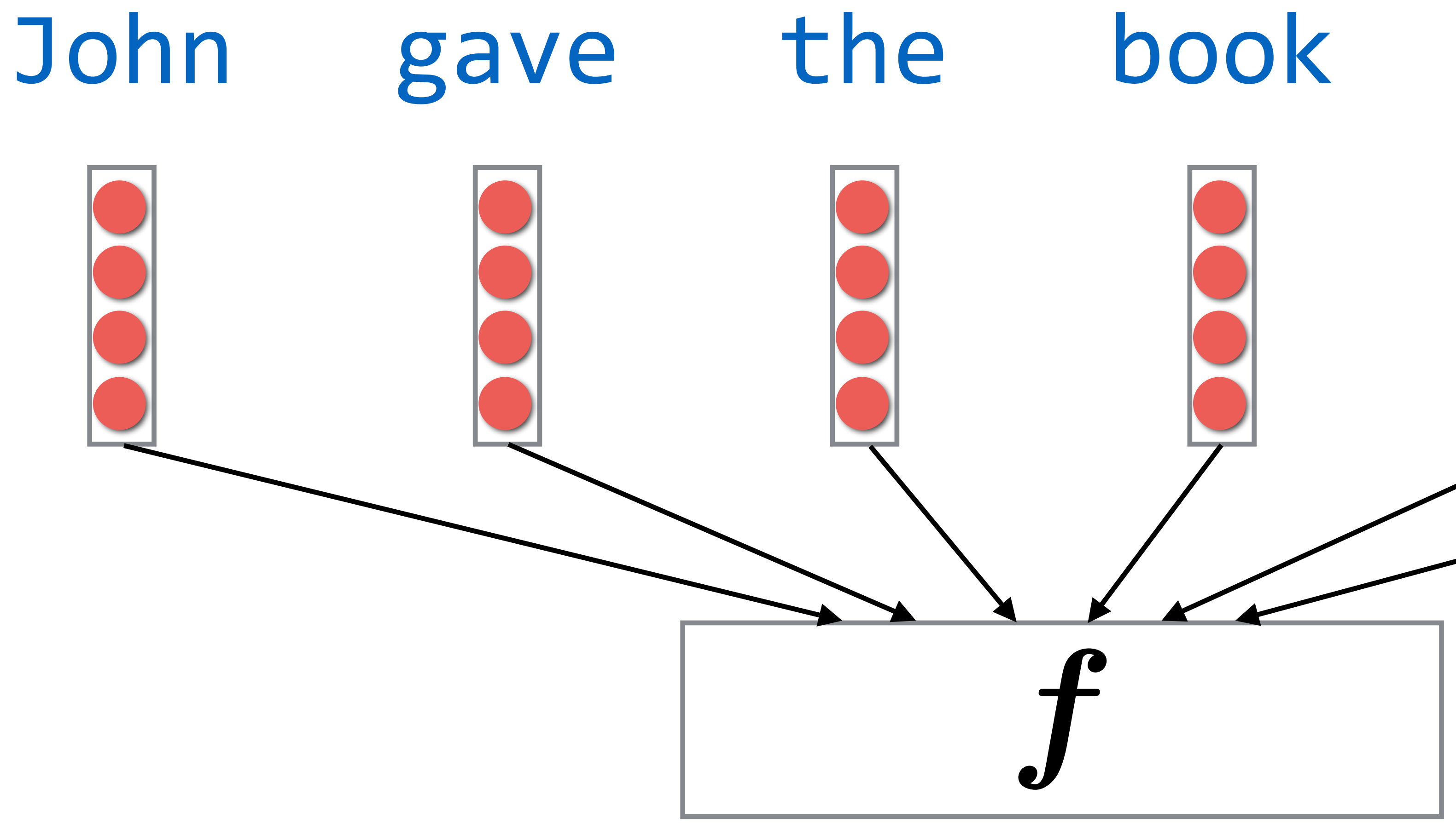
Learning language



Learning language

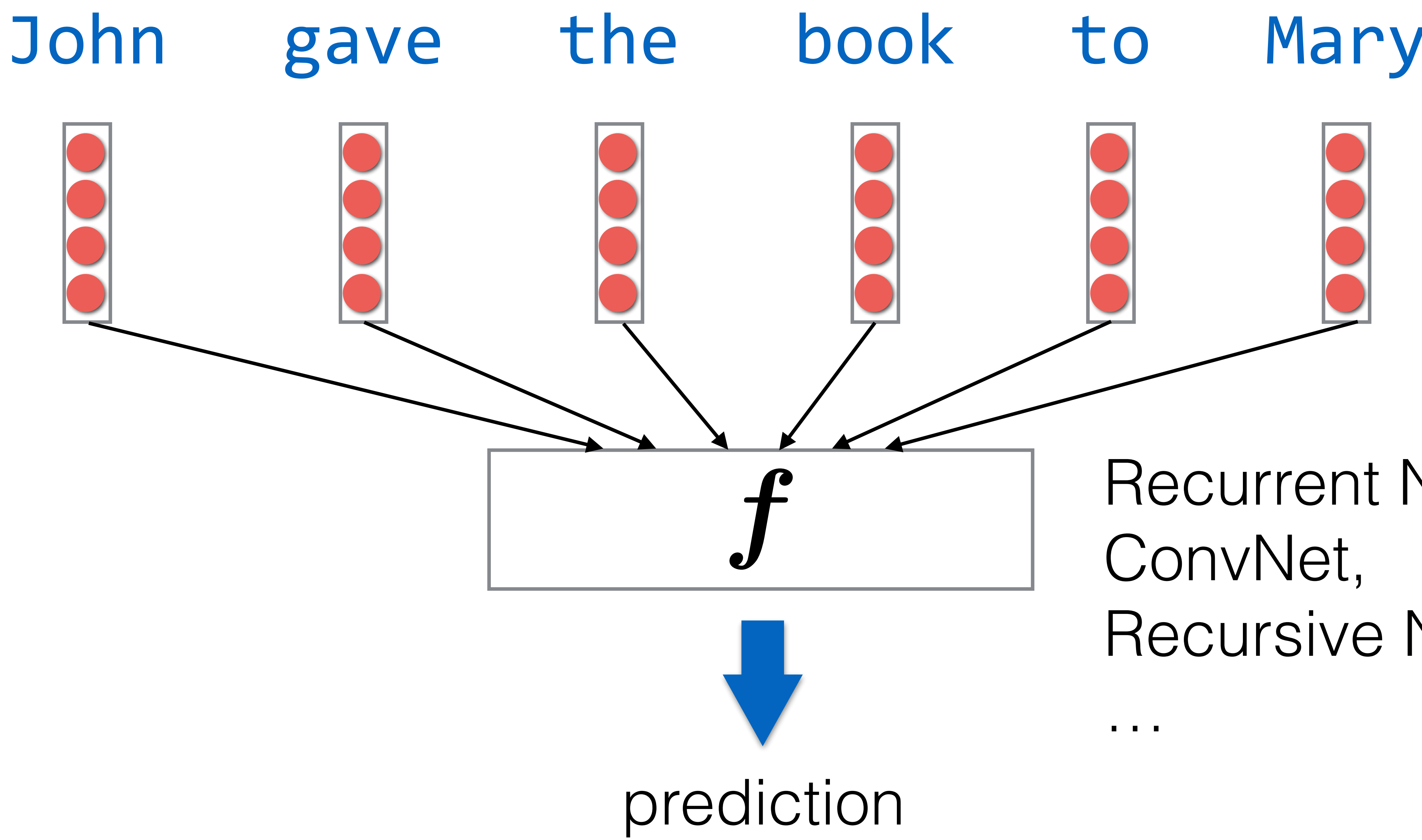


Learning language



Recurrent NN,
ConvNet,
Recursive NN,
...

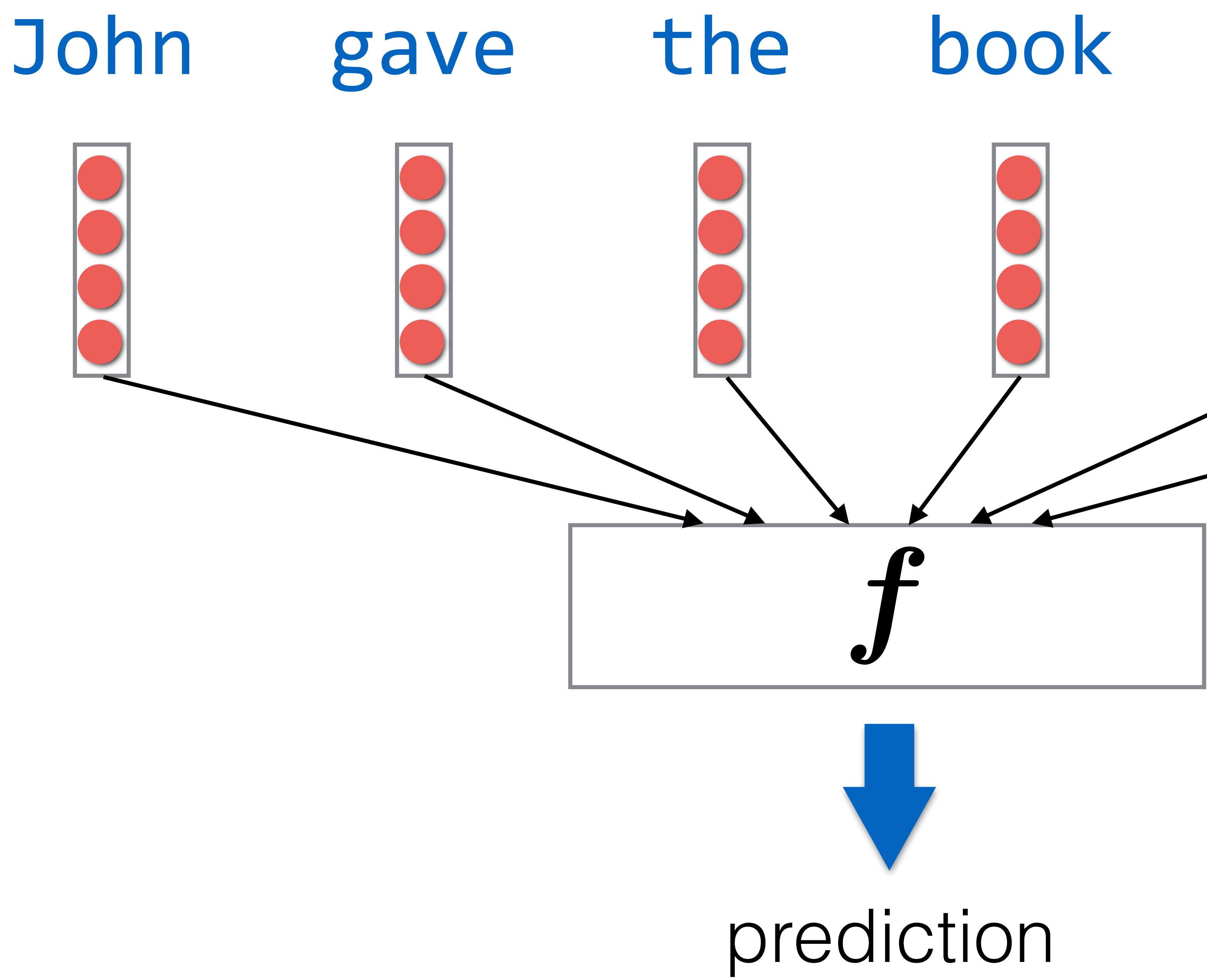
Learning language



Recurrent NN,
ConvNet,
Recursive NN,
...

Learning language

Memorize



Recurrent NN,
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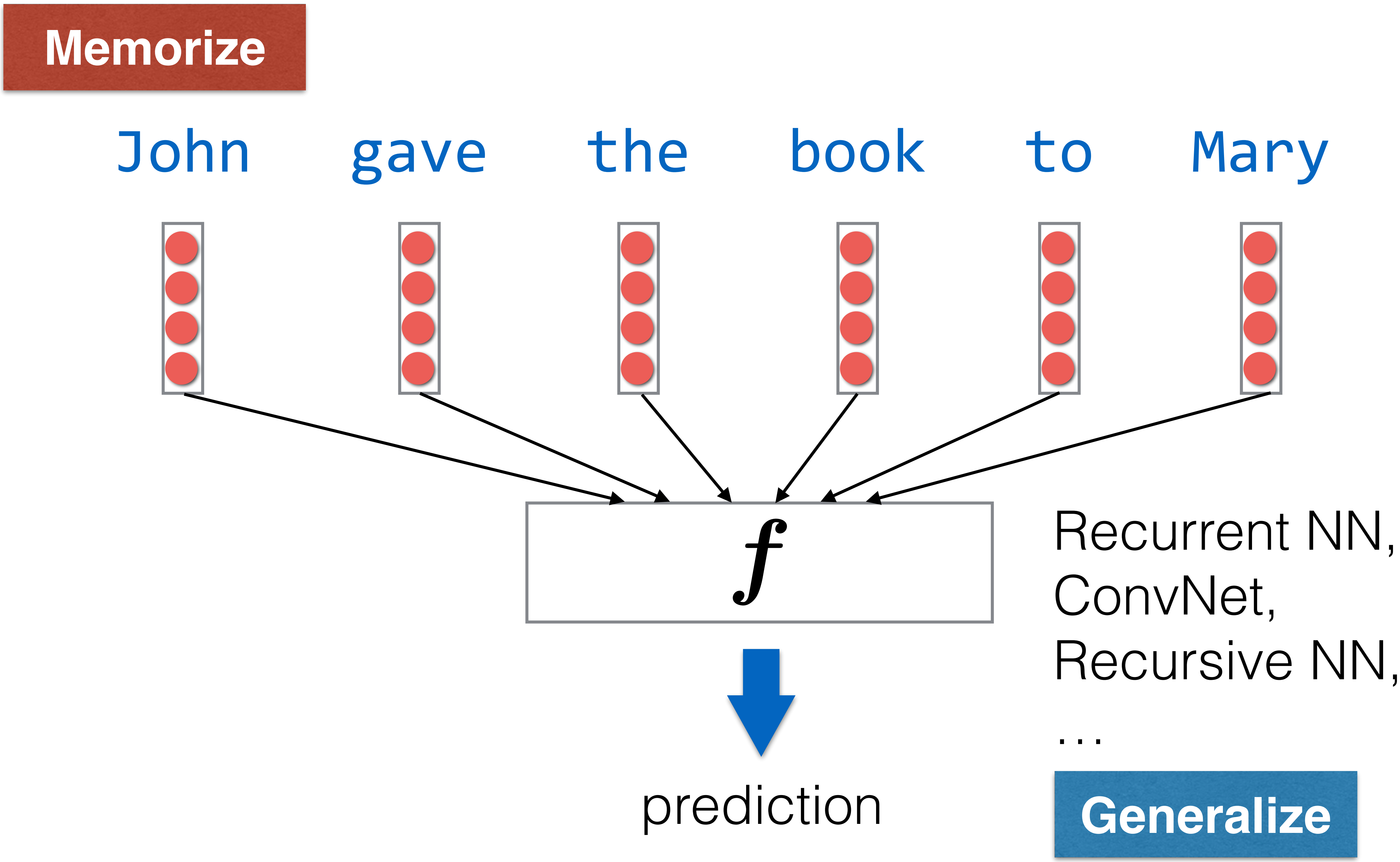
...

Learning language



Learning language

CHALLENGE 1: IDIOMS

CHALLENGE 2: MORPHOLOGY

Learning language

CHALLENGE 1: IDIOMS

`John saw the football` $\textsc{see}(\textsc{John}, \textsc{football})$

`John saw the bucket` $\textsc{see}(\textsc{John}, \textsc{bucket})$

CHALLENGE 2: MORPHOLOGY

Learning language

CHALLENGE 1: IDIOMS

`John saw the football`	$\textsc{see}(\textsc{John}, \textsc{football})$
`John saw the bucket`	$\textsc{see}(\textsc{John}, \textsc{bucket})$
`John kicked the football`	$\textsc{kick}(\textsc{John}, \textsc{football})$
`John kicked the bucket`	$\textsc{die}(\textsc{John})$

CHALLENGE 2: MORPHOLOGY

Learning language

CHALLENGE 1: IDIOMS

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`John saw the bucket` $\textsc{see}(\textsc{John}, \textsc{bucket})$

`John kicked the football` $\textsc{kick}(\textsc{John}, \textsc{football})$

`John kicked the bucket` $\textsc{die}(\textsc{John})$

CHALLENGE 2: MORPHOLOGY

Learning language

CHALLENGE 1: IDIOMS

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`John saw the bucket`	$\textsc{see}(\textsc{John}, \textsc{bucket})$
`John kicked the football`	$\textsc{kick}(\textsc{John}, \textsc{football})$
`John kicked the bucket`	$\textsc{die}(\textsc{John})$

CHALLENGE 2: MORPHOLOGY

`cool` | `coooool` | `coooooooool`

Learning language

CHALLENGE 1: IDIOMS

John saw the football — SEE(JOHN, FOOTBALL)

John saw the bucket — SEE(JOHN, BUCKET)

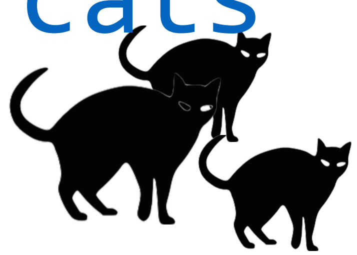
John kicked the football — KICK(JOHN, FOOTBALL)

John kicked the bucket — DIE(JOHN)

CHALLENGE 2: MORPHOLOGY

cool | coooool | coooooooool

cat + s = cats



Learning language

CHALLENGE 1: IDIOMS

`John saw the football` $\textsc{see}(\textsc{John}, \textsc{football})$

`John saw the bucket` $\textsc{see}(\textsc{John}, \textsc{bucket})$

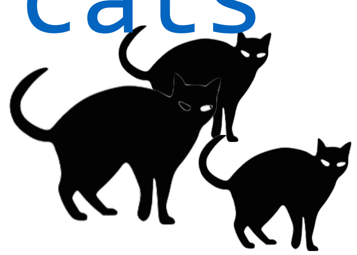
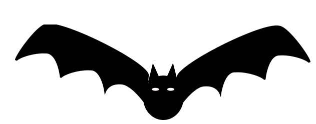
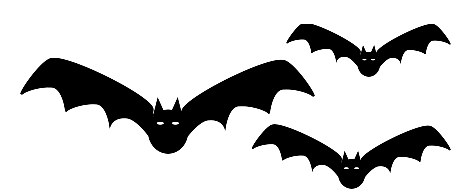
`John kicked the football` $\textsc{kick}(\textsc{John}, \textsc{football})$

`John kicked the bucket` $\textsc{die}(\textsc{John})$

CHALLENGE 2: MORPHOLOGY

`cool` | `coooool` | `coooooooool`

$\texttt{cat} + \texttt{s} = \texttt{cats}$ $\texttt{bat} + \texttt{s} = \texttt{bats}$

Learning language

CHALLENGE 1: IDIOMS

John saw the football	$\text{SEE}(\text{JOHN}, \text{FOOTBALL})$
John saw the bucket	$\text{SEE}(\text{JOHN}, \text{BUCKET})$
John kicked the football	$\text{KICK}(\text{JOHN}, \text{FOOTBALL})$
John kicked the bucket	$\text{DIE}(\text{JOHN})$

CHALLENGE 2: MORPHOLOGY

cool | cooooool | coooooooool

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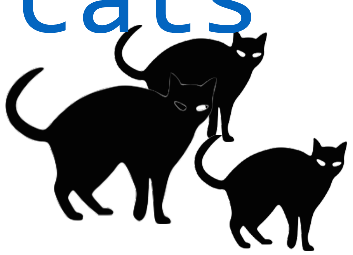
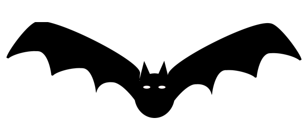
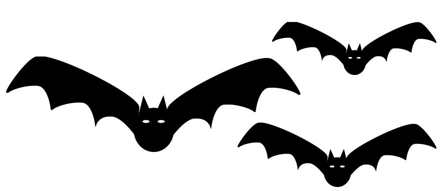


bat + s = bats





Compositional words

`cats`

Memorize

Generalize

Compositional words

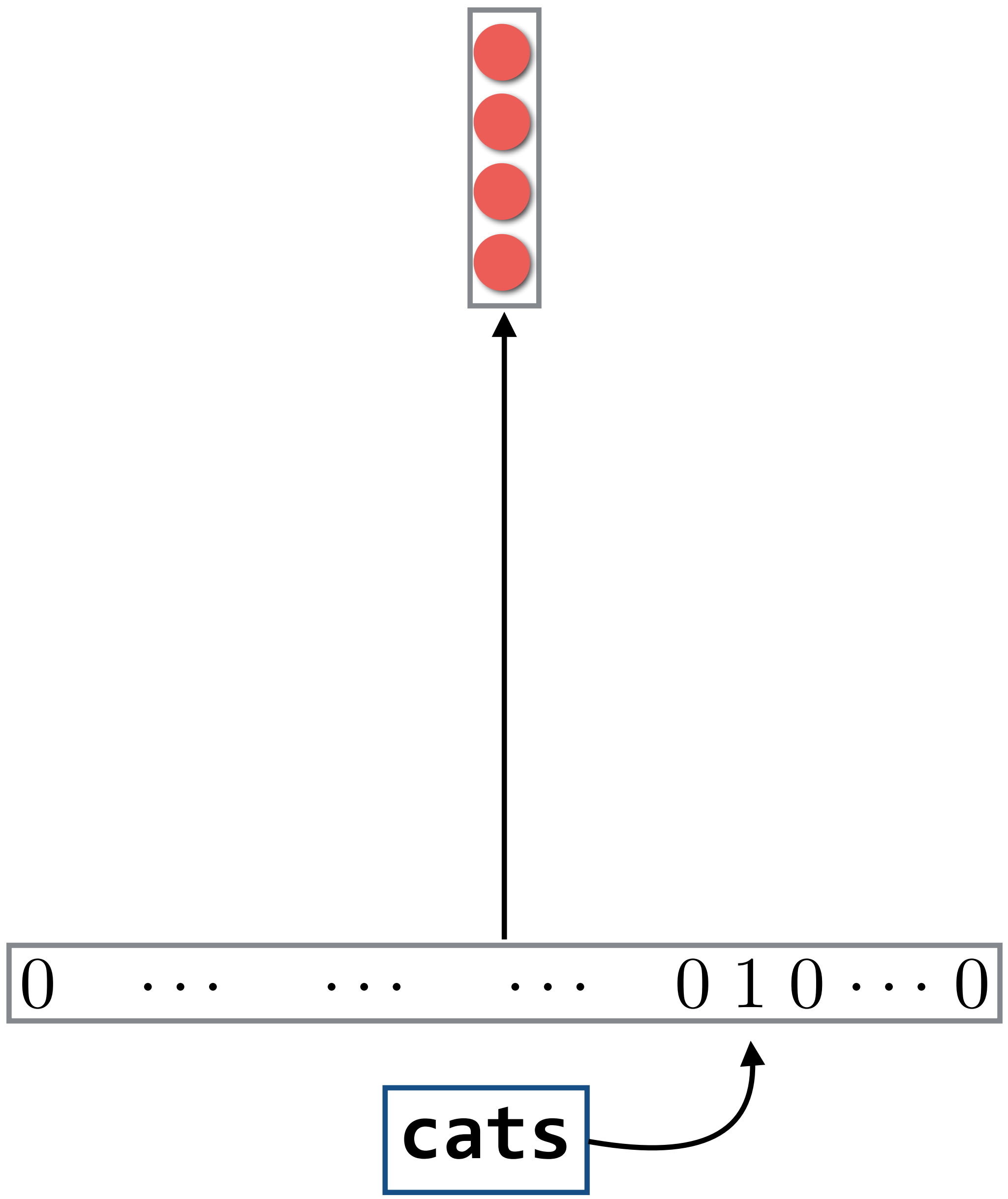
$$\boxed{0 \quad \cdots \quad \cdots \quad \cdots \quad 0\;1\;0 \cdots 0}$$

