Deep Learning for Broad Coverage Semantics: SRL, Coreference, and Beyond

Luke Zettlemoyer[†*]

Joint work with **Luheng He**[†], **Kenton Lee**[†], **Matthew Peters***, Christopher Clark[†], Matthew Gardner*, Mohit Iyyer***,** Mandar Joshi[†], Mike Lewis[‡], Julian Michael[†], Mark Neumann*

[†] Paul G. Allen School of Computer Science & Engineering, University of Washington,
[‡] Facebook AI Research
[*] Allen Institute for Artificial Intelligence

PAUL G. ALLEN SCHOOL OF COMPUTER SCIENCE & ENGINEERING

ALLEN INSTITUTE for ARTIFICIAL INTELLIGENCE

Three Simple Steps that will Revolutionize Your ML Research

Step 1:

Step 2:

Step 3:

Three Simple Steps that will Revolutionize Your ML Research

Step 1: Gather lots of training data!

Step 2:

Step 3:

Three Simple Steps that will Revolutionize Your ML Research

Step 1: Gather lots of training data!

IMAGENET European Parliament twitter . . .

Step 2:

Step 3:

Three Simple Steps that will Revolutionize Your ML Research

Step 1: Gather lots of training data!

European Parliament

twitter

. . .

Step 2: Apply Deep Learning!!

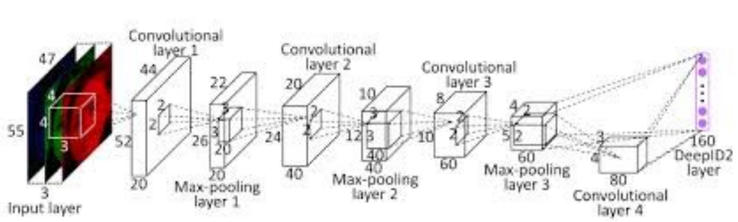
Step 3:

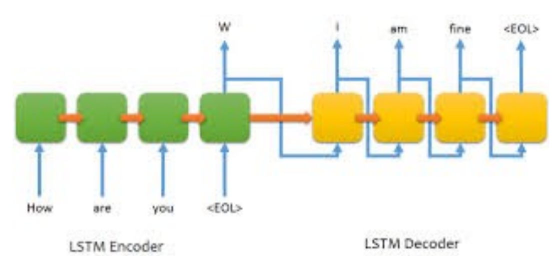
Three Simple Steps that will Revolutionize Your ML Research

Step 1: Gather lots of training data!

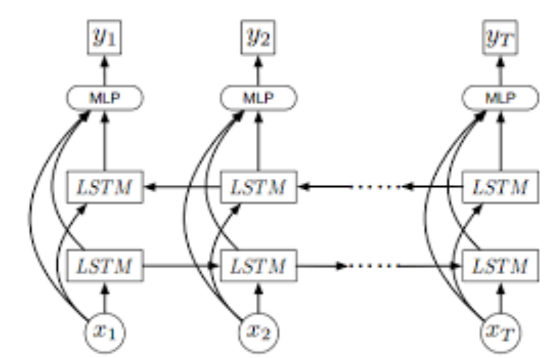
. . .

Step 2: Apply Deep Learning!!





. . .



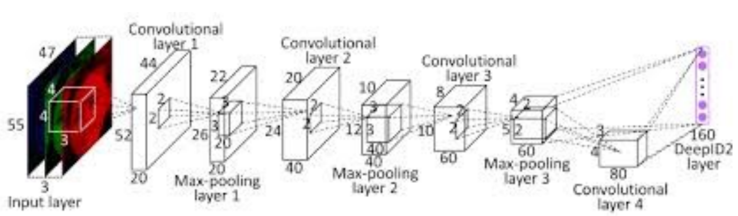
Step 3:

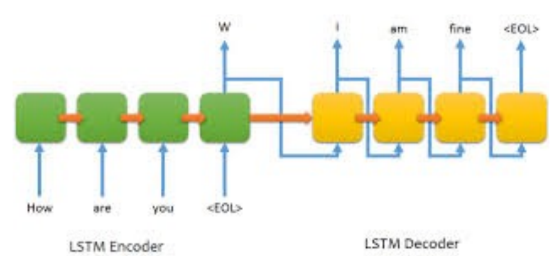
Three Simple Steps that will Revolutionize Your ML Research

Step 1: Gather lots of training data!