cats

Memorize

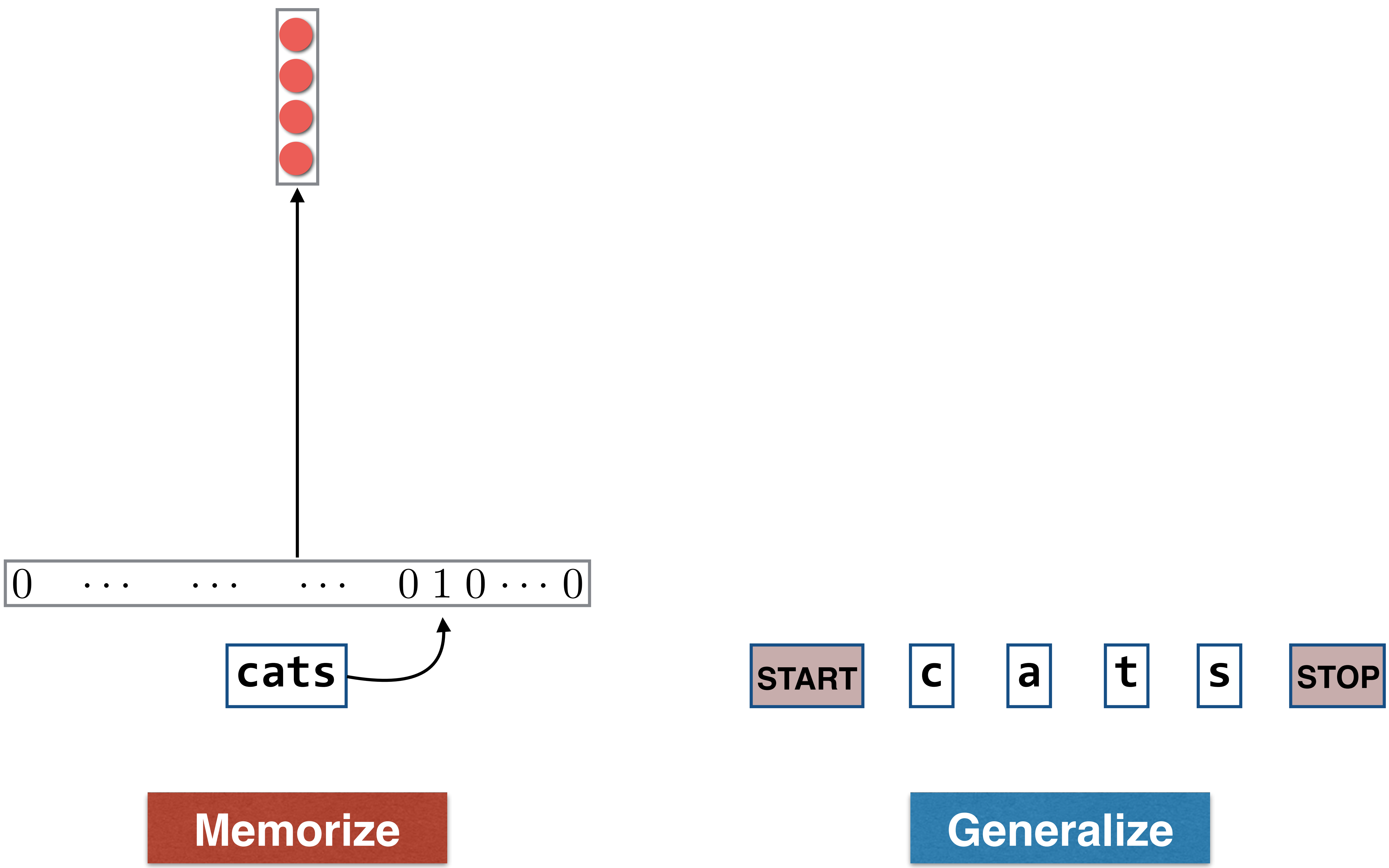
Generalize

Compositional words



Memorize **Generalize**

Compositional words



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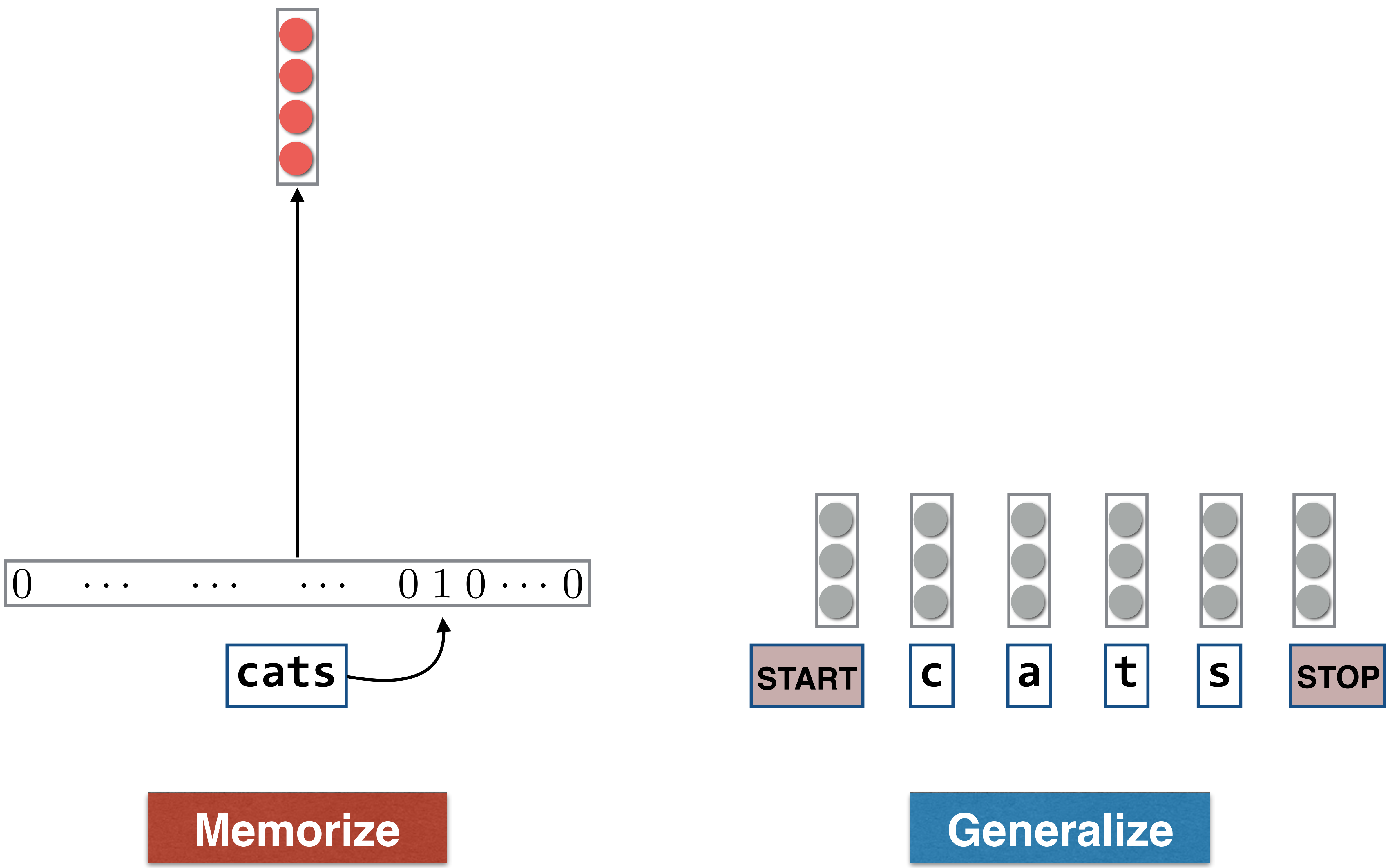

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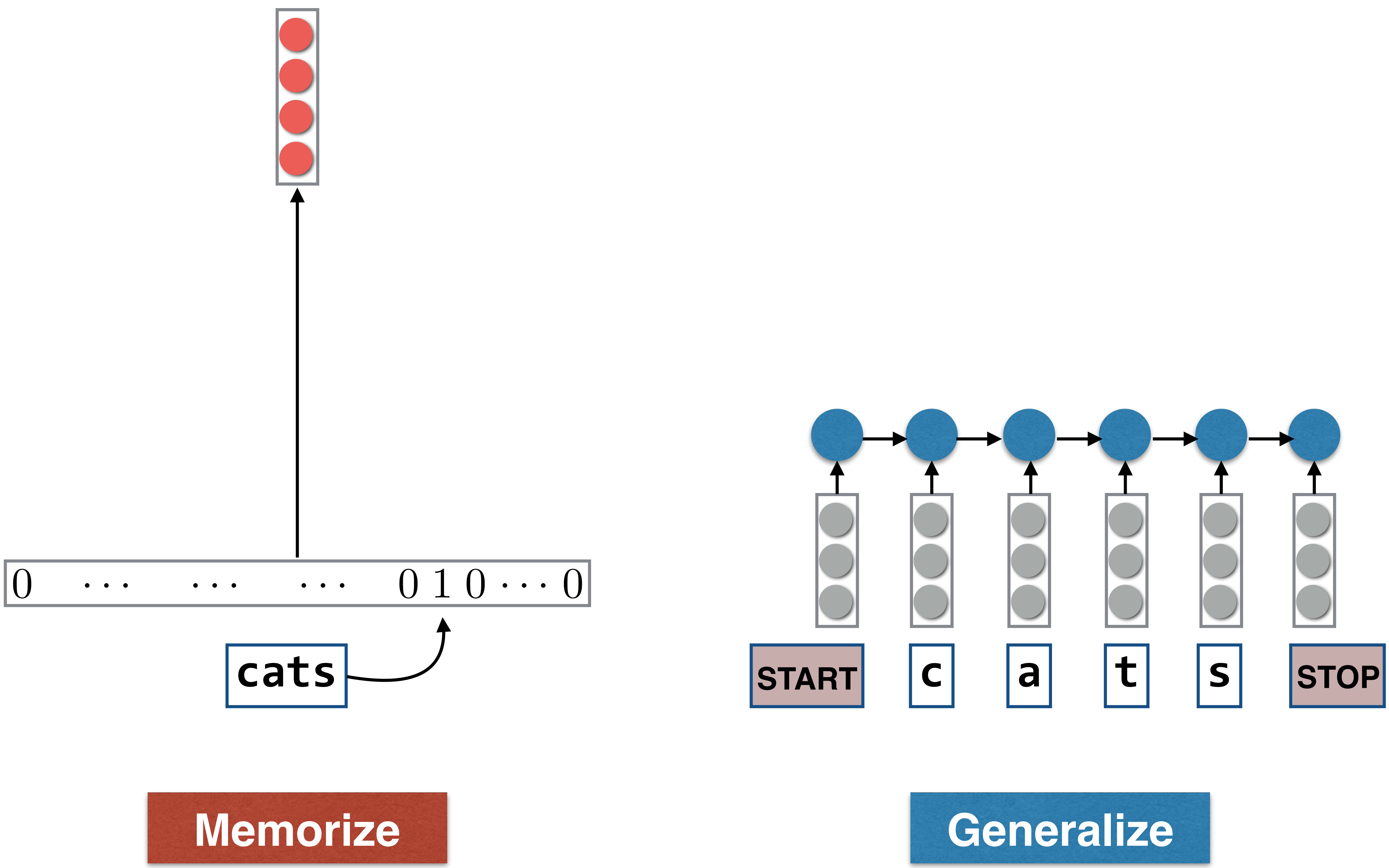
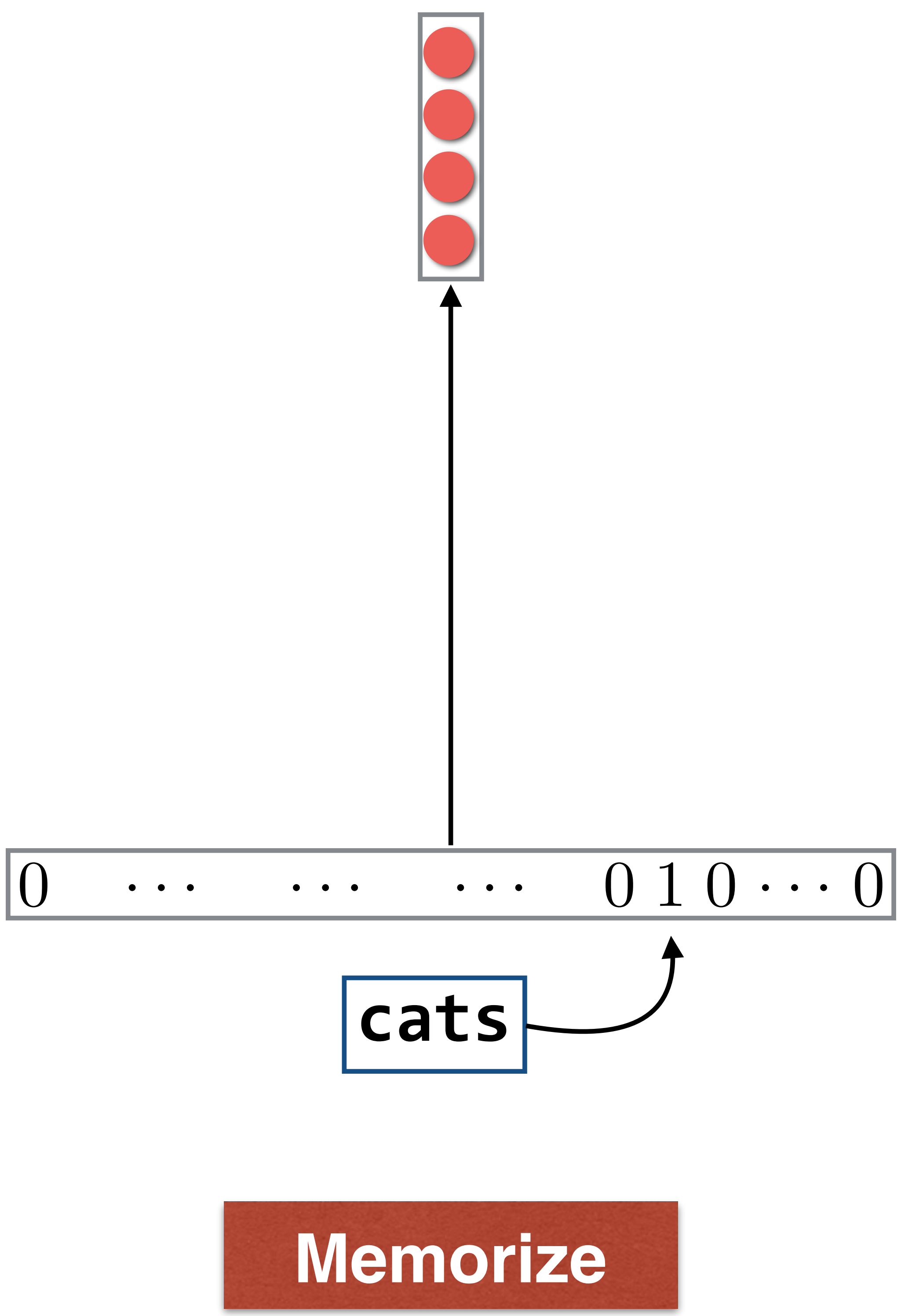
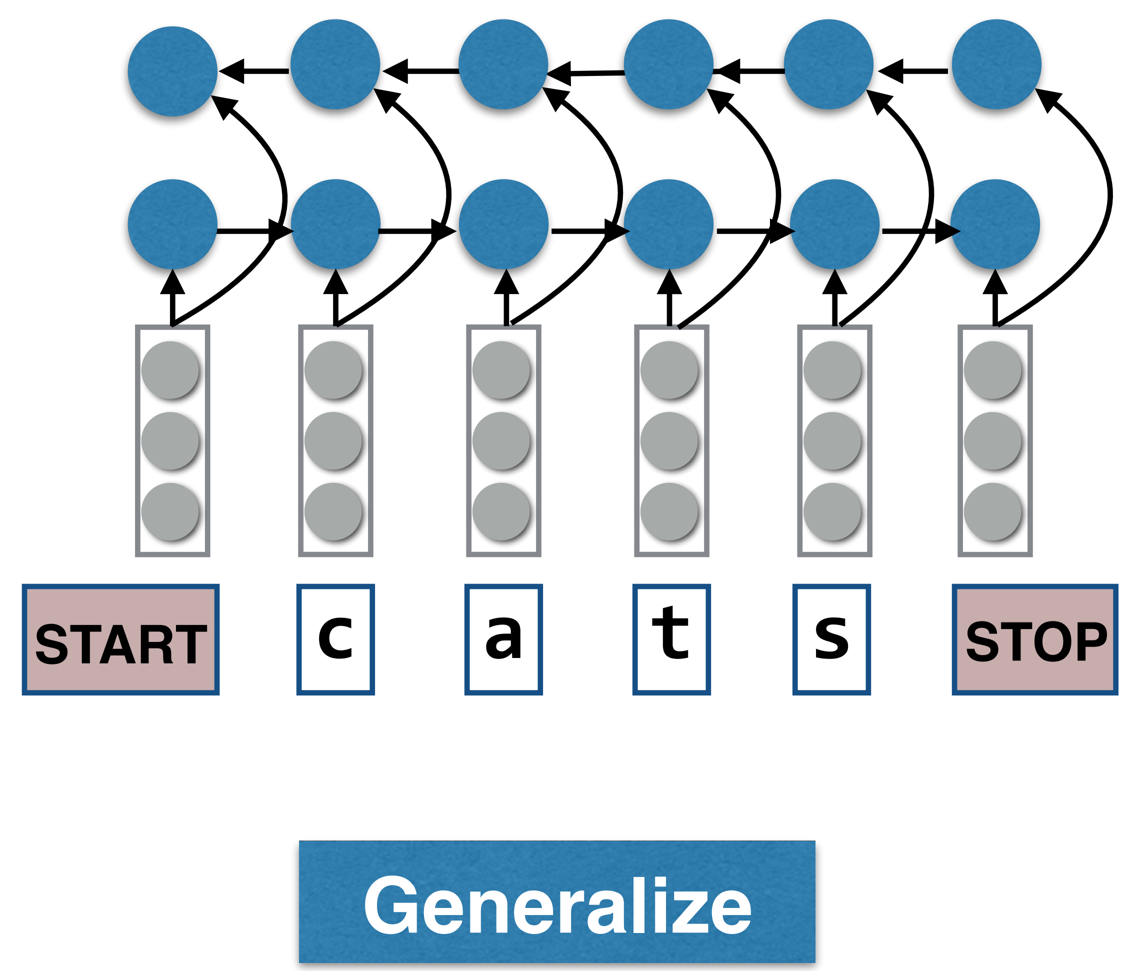


Compositional words





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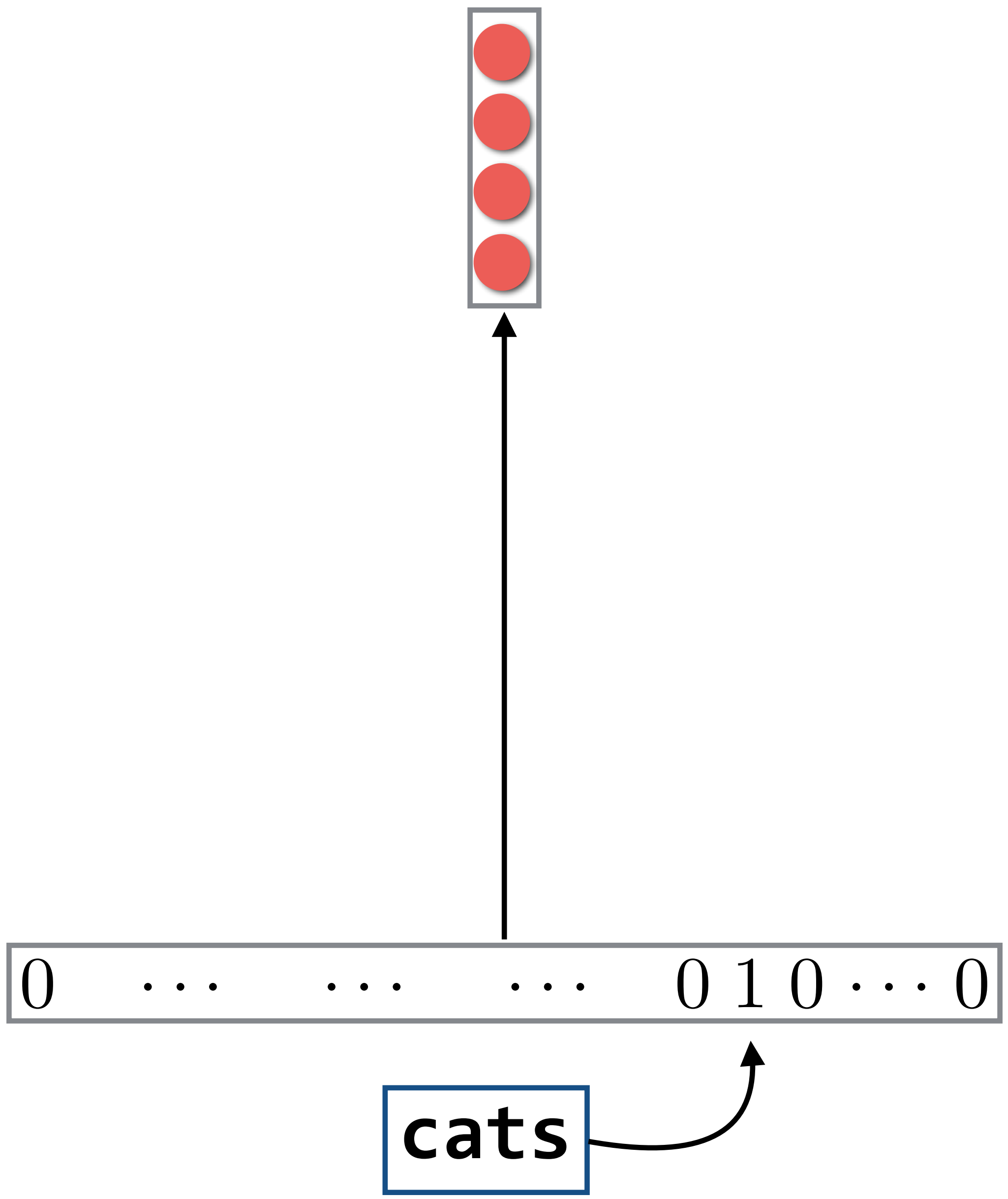
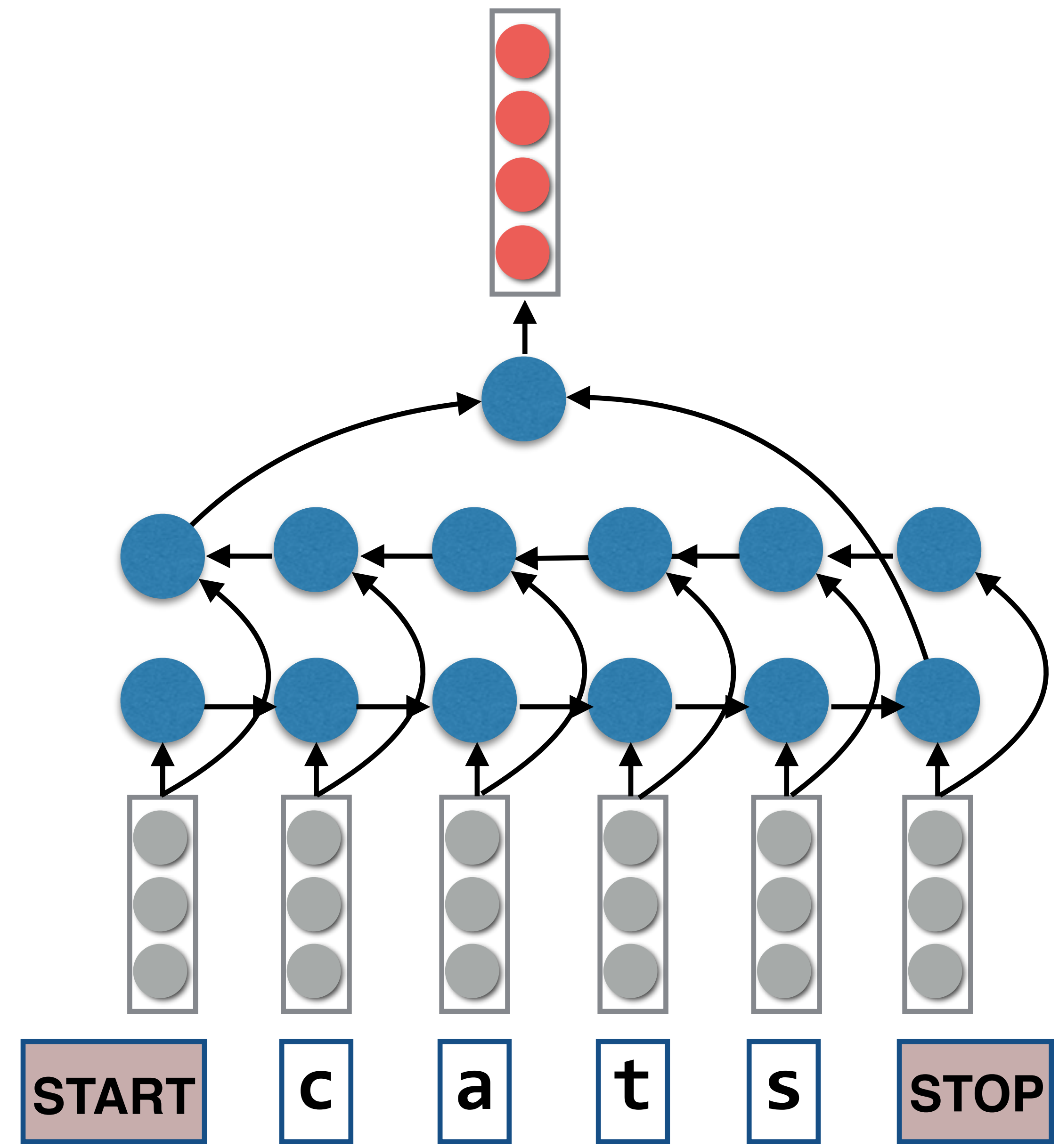


Memorize



Generalize

Compositional words
Questions

- Does a “compositional” model have the capacity to learn the “arbitrariness” that is required?
  - We might think so—RNNs/LSTMs can definitely overfit!
- Will we see better improvements in languages with more going on in the morphology?