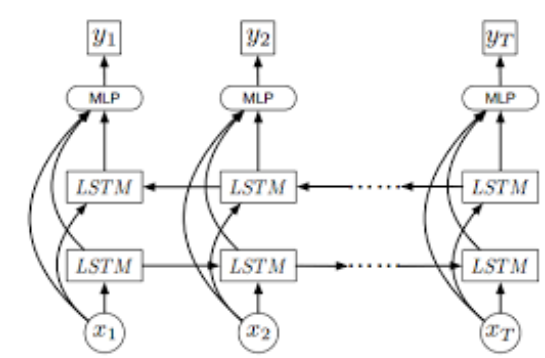
IMAGENET European Parliament twitter . . .

Step 2: Apply Deep Learning!!





. . .



Step 3: Observe Impressive Gains!!!

Broad Coverage Semantics

Example Tasks:

Coreference: clustering NPs

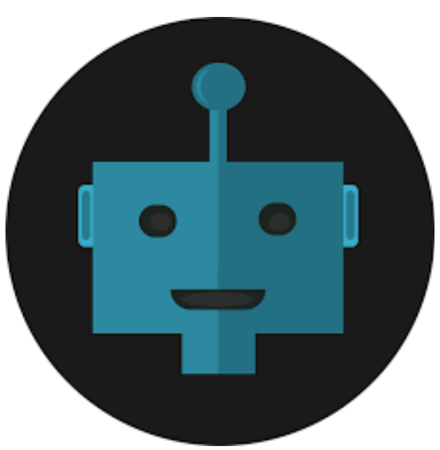
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Semantic Role Labeling: who did what, etc.

ARG0	NASA
PRED	*observe*
ARG1	an X-ray flare 400 times brighter than usual
TMP	On January 5, 2015

Many applications:

Question Answering



Information Extraction

Machine Translation

Does the Recipe Work for Broad Coverage Semantics?

Step 1: Gather lots of training data!

Step 2: Apply Deep Learning!!

Step 3: Observe Impressive Gains!!!

Does the Recipe Work for Broad Coverage Semantics?

Step 1: Gather lots of training data!

Challenge 1: Data is costly and limited (e.g. linguists required to label PennTreebank / OntoNotes)

Step 2: Apply Deep Learning!!

Step 3: Observe Impressive Gains!!!

Does the Recipe Work for Broad Coverage Semantics?

Step 1: Gather lots of training data!

Challenge 1: Data is costly and limited (e.g. linguists required to label PennTreebank / OntoNotes)

Step 2: Apply Deep Learning!!

Challenge 2: Pipeline of structured prediction problems with cascading errors (e.g. POS->Parsing->SRL->Coref)

Step 3: Observe Impressive Gains!!!

New Learning Approaches

New state-of-the-art results for two tasks:

Coreference:

A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Semantic Role Labeling:

ARG0	NASA
PRED	*observe*
ARG1	an X-ray flare 400 times brighter than usual
TMP	On January 5, 2015

Common themes:

- End-to-end training of deep neural networks
- No preprocessing (e.g., no POS, no parser, etc.)
- Large gains in accuracy with simpler models and no extra training data

role label

who
what
when
where
why
…

Semantic Role Labeling (SRL)

predicate → argument

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

My mug *broke* into pieces immediately.

Semantic Role Labeling (SRL)

role label

who
what
when
where
why
...