Example
Dependency parsing

I saw her duck

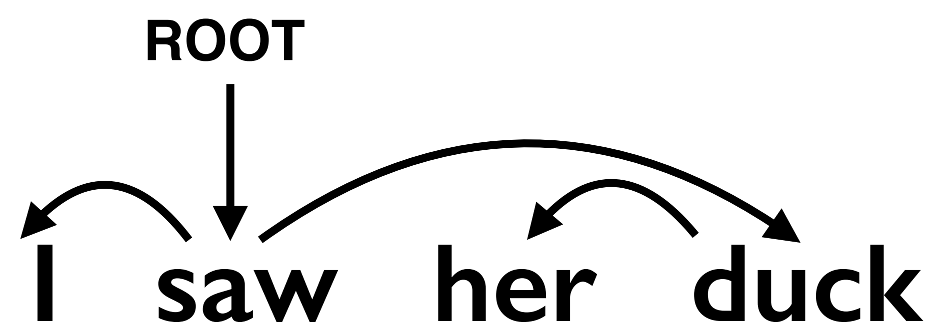
Example

Dependency parsing

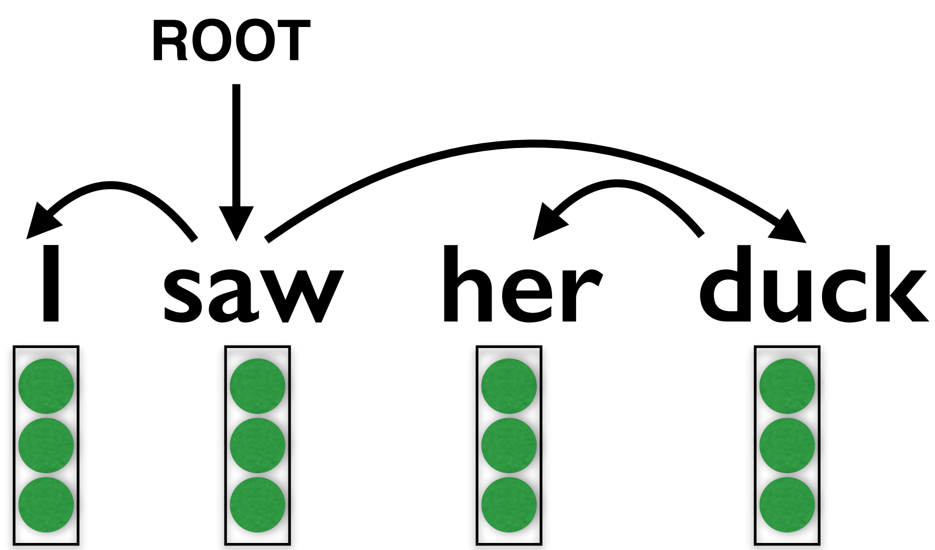
I saw her duck

Example

Dependency parsing

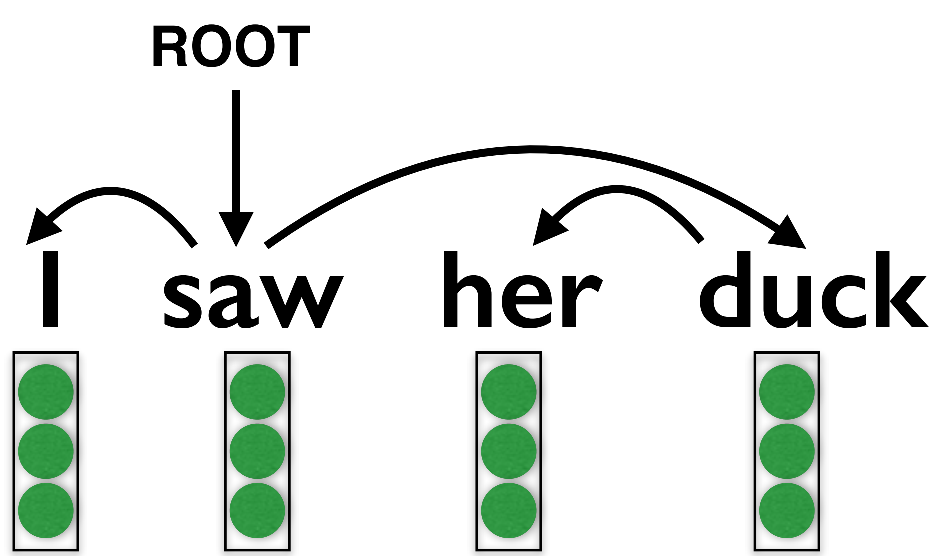


Example
Dependency parsing

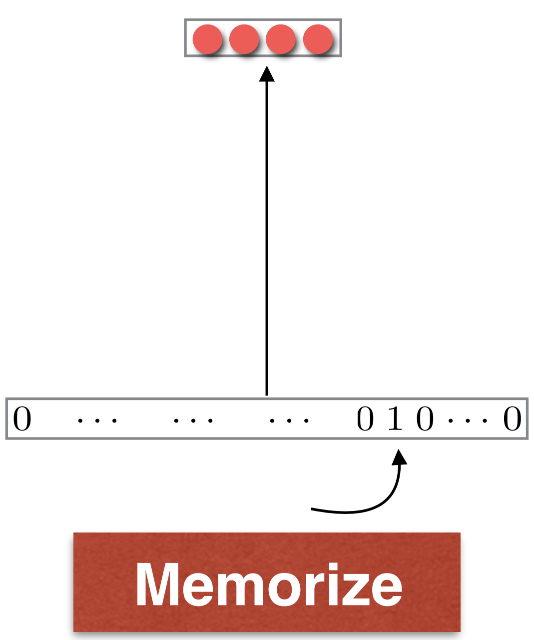


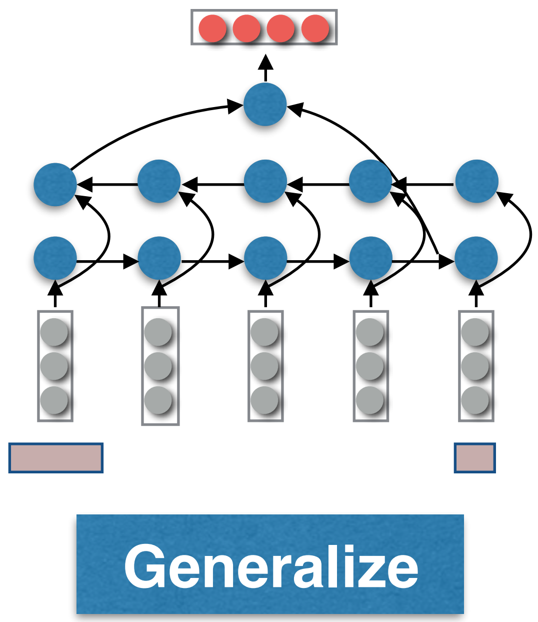
Example

Dependency parsing



Word embedding models:





Dependency parsing

CharLSTM > Word Lookup

	Word	Chars	Δ
English	91.2	91.5	**+0.3**

Dependency parsing
CharLSTM > Word Lookup

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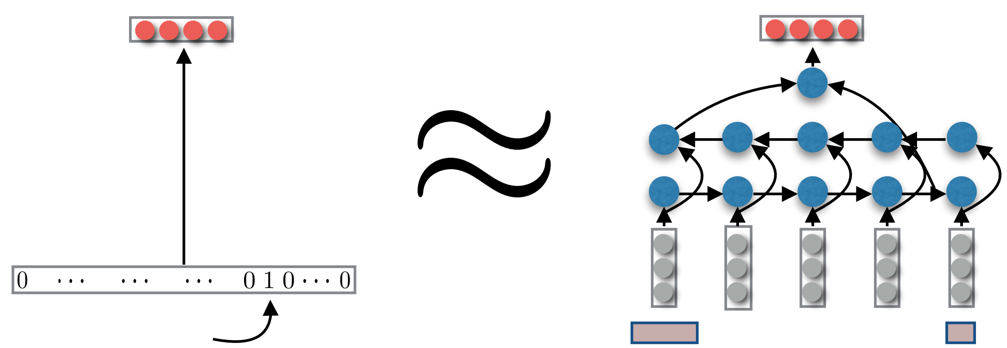
In English parsing, the character LSTM
is roughly equivalent to the lookup approach.



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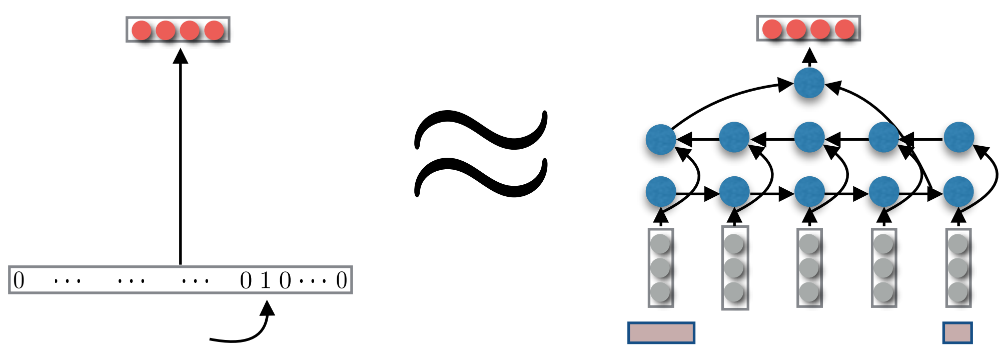

What about languages with richer lexicons?

Turkish: ***Muvaffakiyetsizleştiricileştiriveremeyebileceklerimizdenmişsinizcesine***

Hungarian: ***Megszentségteleníthetetlenségeskedéseitekért***

Dependency parsing
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	Word	Chars	Δ
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Dependency parsing
CharLSTM > Word Lookup

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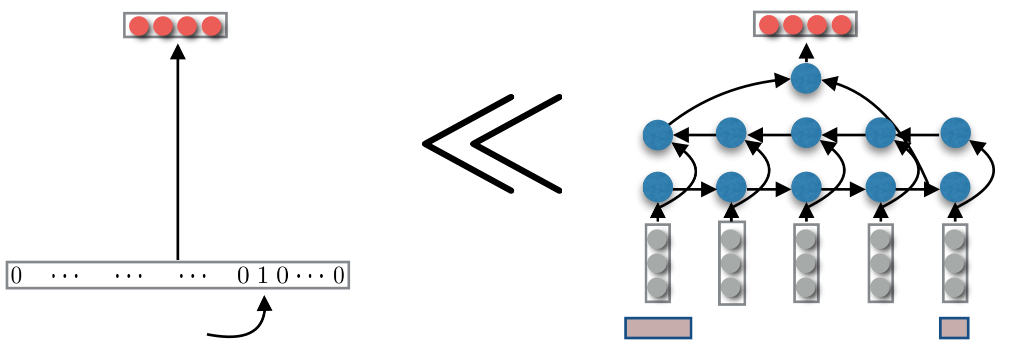
Turkish	71.7	76.3	**+4.6**
Hungarian	72.8	80.4	**+7.6**
Basque	77.1	85.2	**+8.1**
Korean	78.7	88.4	**+9.7**

In **agglutinative** languages,



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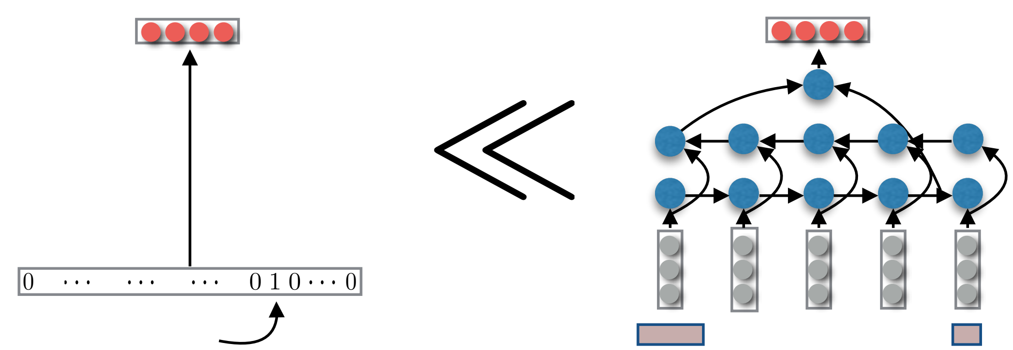
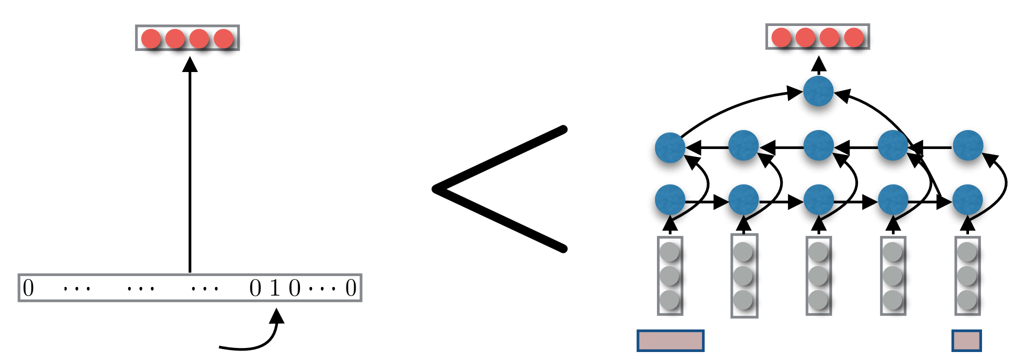
Swedish	76.4	79.2	**+3.2**
Swedish	76.4	79.2	**+2.8**
Arabic	85.2	86.1	**+0.9**

In **agglutinative** languages,



In **fusional/templatic** languages,



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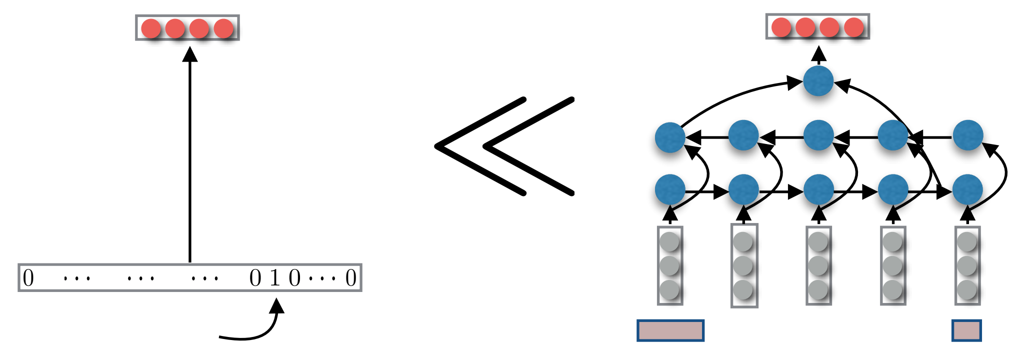

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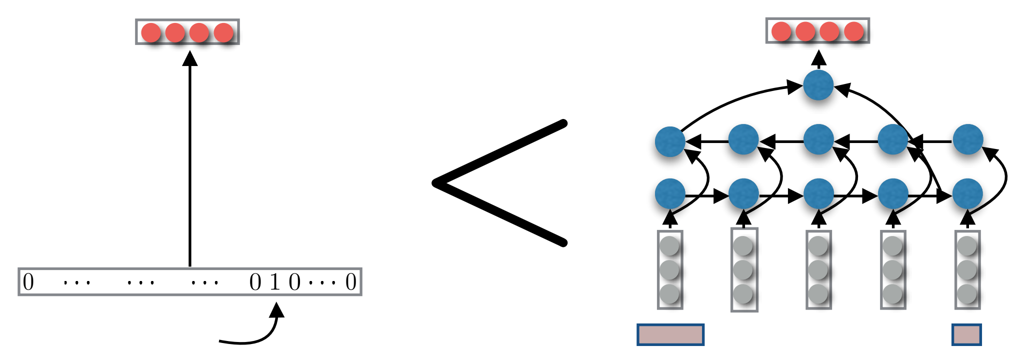


In **analytic** languages, the models are roughly equivalent.

Language modeling
Word similarities

query **increased** **John**

Language modeling
Word similarities

query	**increased**	**John**
5 nearest neighbors	reduced	Richard
	improved	George
	expected	James
	decreased	Robert
	targeted	Edward

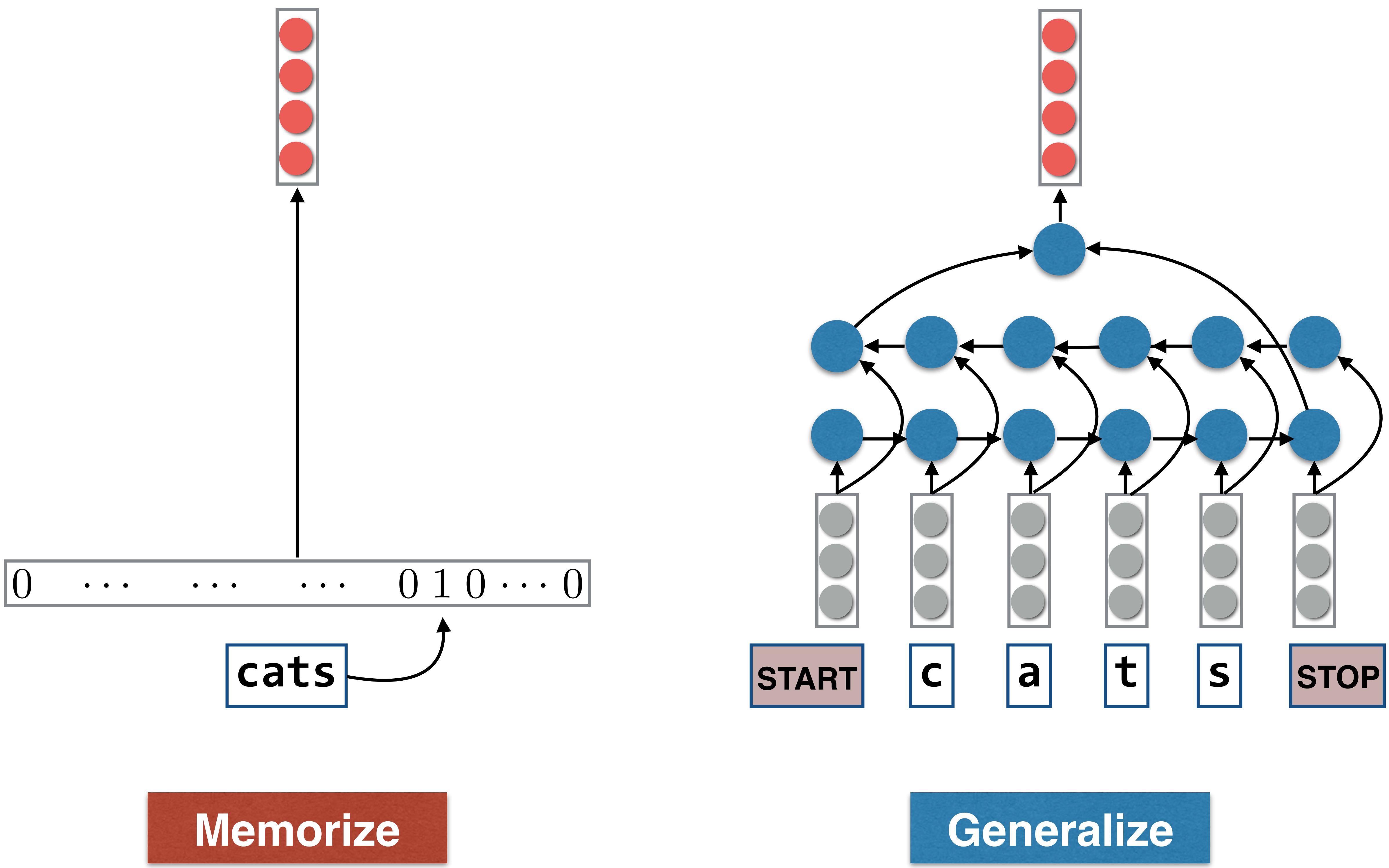
Language modeling
Word similarities

query	increased	John	Noahshire	phding
5 nearest neighbors	reduced	Richard	Nottinghamshire	mixing
	improved	George	Bucharest	modelling
	expected	James	Saxony	styling
	decreased	Robert	Johannesburg	blaming
	targeted	Edward	Gloucestershire	christening

Character vs. word modeling
Summary

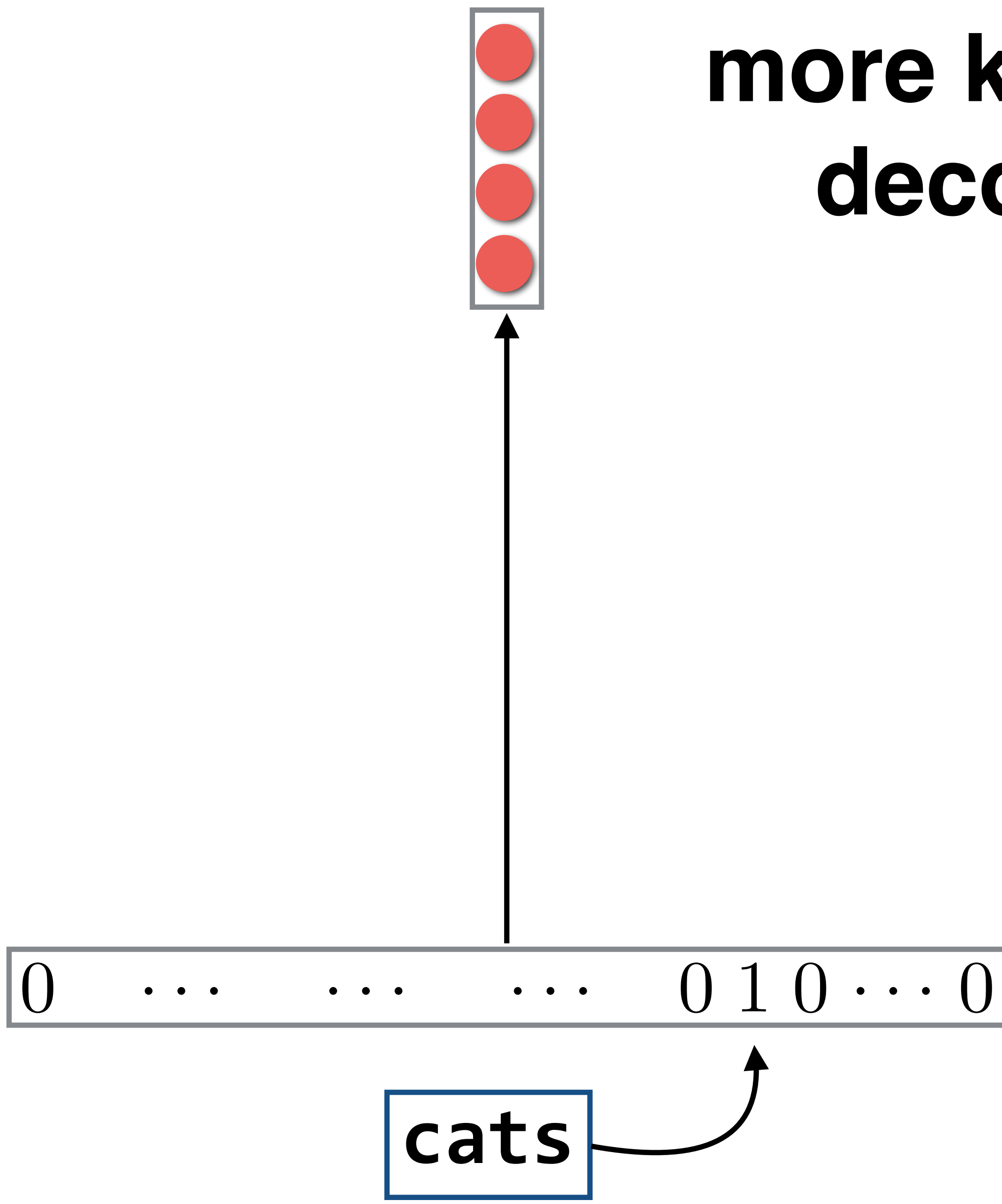
- Lots of exciting work from a variety of places
  - Google Brain: language models
  - Harvard/NYU (Kim, Rush, Sontag): language models
  - NYU/FB: document representation “from scratch”
  - CMU (me, Cohen, Salakhutdinov): Twitter, morphologically rich languages, translation
- Now for something a bit more controversial…

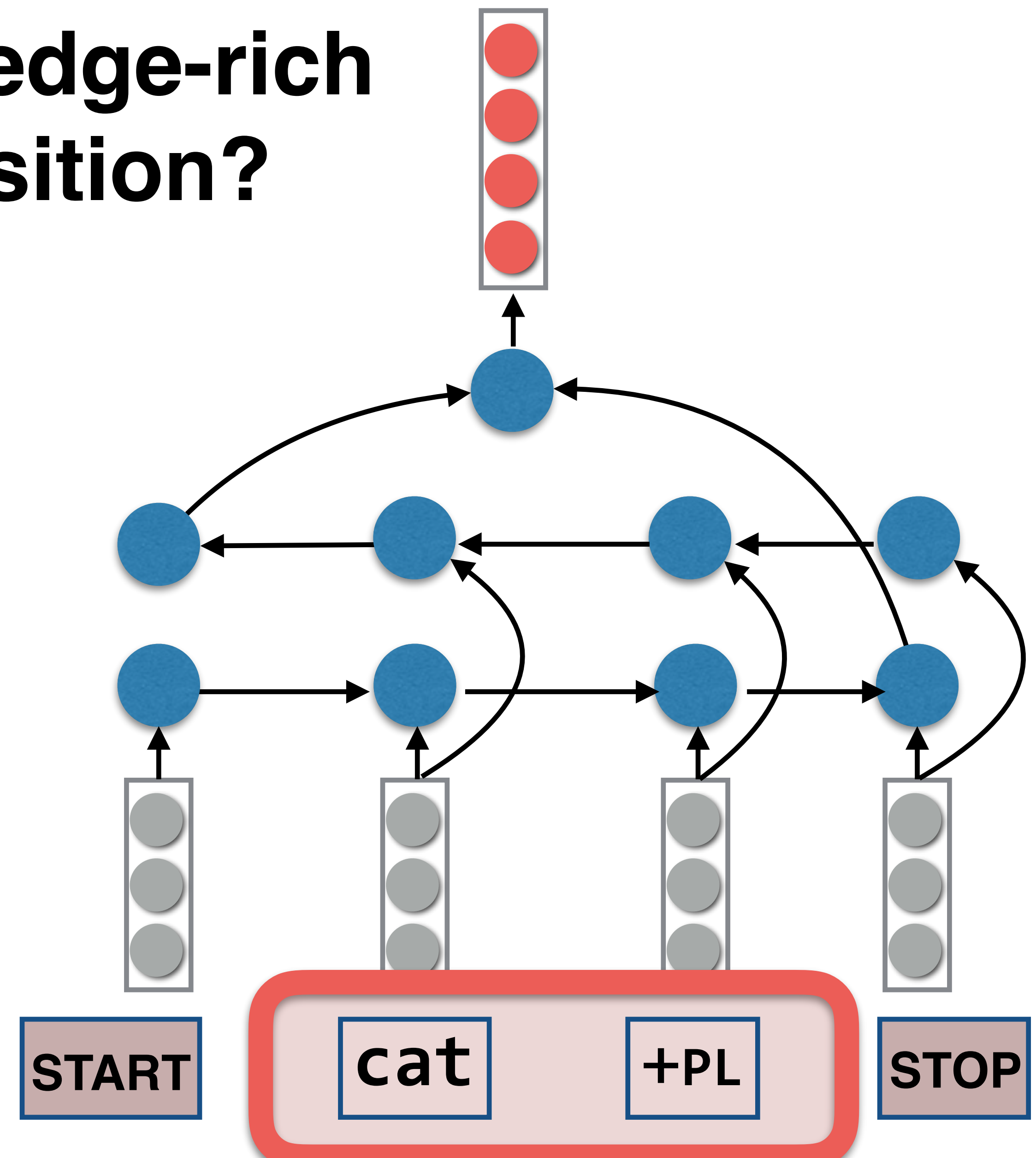
Structure-aware words



Structure-aware words

Would we benefit from a more knowledge-rich decomposition?





Memorize

Generalize

Open Vocabulary LMs

- Rather than assuming a fixed vocabulary, model any sequence in Σ^* where Σ is the inventory of characters.

Open Vocabulary LMs
Turkish

Kosova
,
tekrar
eden
şikayetler
ışığında
özelleştirme
sürecini
incelemeye
alıyor
.

Open Vocabulary LMs
Turkish morphology

	Morphological Analysis	
Kosova	Kosova+Noun+Prop+A3sg+Pnon+Nom	
,	,+Punc	
tekrar	tekrar+Adverb	tekrar+Noun+A3sg+Pnon+Nom
eden	et+Verb+Pos^DB+Adj+PresPart	ede+Noun+A3sg+P2sg+Nom
şikayetler	şikayet+Noun+A3pl+Pnon+Nom	
ışığında	ışık+Noun+A3sg+P3sg+Loc	ışık+Noun+A3sg+P2sg+Loc
özelleştirme	özel+Adj^DB+Verb+Become^DB+Verb+Caus+Pos^DB+Noun+Inf2+A3sg+Pnon+Nom	özel+Adj^DB+Verb+Become^DB+Verb+Caus+Neg+Imp+A2sg
sürecini	süreç+Noun+A3sg+P3sg+Acc	süreç+Noun+A3sg+P2sg+Acc
incelemeye	incele+Verb+Pos^DB+Noun+Inf2+A3sg+Pnon+Dat	incel+Verb^DB+Verb+Able+Neg+Opt+A3sg
alıyor	al+Verb+Pos+Prog1+A3sg	
.	.+Punc	

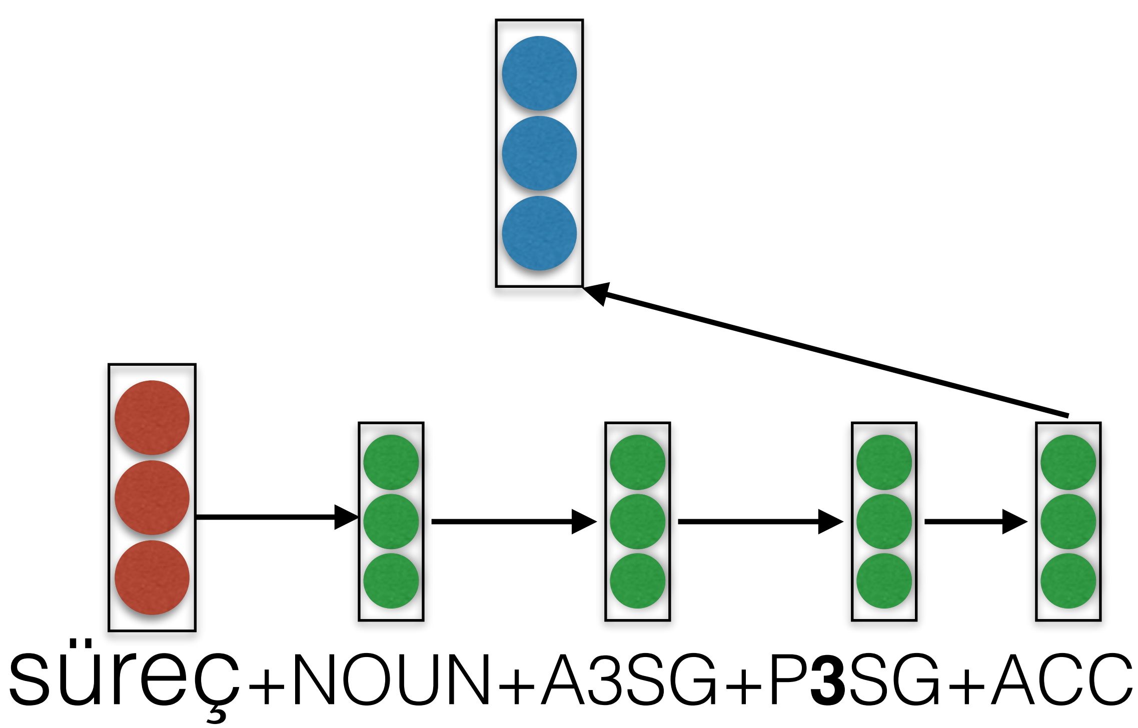
Open Vocabulary LMs

Turkish morphology

	Morphological Analysis	
Kosova	Kosova+Noun+Prop+A3sg+Pnon+Nom	
,	,+Punc	
tekrar	tekrar+Adverb	tekrar+Noun+A3sg+Pnon+Nom
eden	et+Verb+Pos^DB+Adj+PresPart	ede+Noun+A3sg+P2sg+Nom
şikayetler	şikayet+Noun+A3pl+Pnon+Nom	
ışığında	ışık+Noun+A3sg+P3sg+Loc	ışık+Noun+A3sg+P2sg+Loc
özellestirme	özel+Adj^DB+Verb+Become^DB+Verb+Caus+Pos^DB+Noun+Inf2+A3sg+Pnon+Nom	özel+Adj^DB+Verb+Become^DB+Verb+Caus+Neg+Imp+A2sg
sürecini	süreç+Noun+A3sg+P3sg+Acc	süreç+Noun+A3sg+P2sg+Acc
incelemeye	incele+Verb+Pos^DB+Noun+Inf2+A3sg+Pnon+Dat	incel+Verb^DB+Verb+Able+Neg+Opt+A3sg
alıyor	al+Verb+Pos+Prog1+A3sg	
.	.+Punc	

Open Vocabulary LMs
Turkish morphology

	Morphological Analysis	
Kosova	Kosova+Noun+Prop+A3sg+Pnon+Nom	
,	,+Punc	
tekrar	tekrar+Adverb	tekrar+Noun+A3sg+Pnon+Nom
eden	et+Verb+Pos^DB+Adj+PresPart	ede+Noun+A3sg+P2sg+Nom
şikayetler	şikayet+Noun+A3pl+Pnon+Nom	
ışığında	ışık+Noun+A3sg+P3sg+Loc	ışık+Noun+A3sg+P2sg+Loc
özellestirme	özel+Adj^DB+Verb+Become^DB+Verb+Caus+Pos^DB+Noun+Inf2+A3sg+Pnon+Nom	özel+Adj^DB+Verb+Become^DB+Verb+Caus+Neg+Imp+A2sg
sürecini	süreç+Noun+A3sg+P3sg+Acc	süreç+Noun+A3sg+P2sg+Acc
incelemeye	incele+Verb+Pos^DB+Noun+Inf2+A3sg+Pnon+Dat	incel+Verb^DB+Verb+Able+Neg+Opt+A3sg
alıyor	al+Verb+Pos+Prog1+A3sg	
.	.+Punc	



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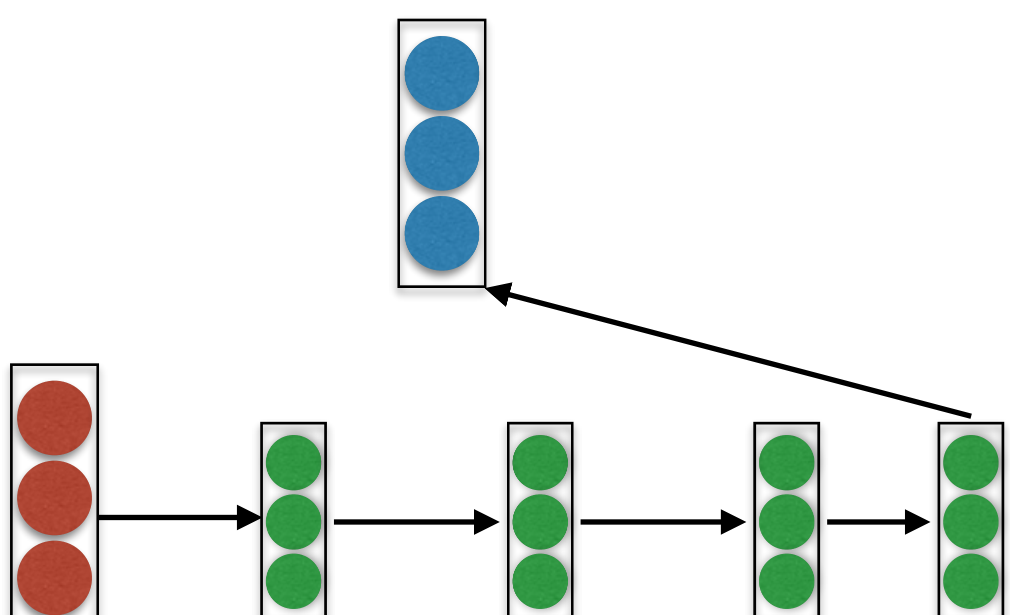
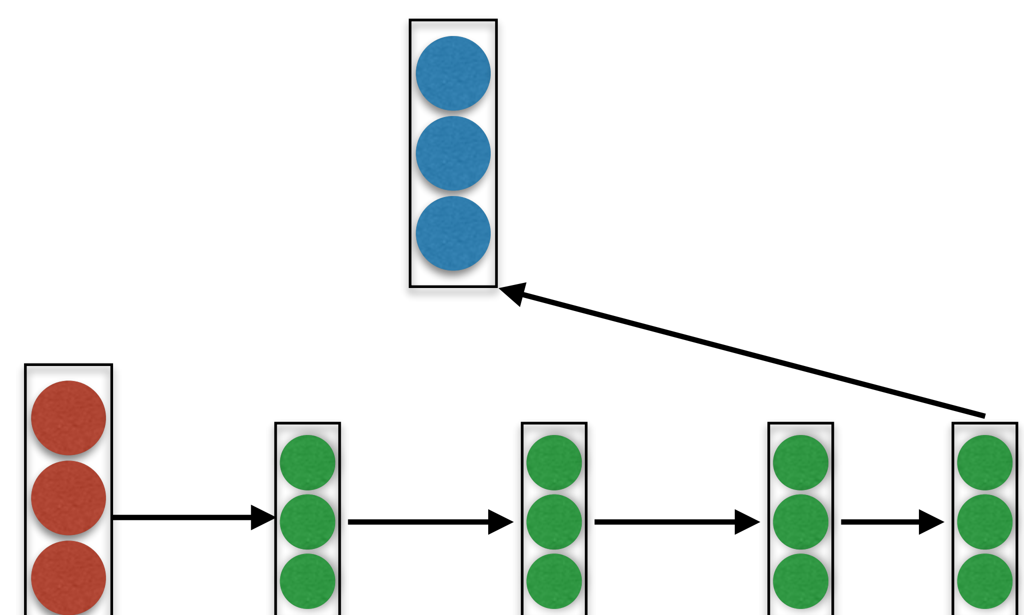
incelemeye	incele+Verb+Pos^DB+Noun+Inf2+A3sg+Pnon+Dat	incel+Verb^DB+Verb+Able+Neg+Opt+A3sg
alıyor	al+Verb+Pos+Prog1+A3sg	
.	.+Punc	



süreç+NOUN+A3SG+P**3**SG+ACC



süreç+NOUN+A3SG+P**2**SG+ACC

Open Vocabulary LMs

Turkish morphology

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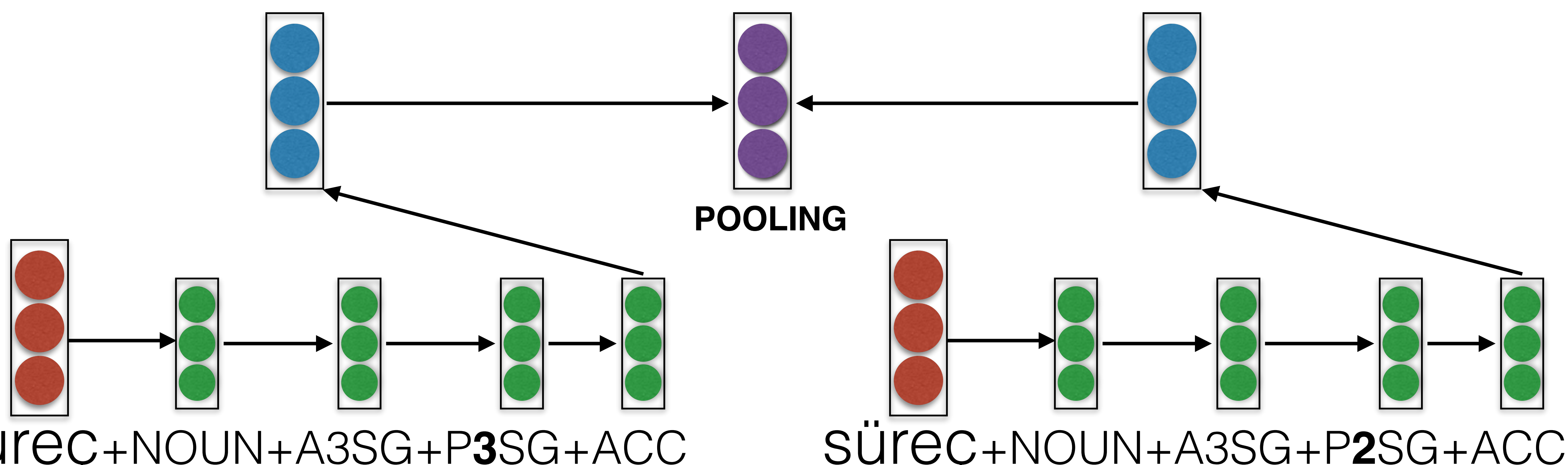
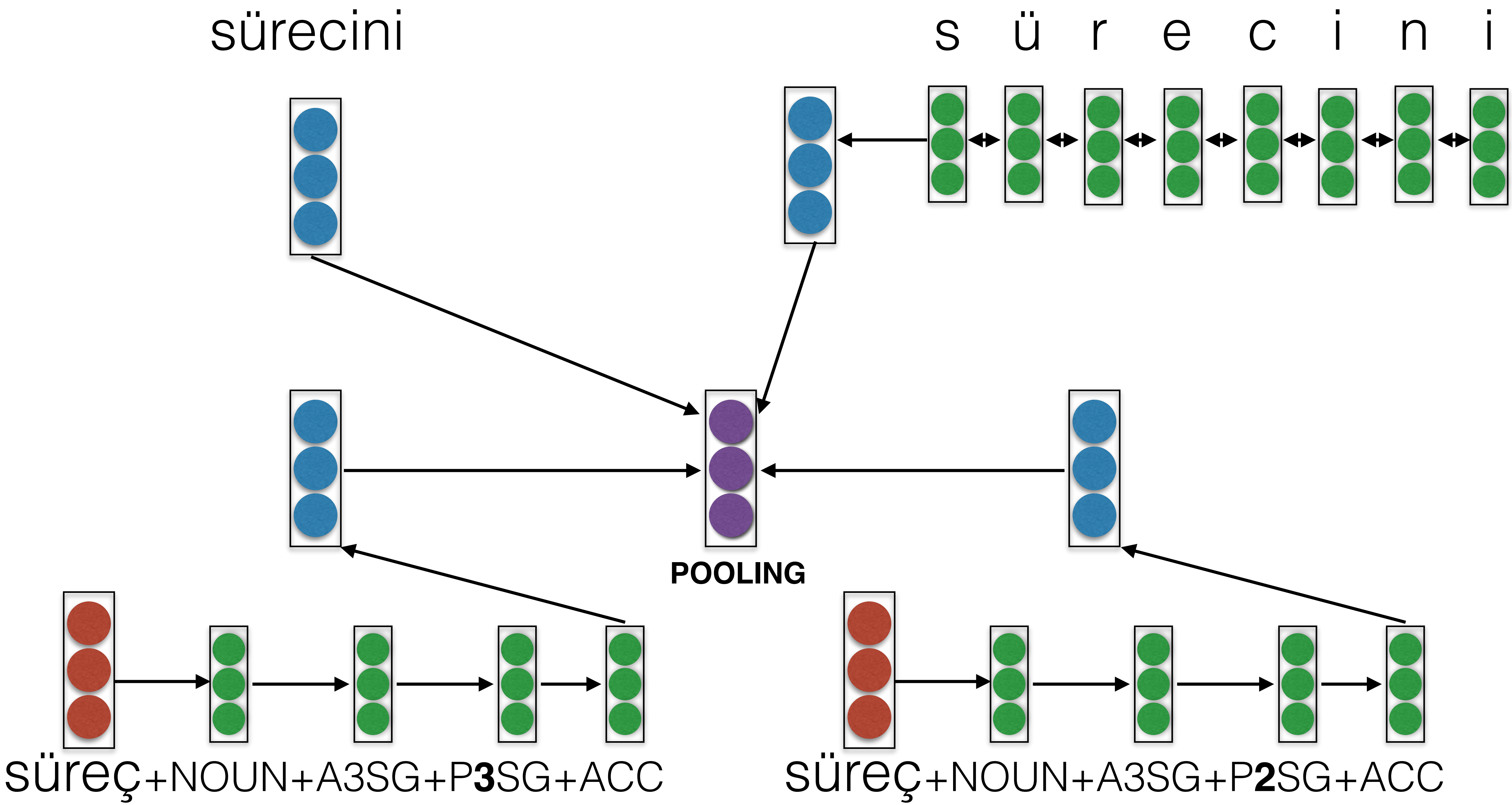
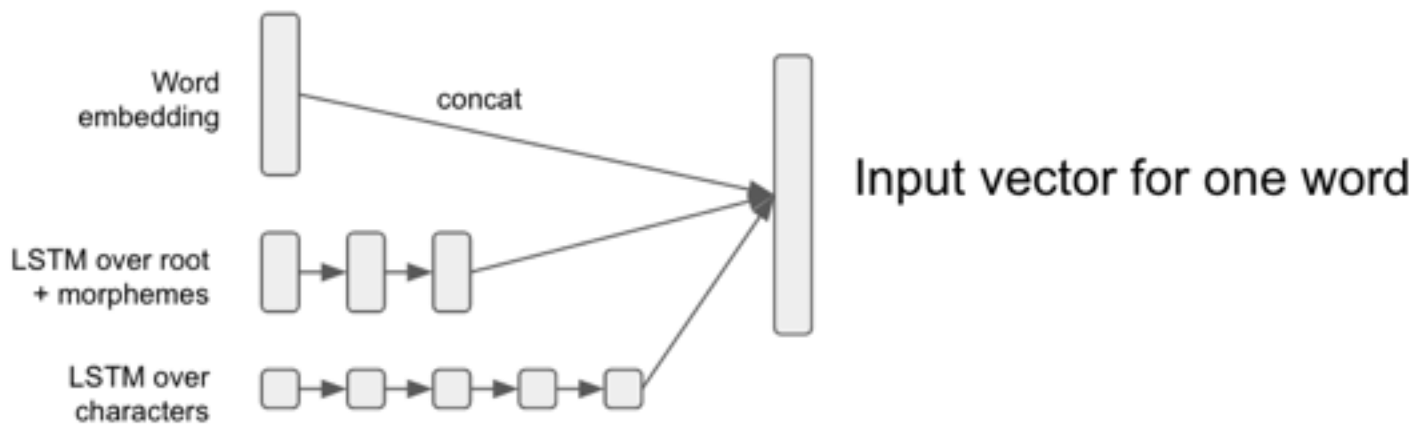