predicate argument

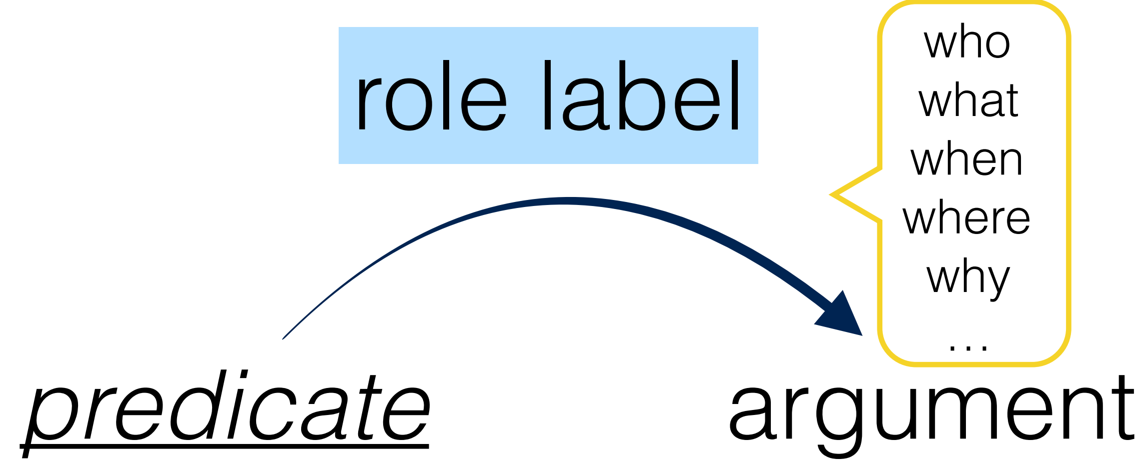
subj v obj prep

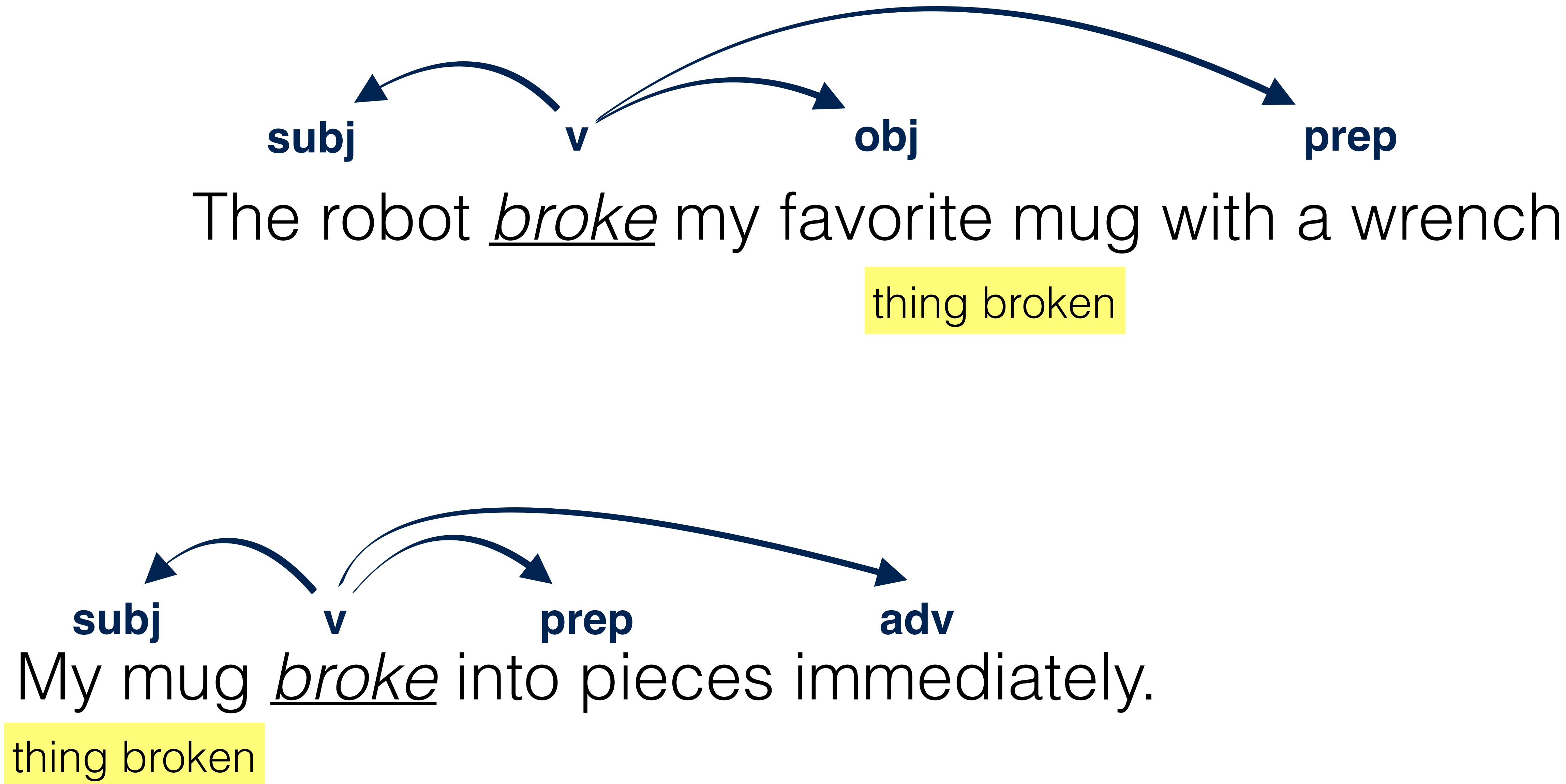
The robot *broke* my favorite mug with a wrench.