Open Vocabulary LMs
Turkish morphology



Input word representation:



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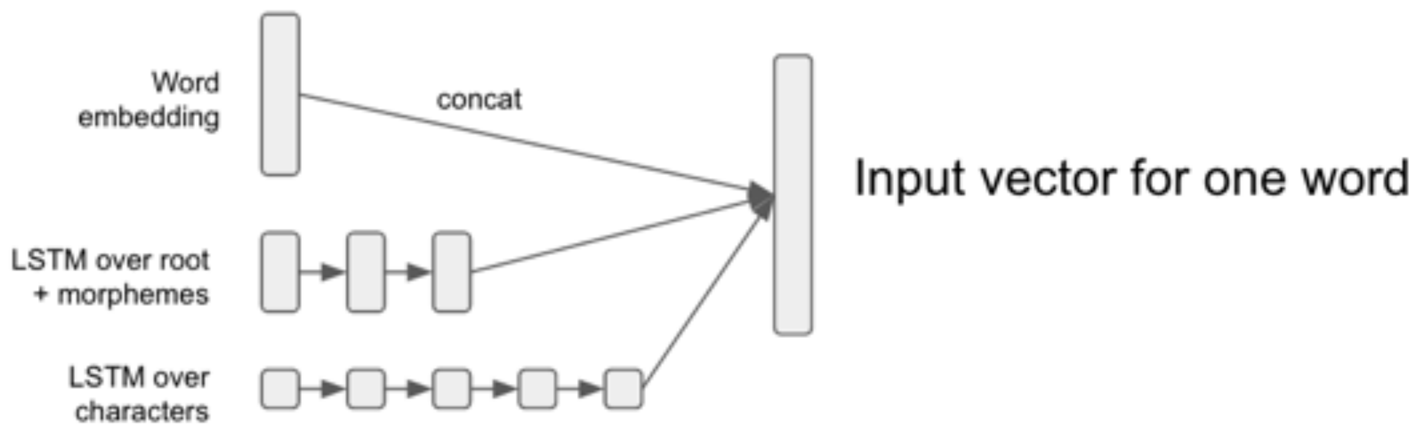
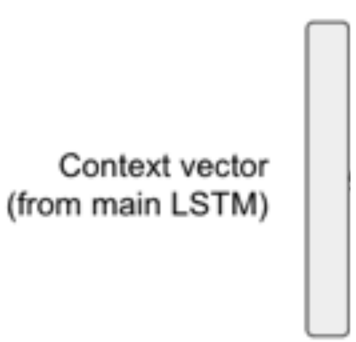


Output generation process: (marginalized)



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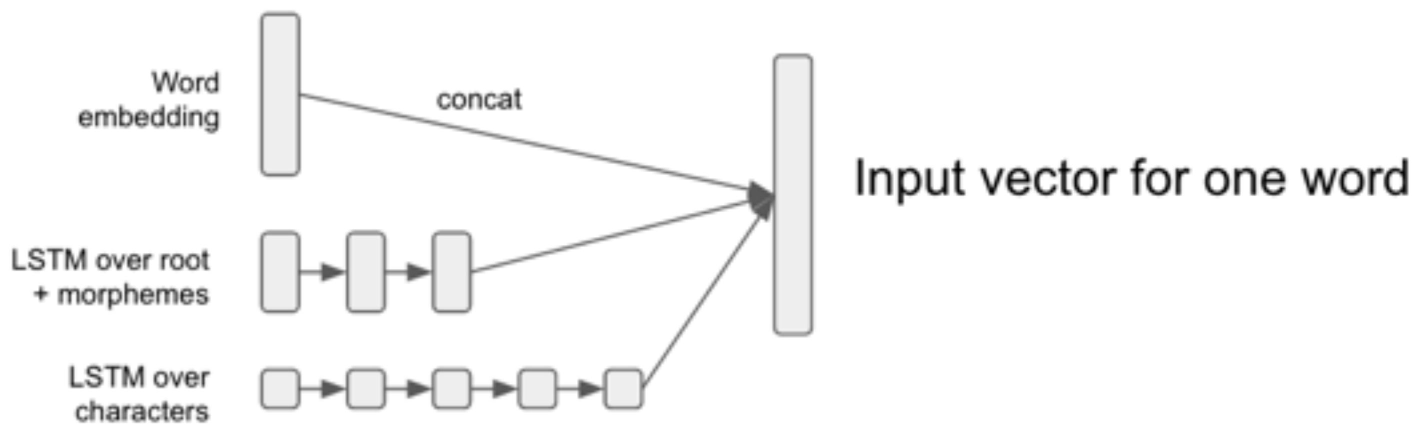

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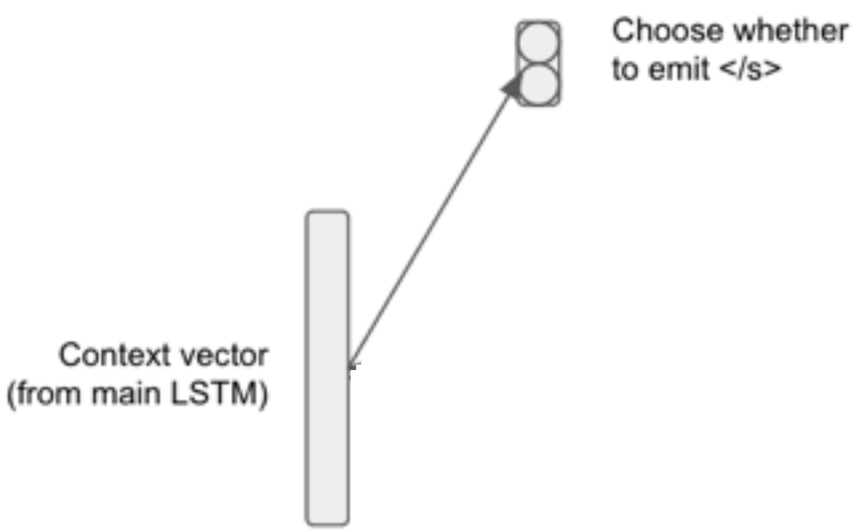

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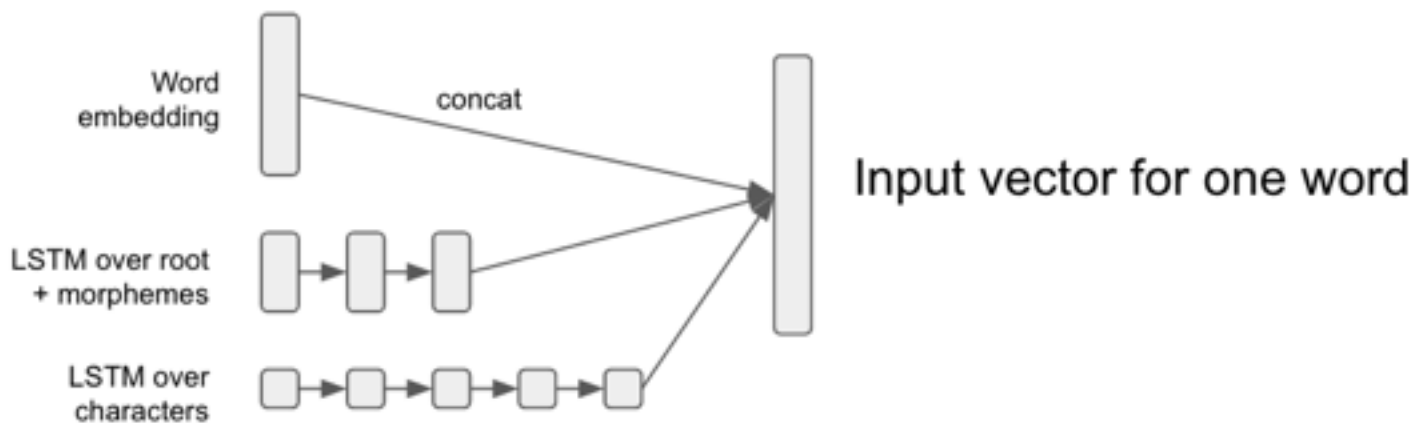

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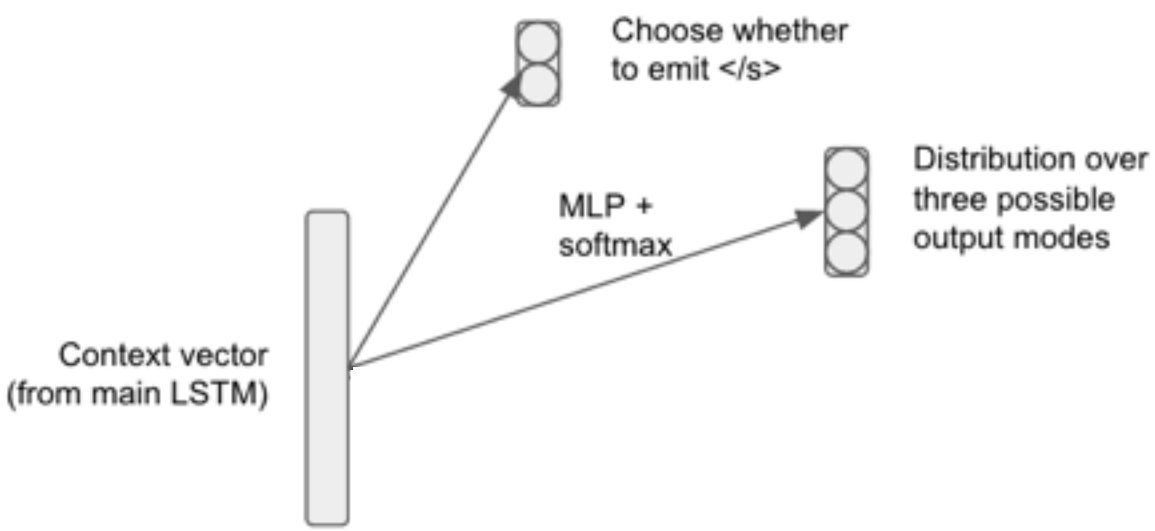

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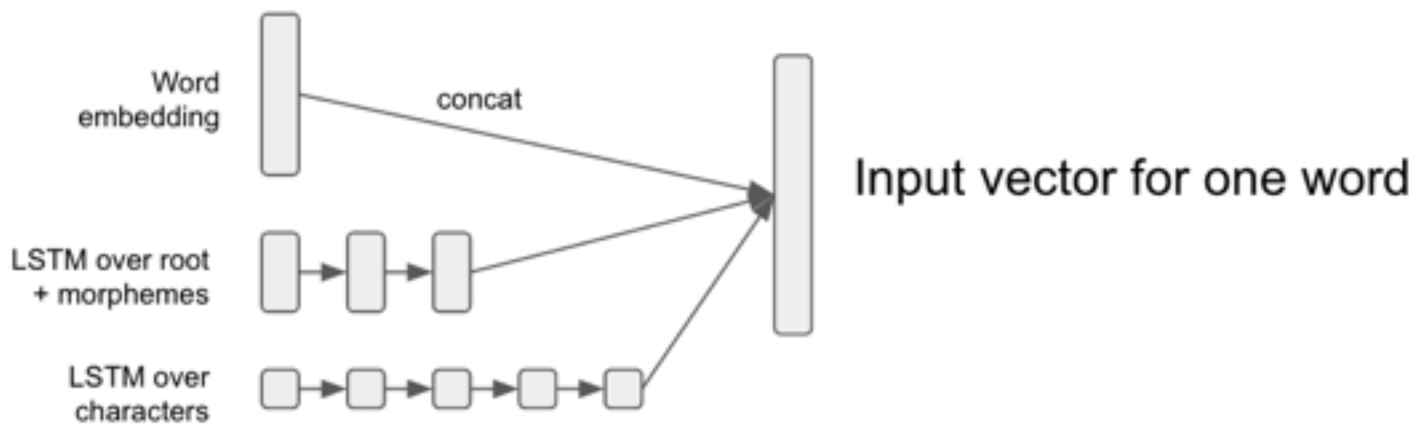

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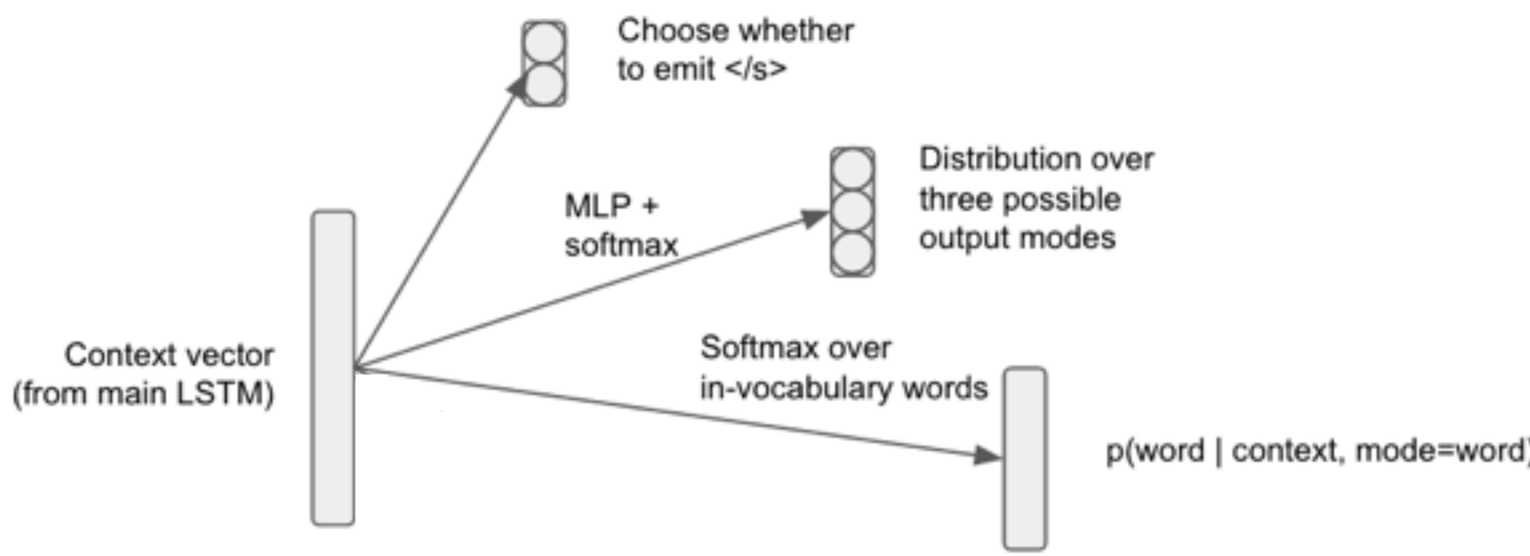

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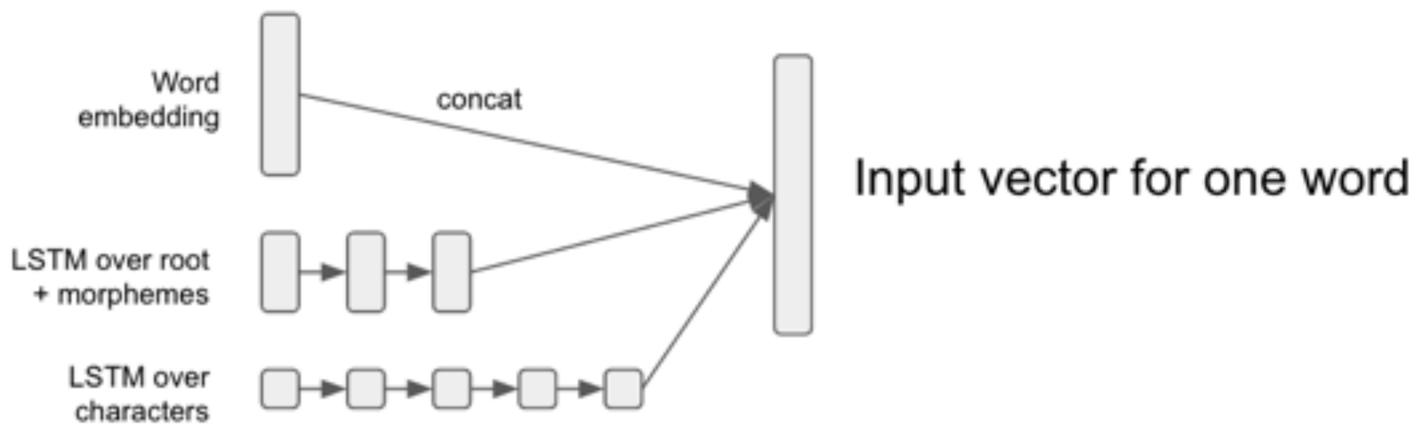

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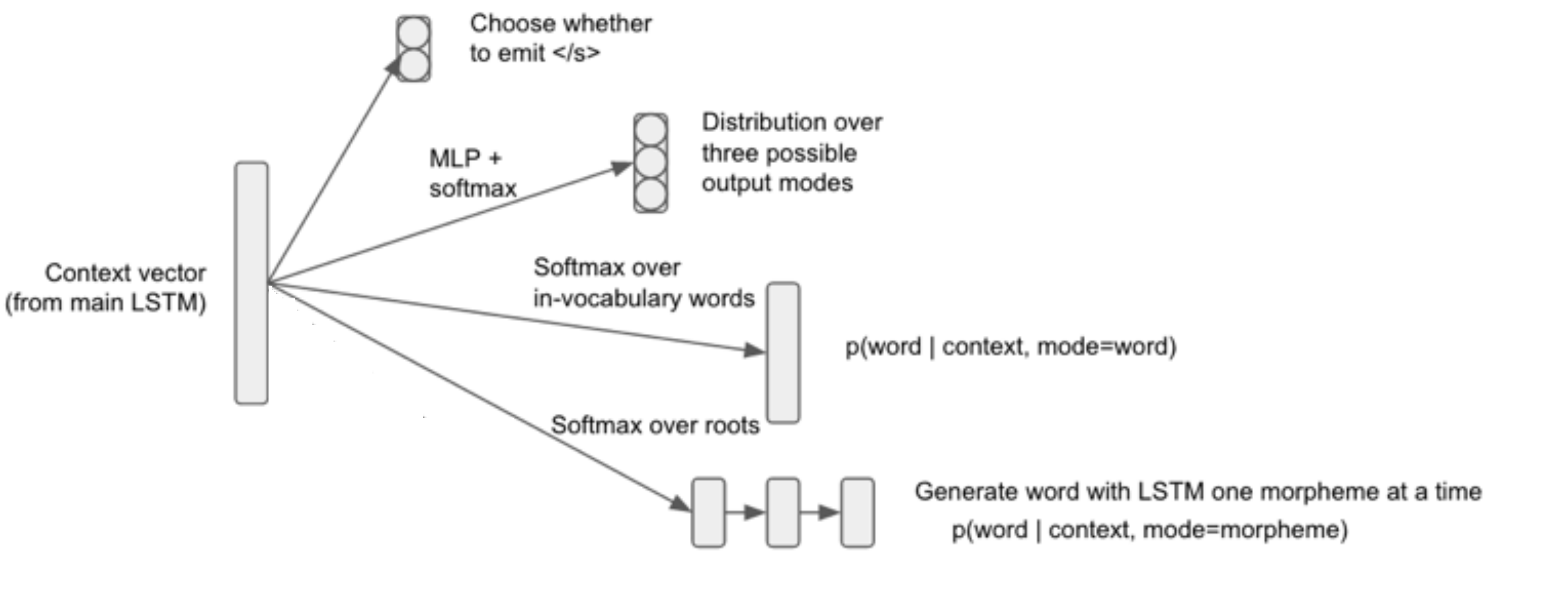

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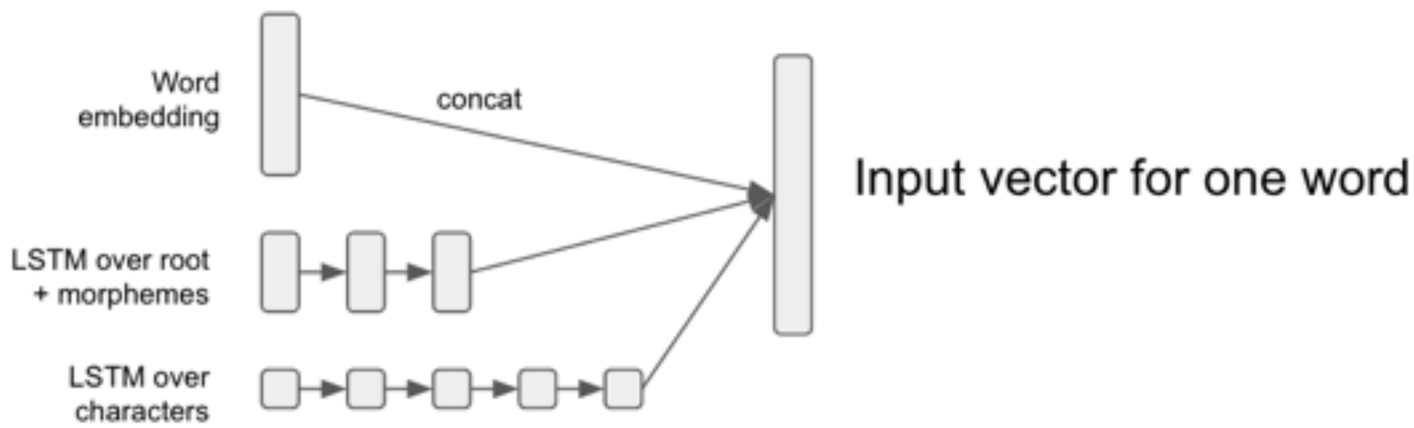

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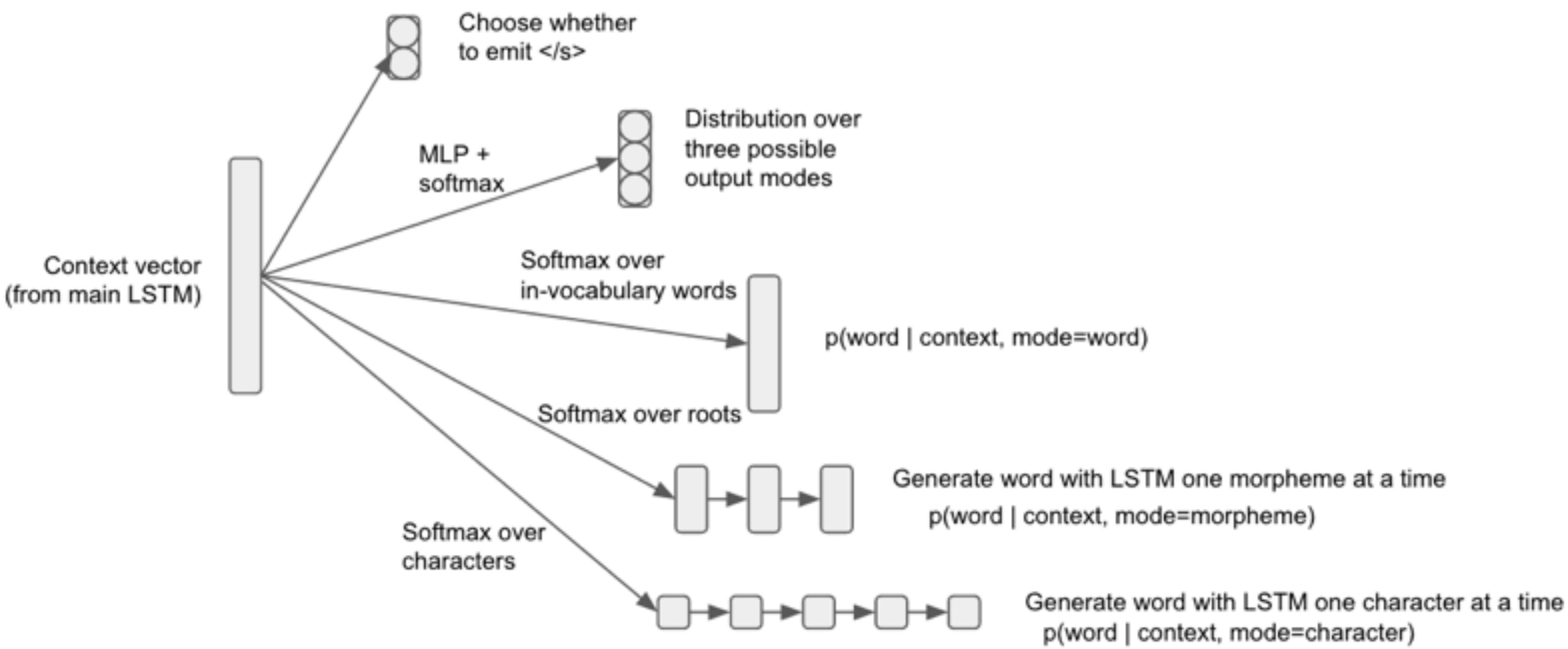

Open Vocabulary LM

	perplexity per word
Characters	18600
Characters +Morphs	8165
Characters +Words	5021
Characters +Words +Morphs	**4116**

Character vs. word modeling
Summary

- Model performance is essentially equivalent in morphologically simple languages (e.g., Chinese, English)
- In morphologically rich languages (e.g., Hungarian, Turkish, Finnish), performance improvements are most pronounced
- We need **far fewer parameters** to represent words as "compositions" of characters
- Word and morpheme level information adds additional value
- **Where else could we add linguistic structural knowledge?**

Modeling syntax
Language is hierarchical

(1) a. The talk I gave did **not** appeal to **anybody**.