subj v prep adv

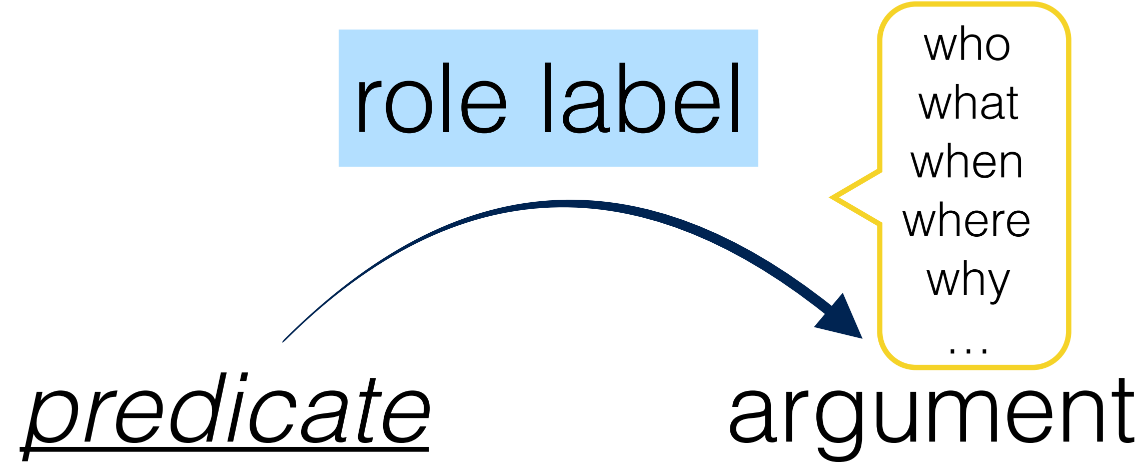
My mug *broke* into pieces immediately.

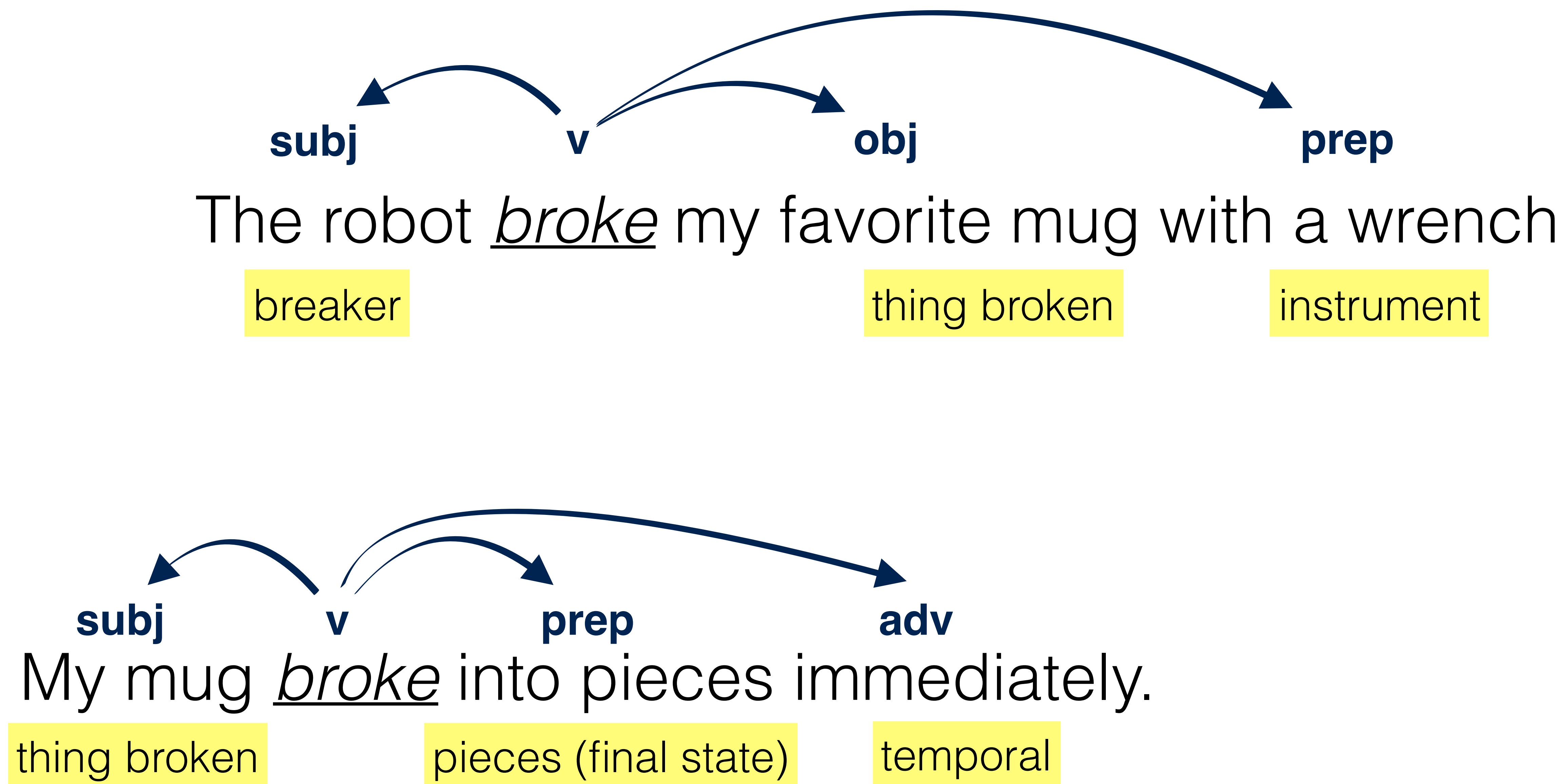
Semantic Role Labeling (SRL)