Examples adapted from Everaert et al. (*TICS* 2015)

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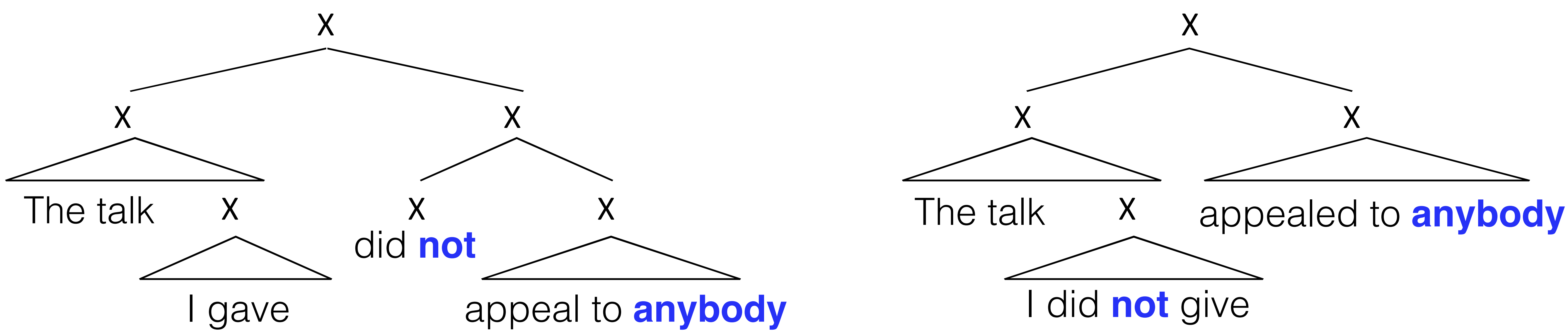

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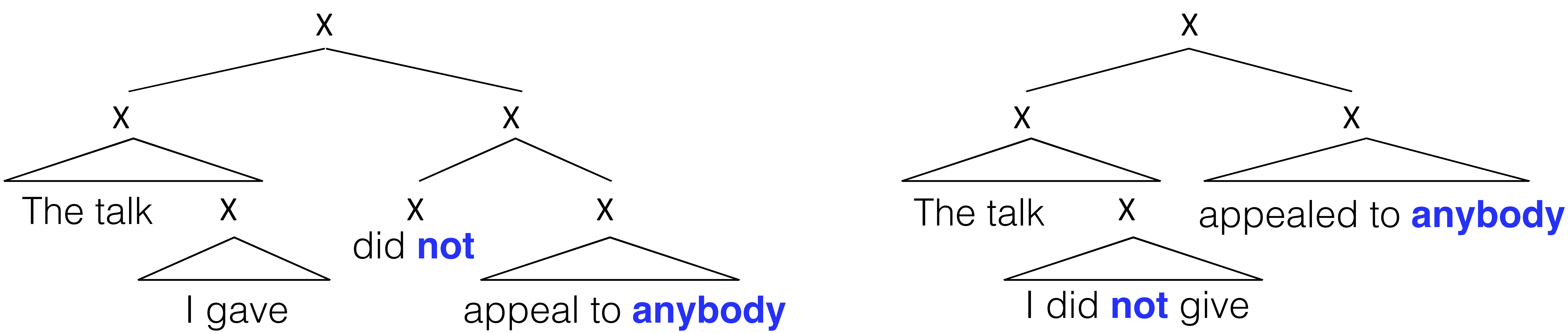

Generalization: **not** must “structurally precede” **anybody**

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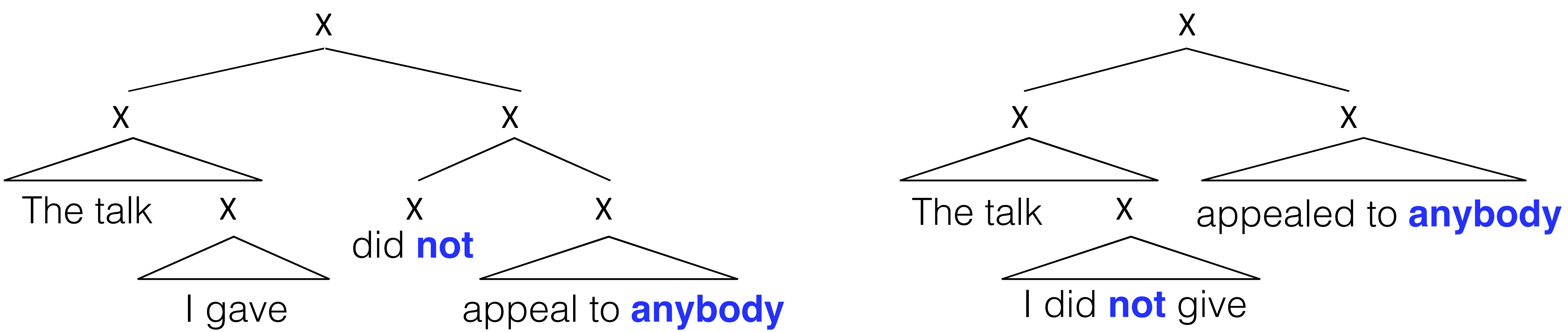

Generalization: **not** must “structurally precede” **anybody**

- many theories of the details of structure
- the psychological reality of structural sensitivty is **not** empirically controversial
- much more than NPIs follow such constraints

Examples adapted from Everaert et al. (*TICS* 2015)

One theory of hierarchy

- Generate symbols sequentially using an RNN

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- Generate symbols sequentially using an RNN
- Add some “control symbols” to rewrite the history periodically
  - Periodically “compress” a sequence into a single “constituent”
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  - RNN predicts next symbol based on the history of compressed elements and non-compressed terminals (“shift” or “generate”)
  - RNN must also predict “control symbols” that decide how big constituents are

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  - RNN must also predict “control symbols” that decide how big constituents are
- We call such models **recurrent neural network grammars**.

Terminals	Stack	Action

Terminals	Stack	Action
		NT(S)

Terminals	Stack	Action
		NT(S)
	(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*)

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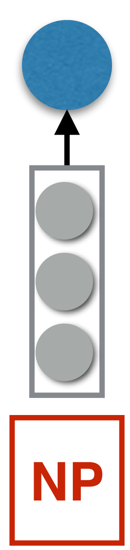

What head type?

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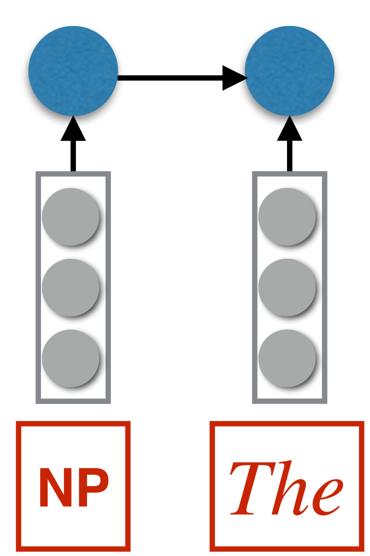

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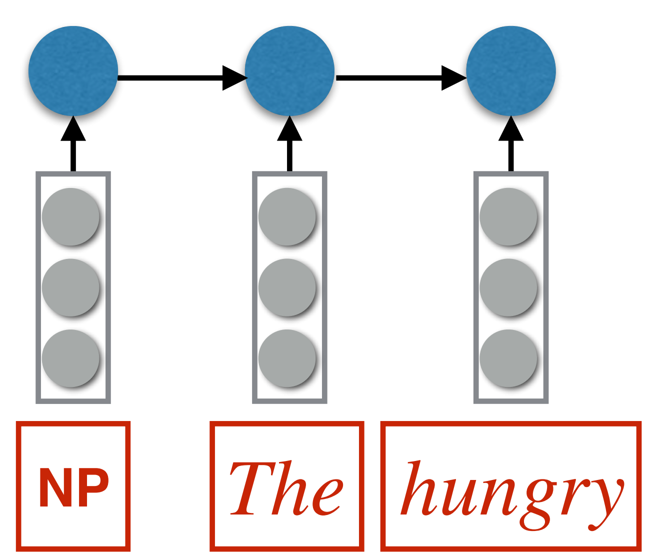

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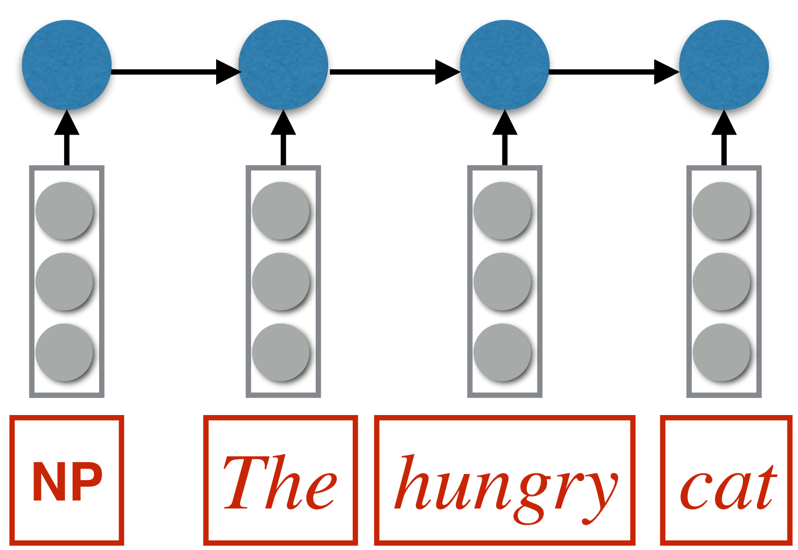

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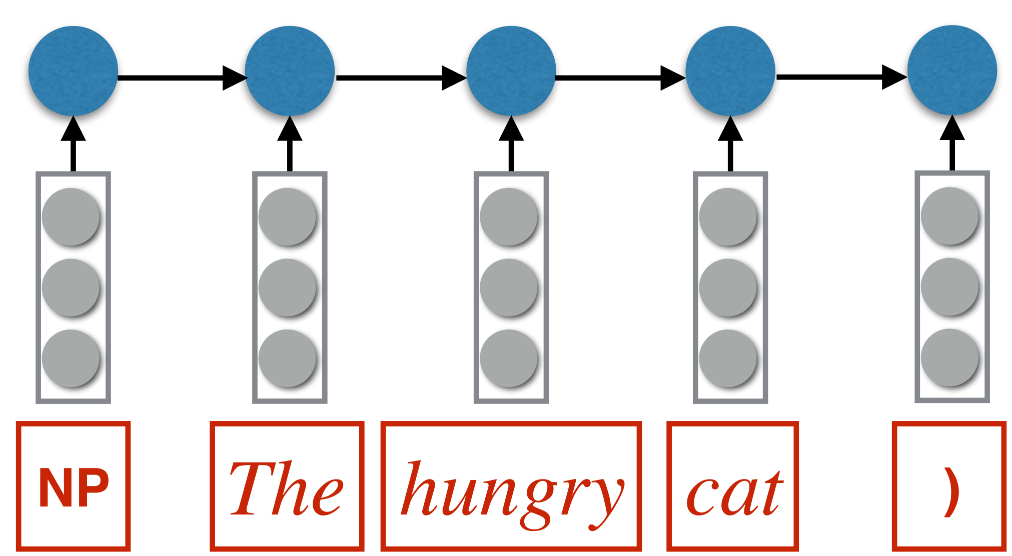

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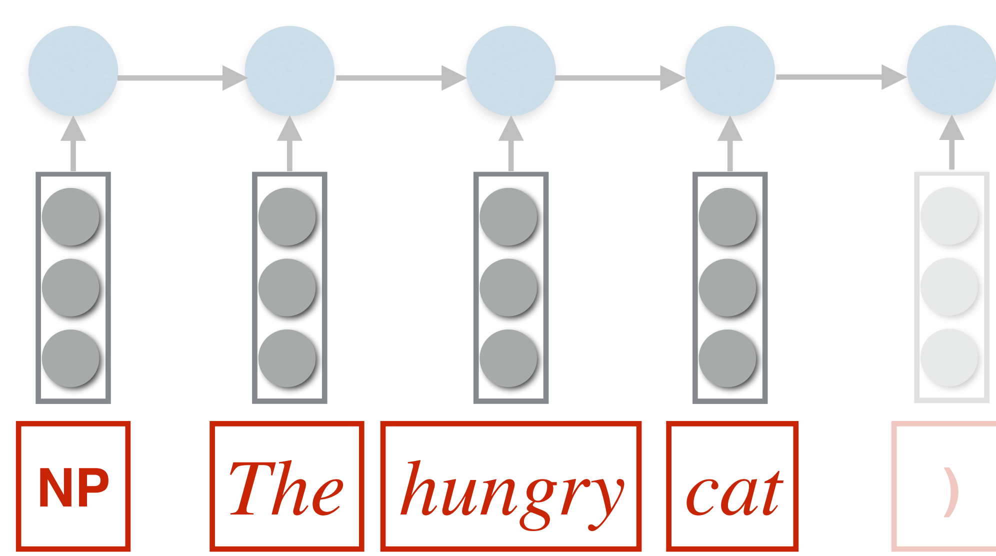

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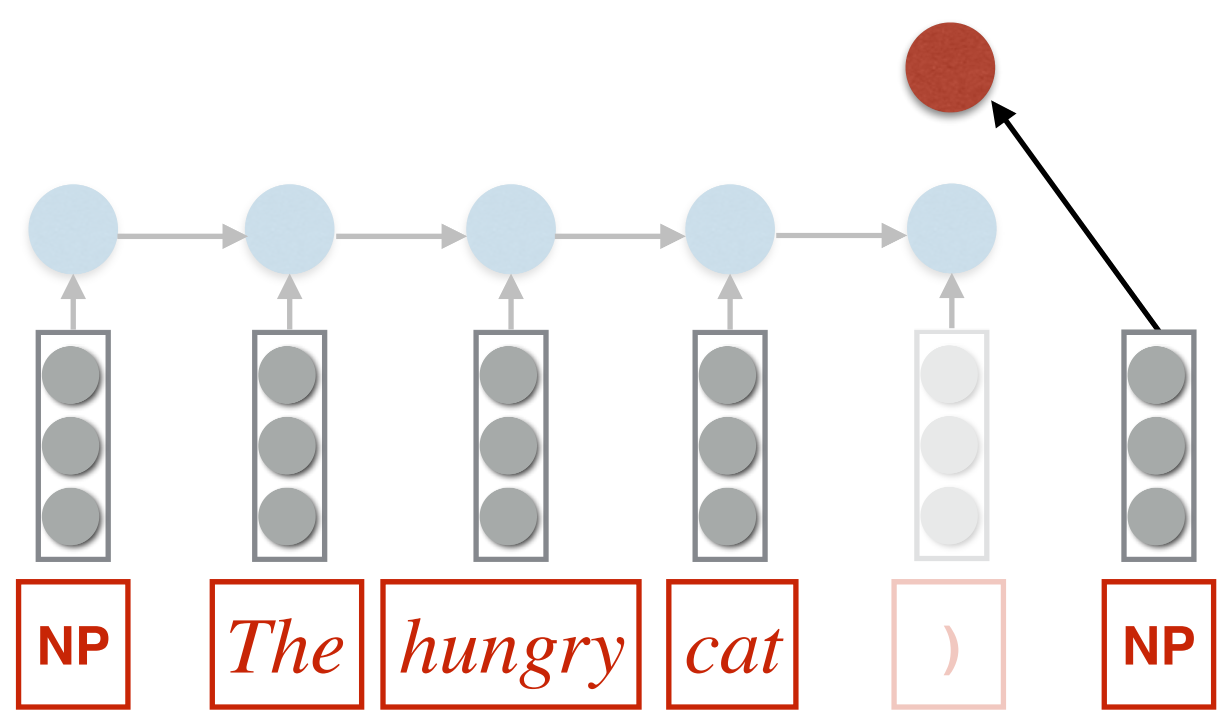

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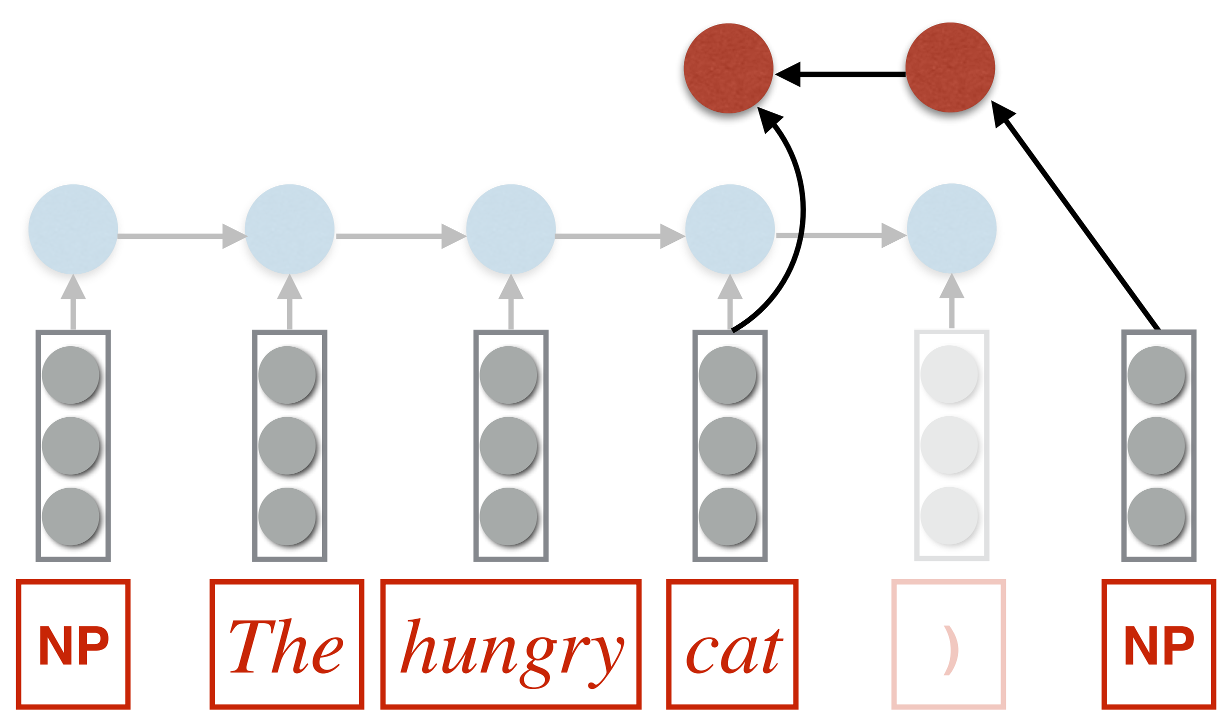

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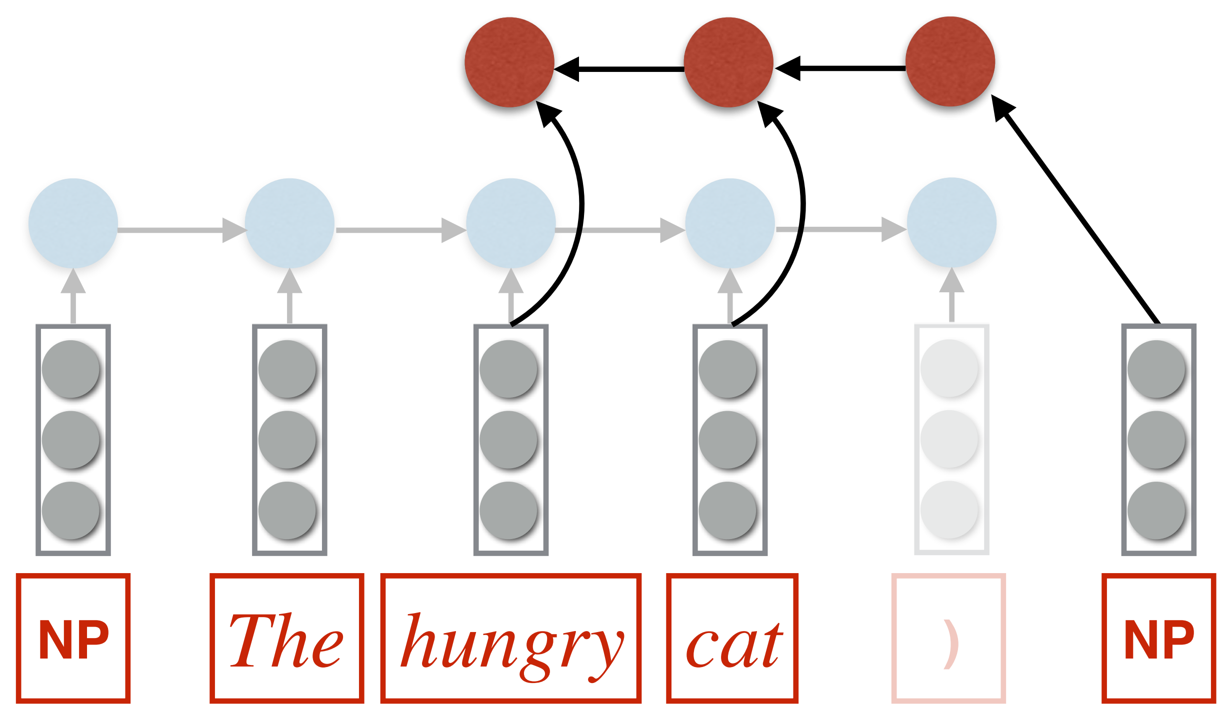

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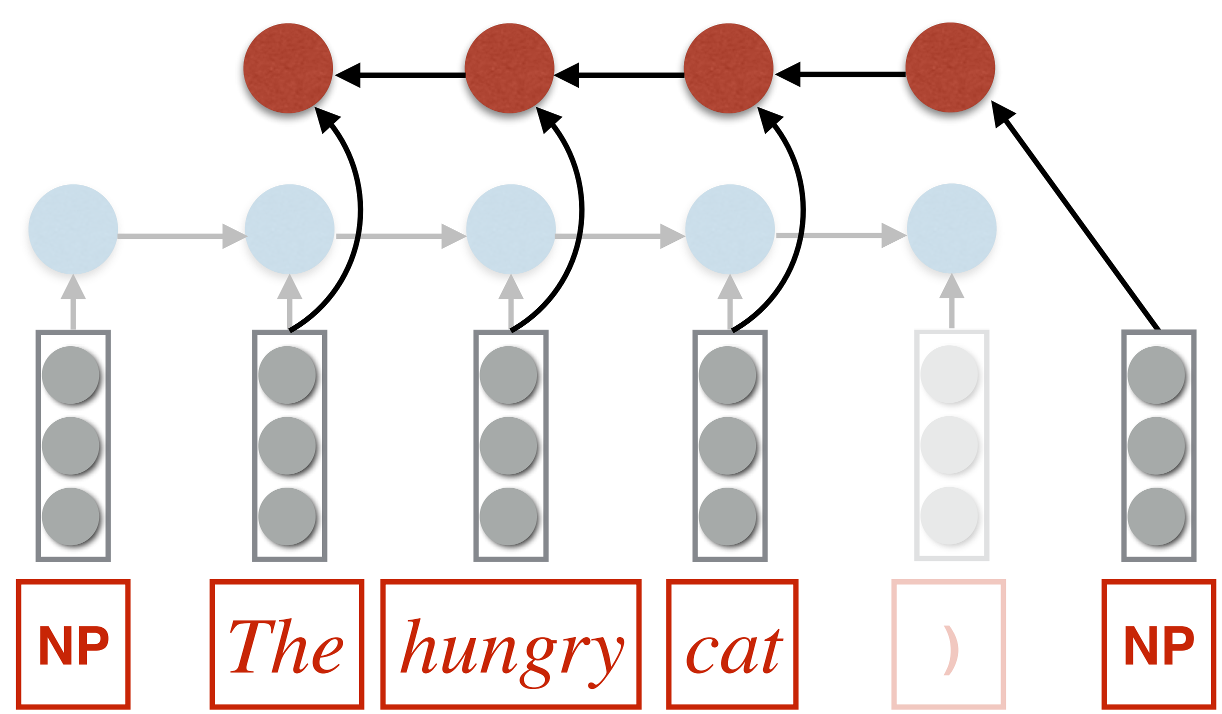

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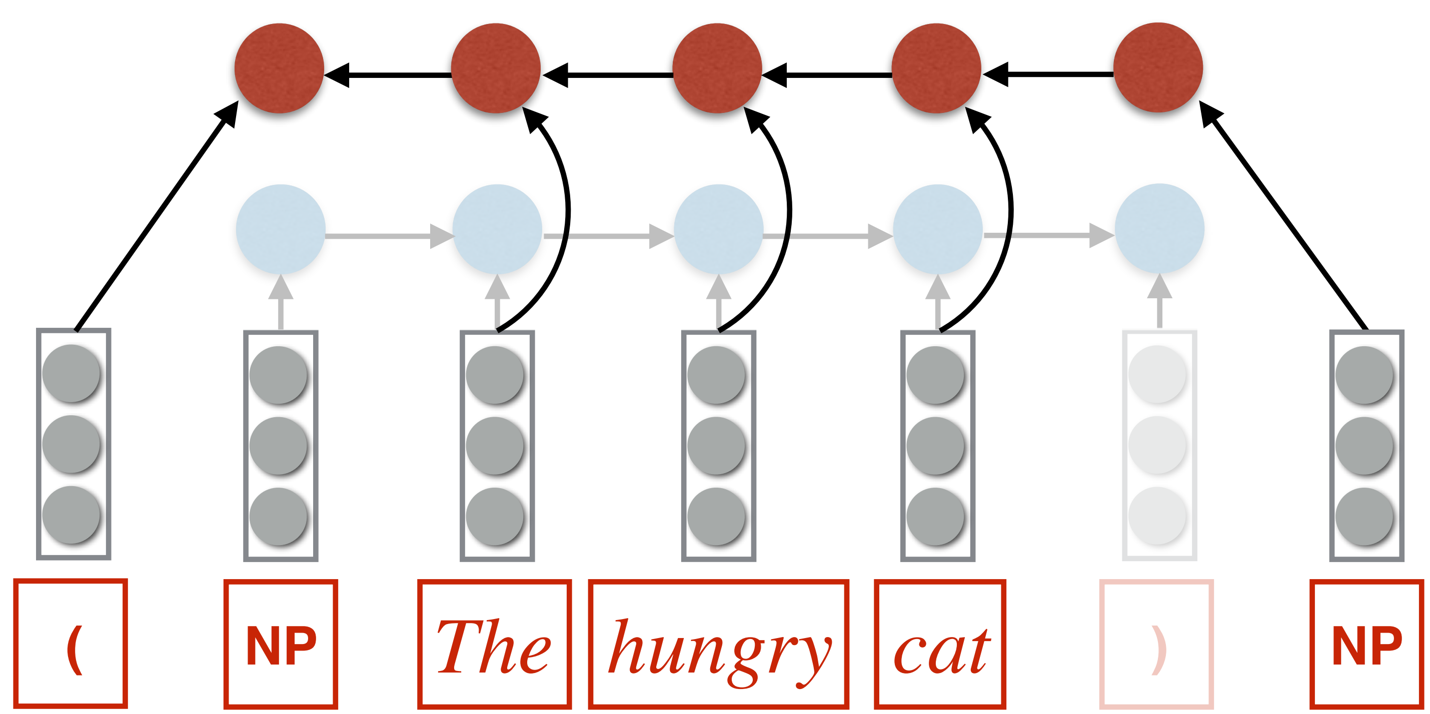

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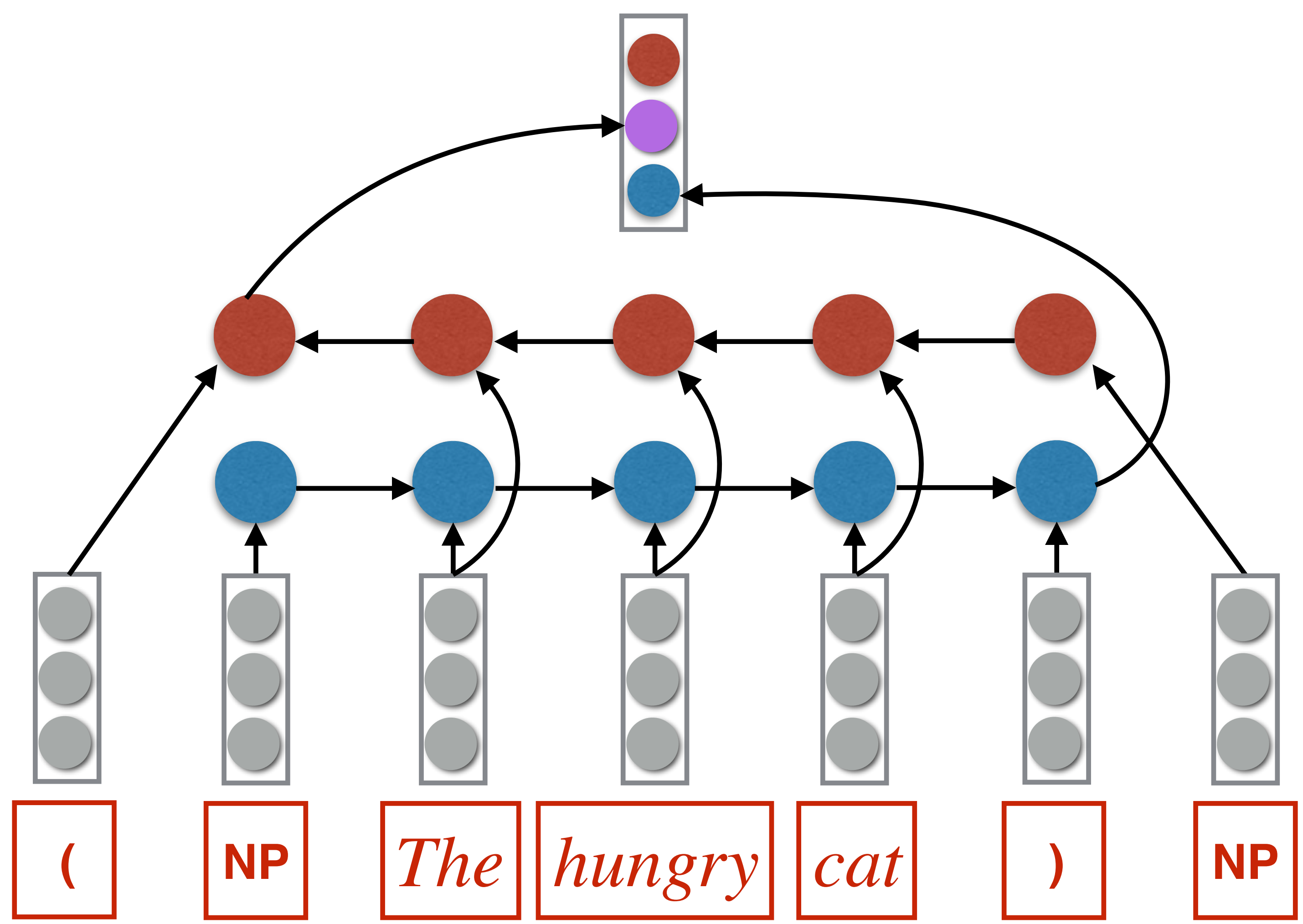
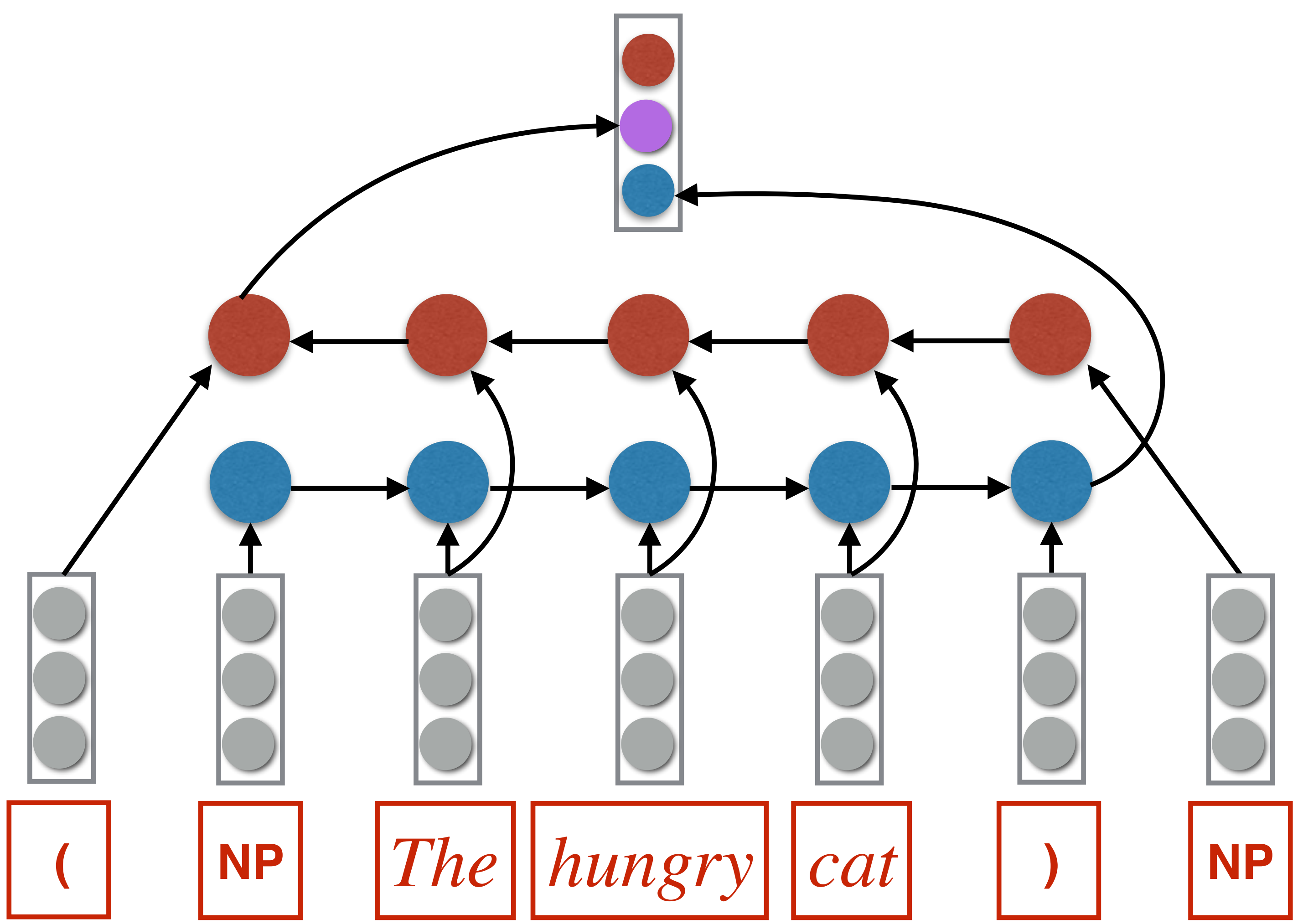


Recursion

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

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



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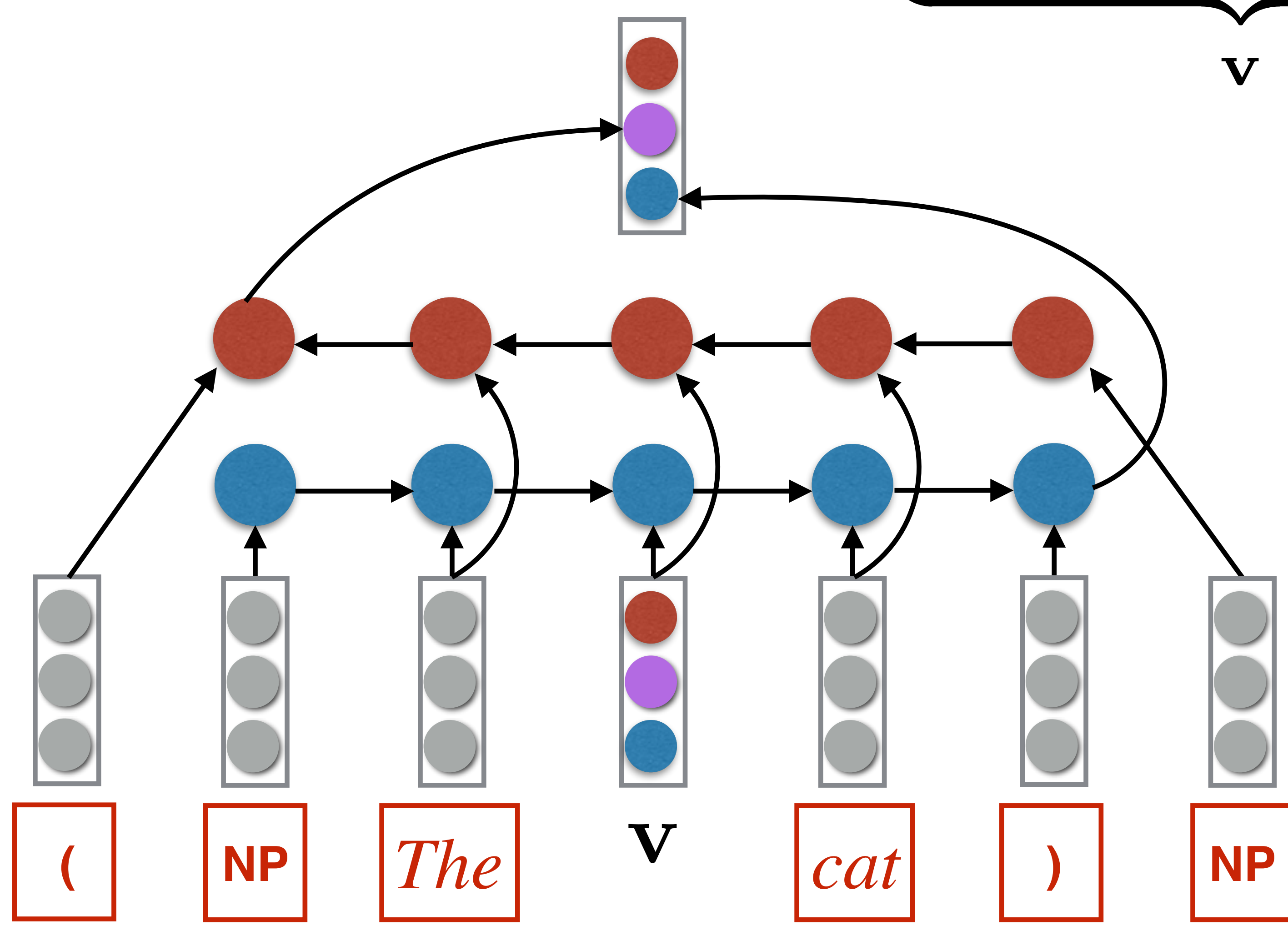
Need representation for: (NP *The hungry cat*)

(NP *The* $\underbrace{\text{(ADJP } \textit{very hungry}\text{)}}_{\mathbf{v}}$ *cat*)



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
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
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English PTB (LM)

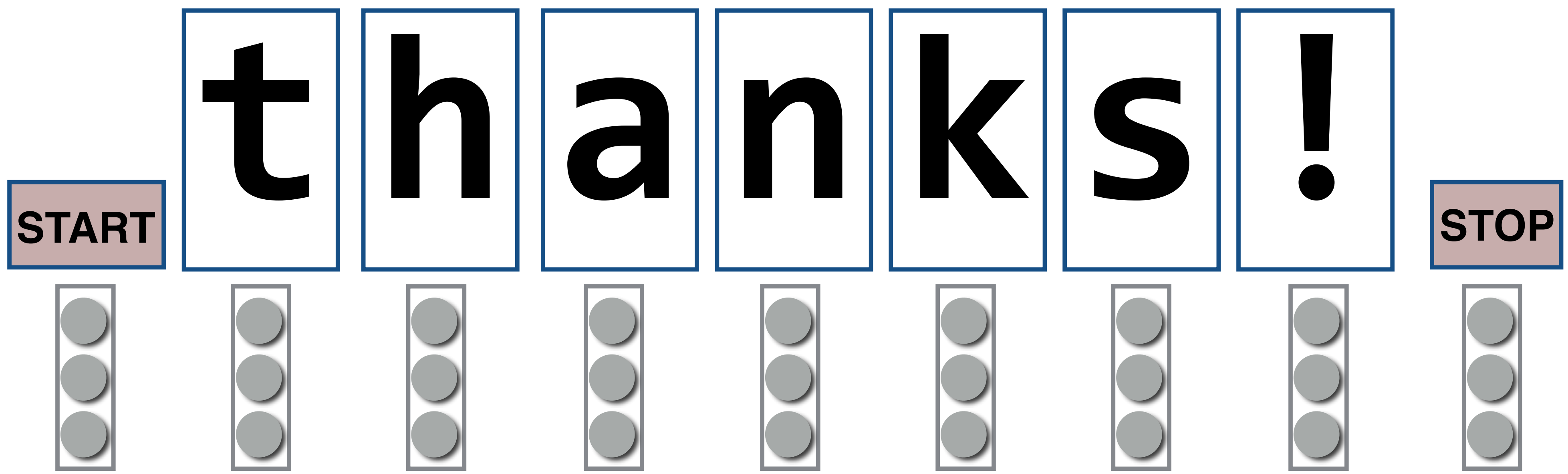
	Perplexity
5-gram IKN	169.3
LSTM + Dropout	113.4
Generative (IS)	**102.4**

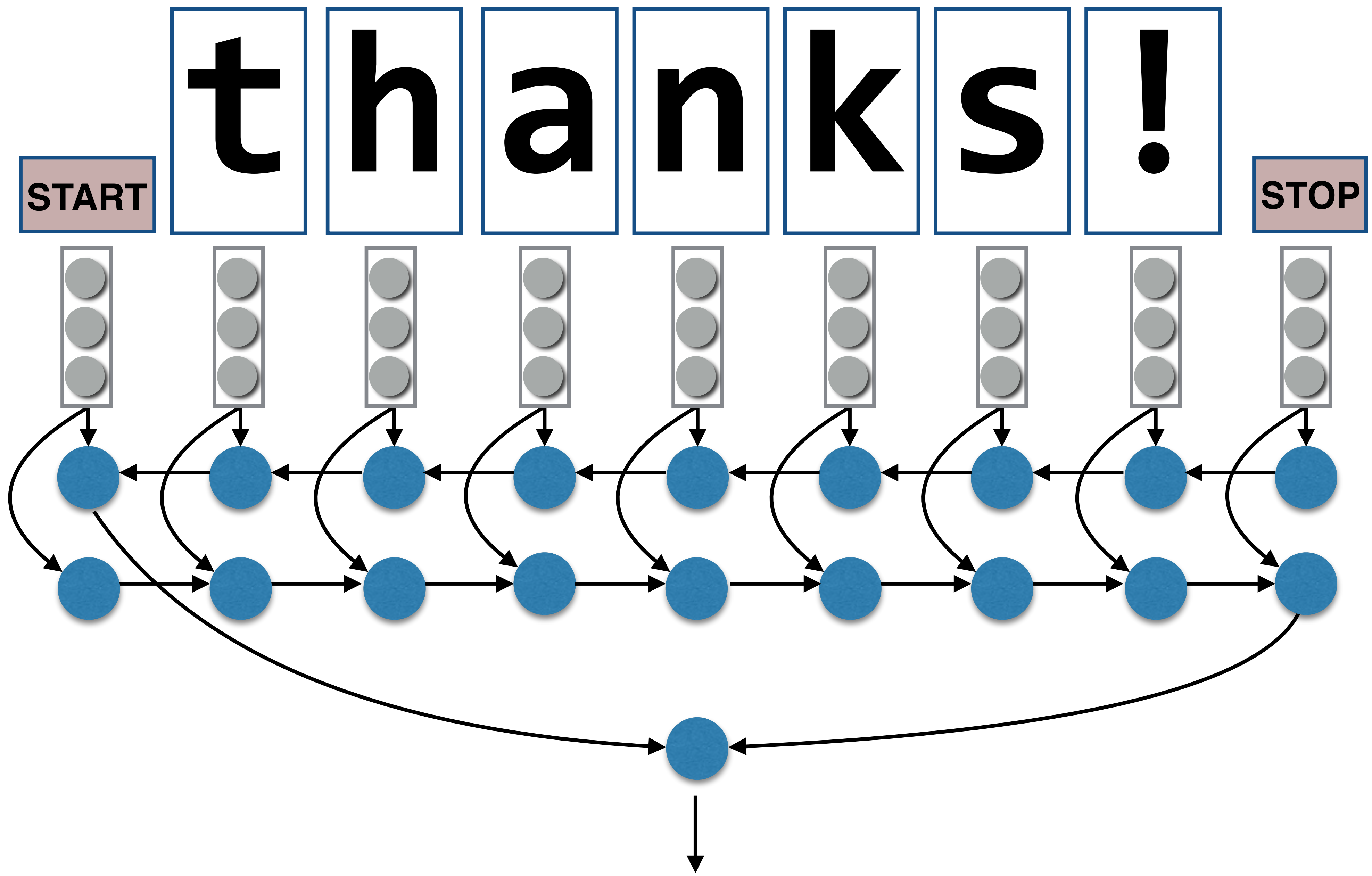
Chinese CTB (LM)

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

This Talk, In a Nutshell

- **Facts about language:**
  - **Arbitrariness** and **compositionality** exist at all levels
  - Language is sensitive to **hierarchy**, not **strings**
- **My work's hypothesis:**
  Models designed with these considerations structure explicit will outperform models that don't


START
thanks!
STOP



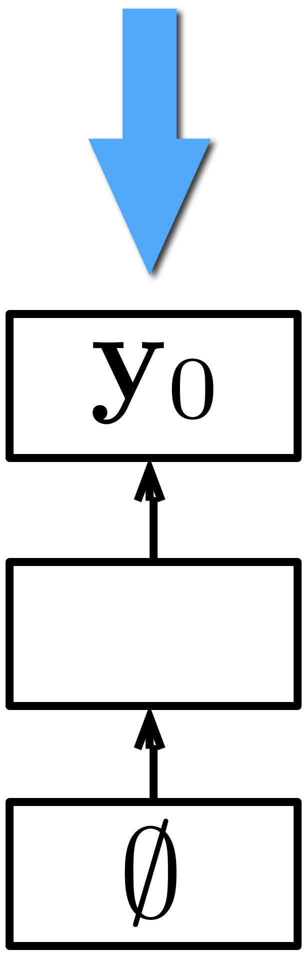
questions?

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)

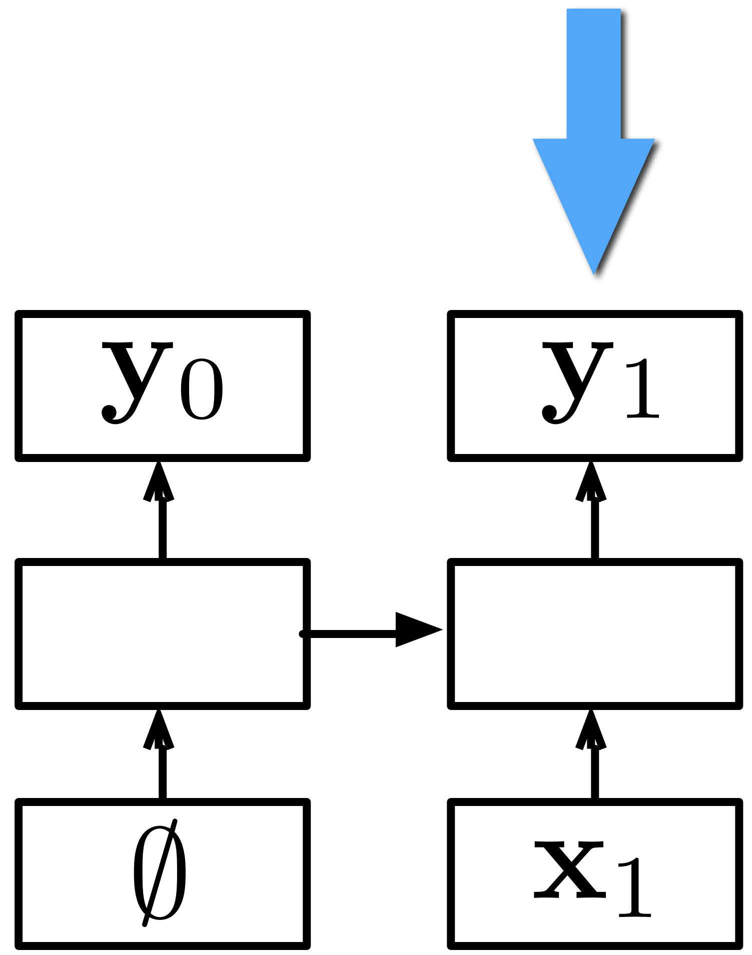
Implementing RNNGs

Stack RNNs



PUSH

Implementing RNNGs
Stack RNNs



POP

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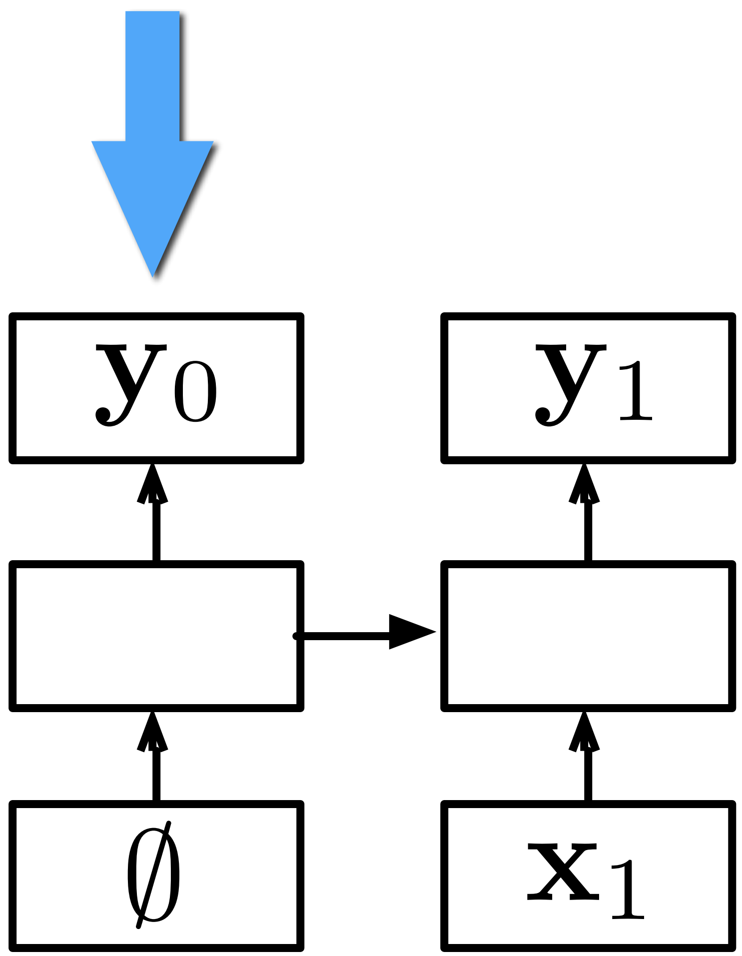
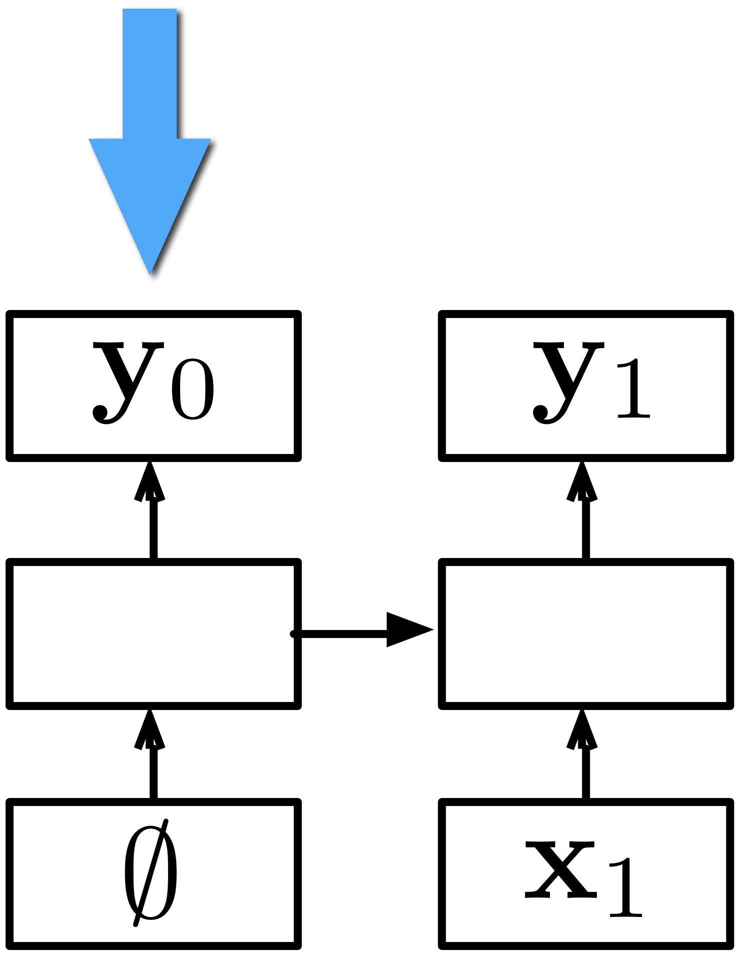


Implementing RNNGs
Stack RNNs



PUSH

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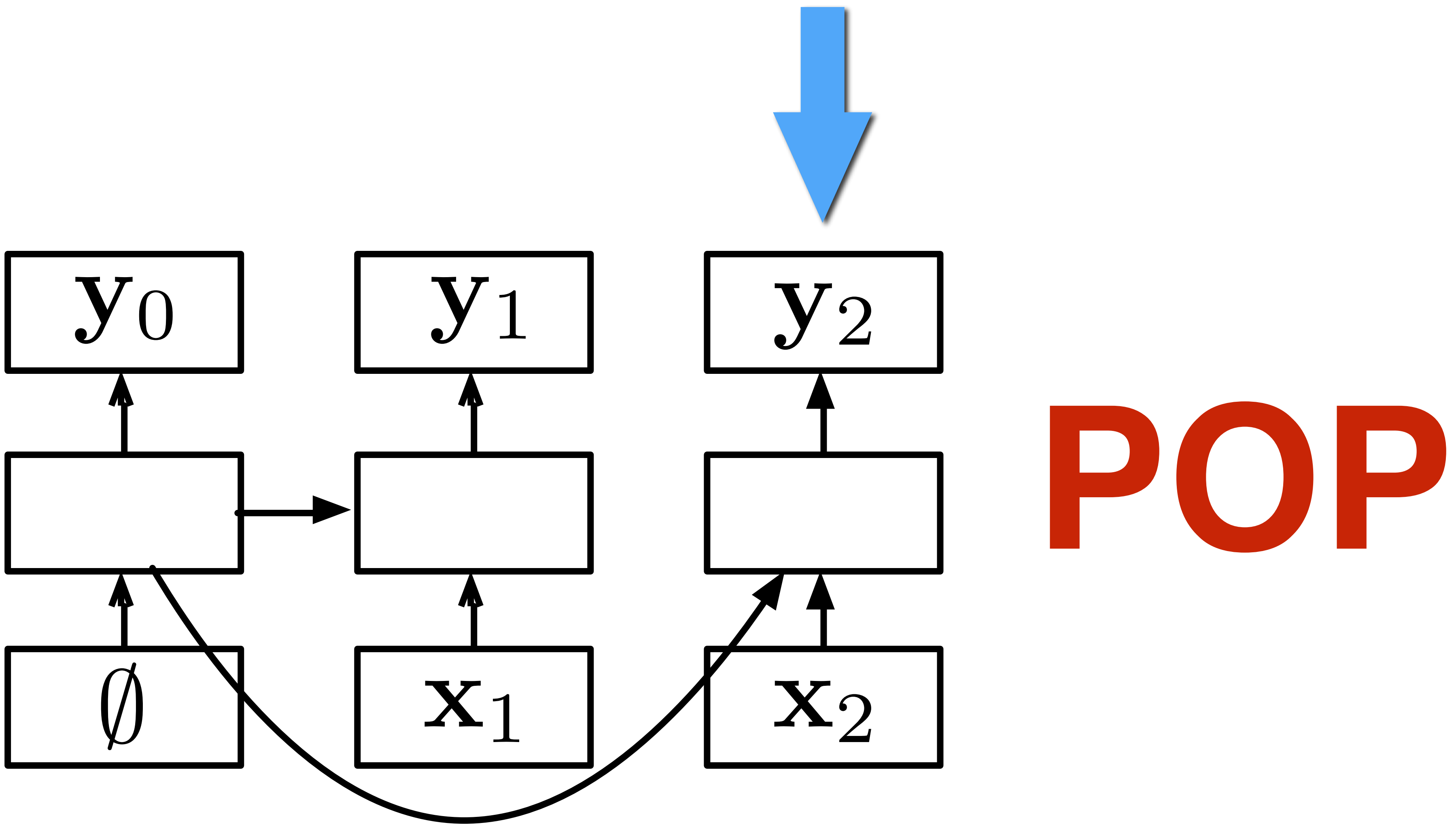

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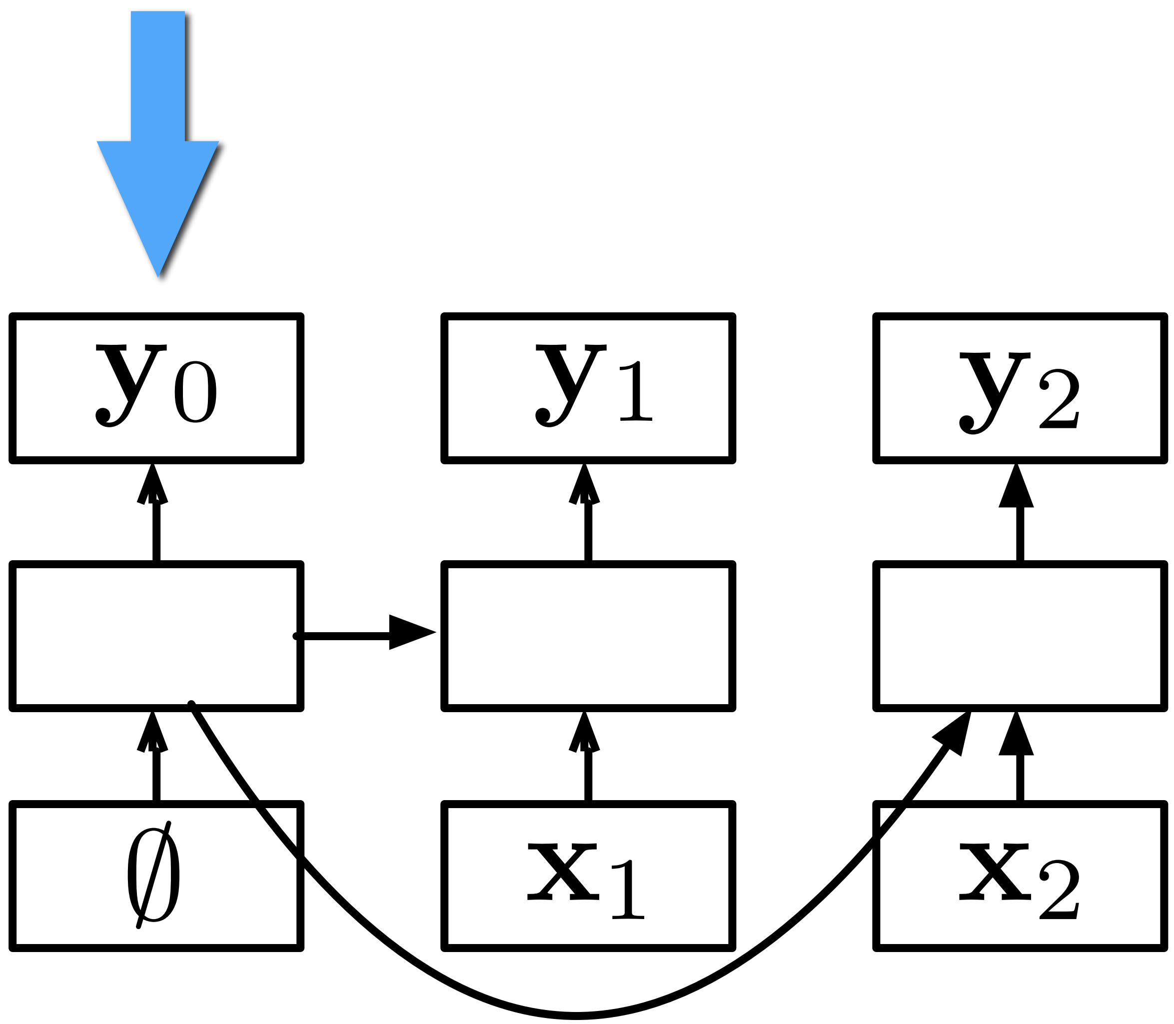

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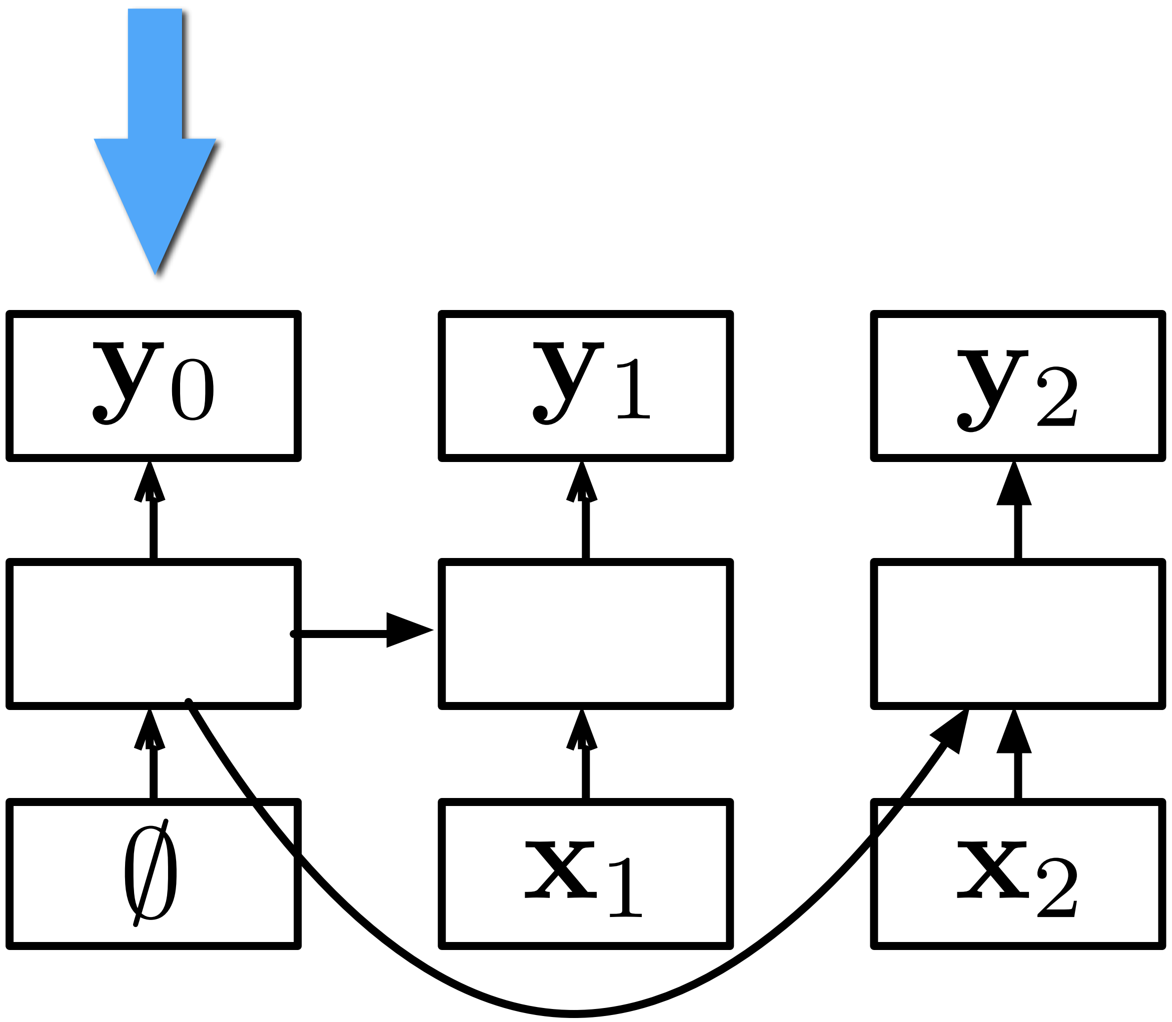

PUSH

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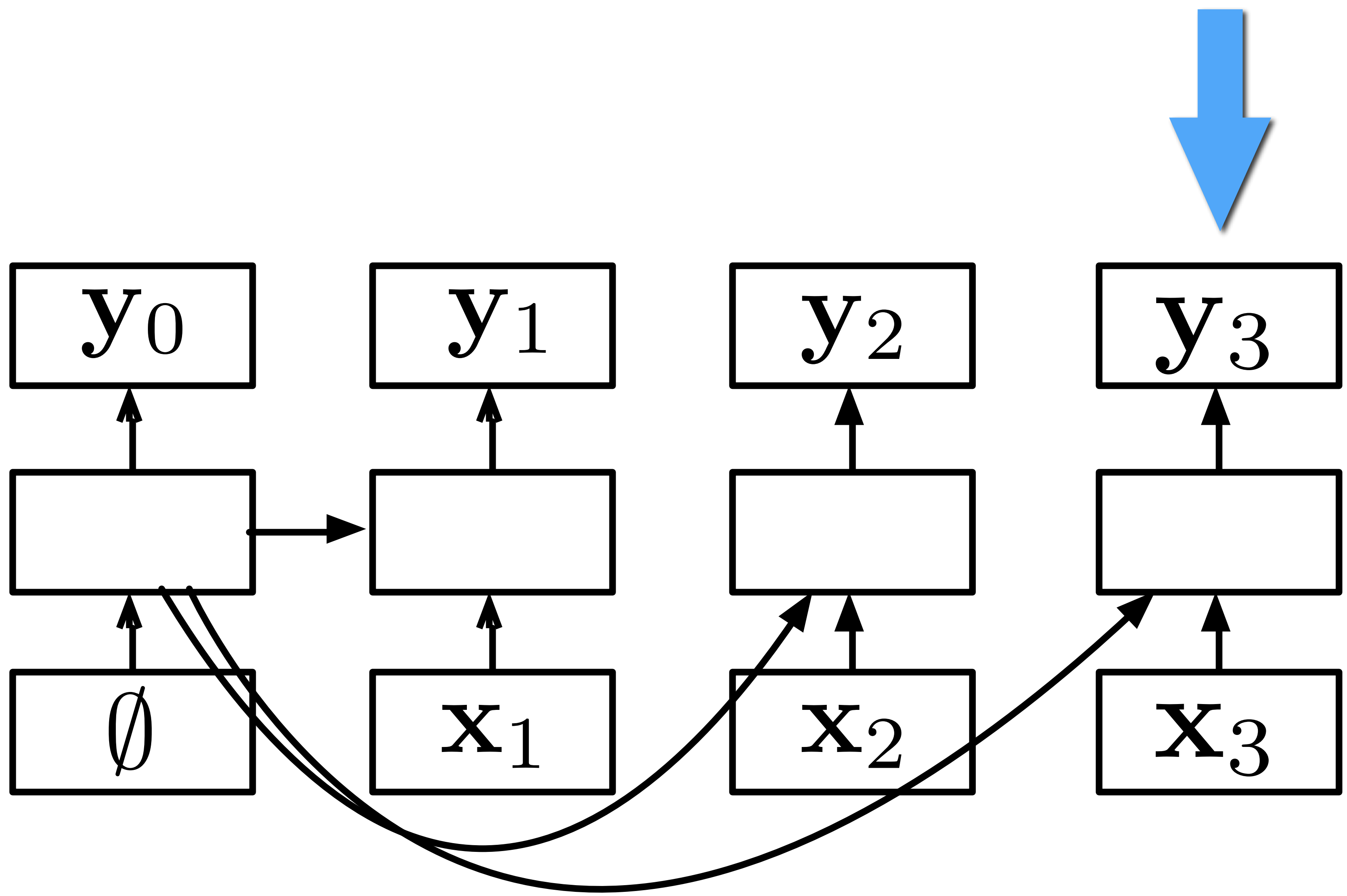

Importance Sampling

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