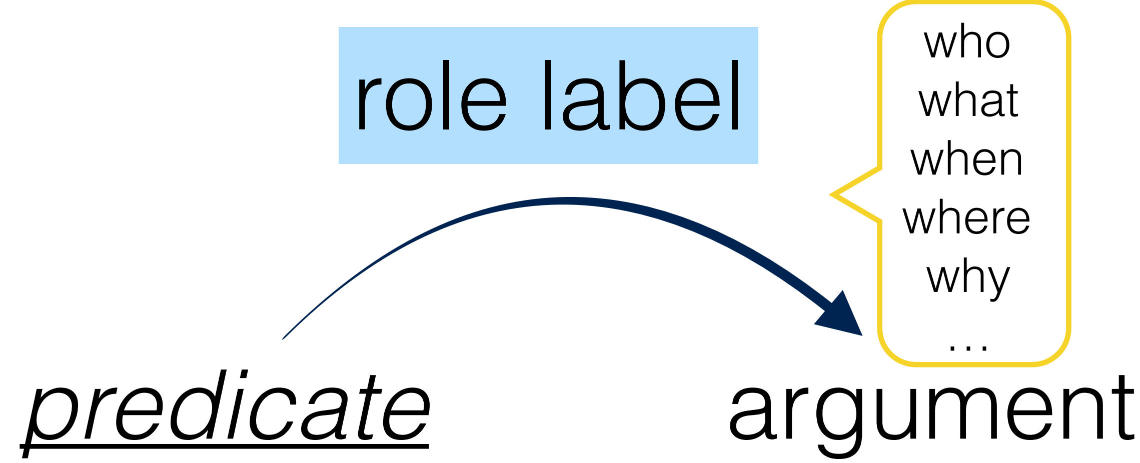


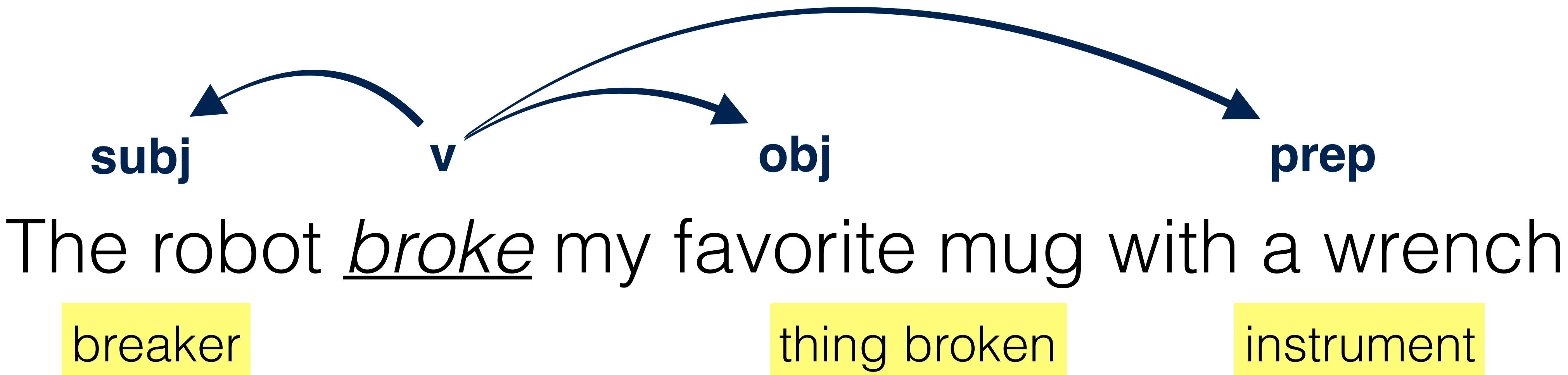
Semantic Role Labeling (SRL)

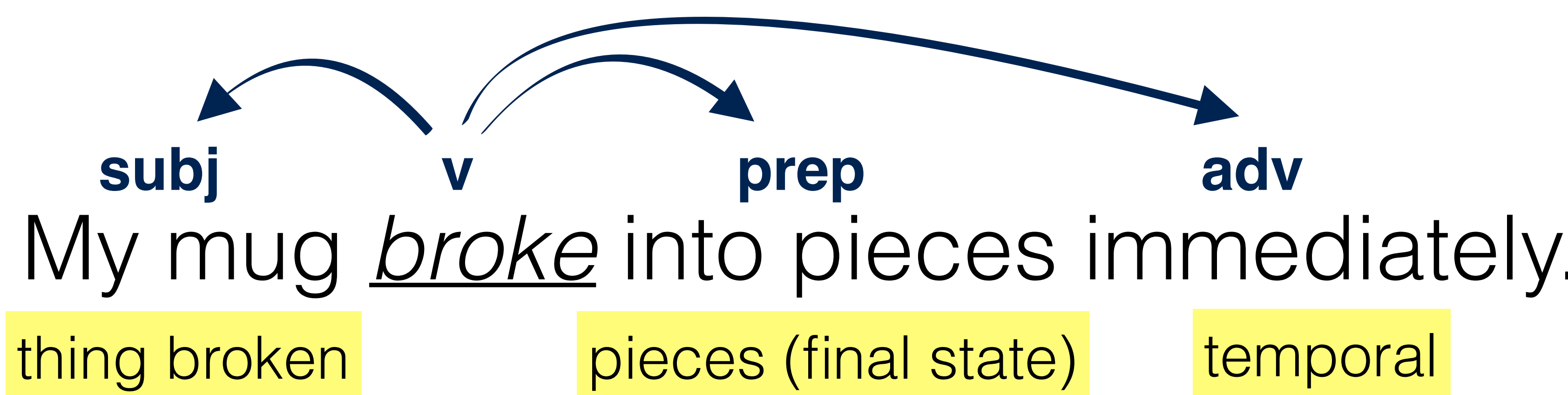




Semantic Role Labeling (SRL)



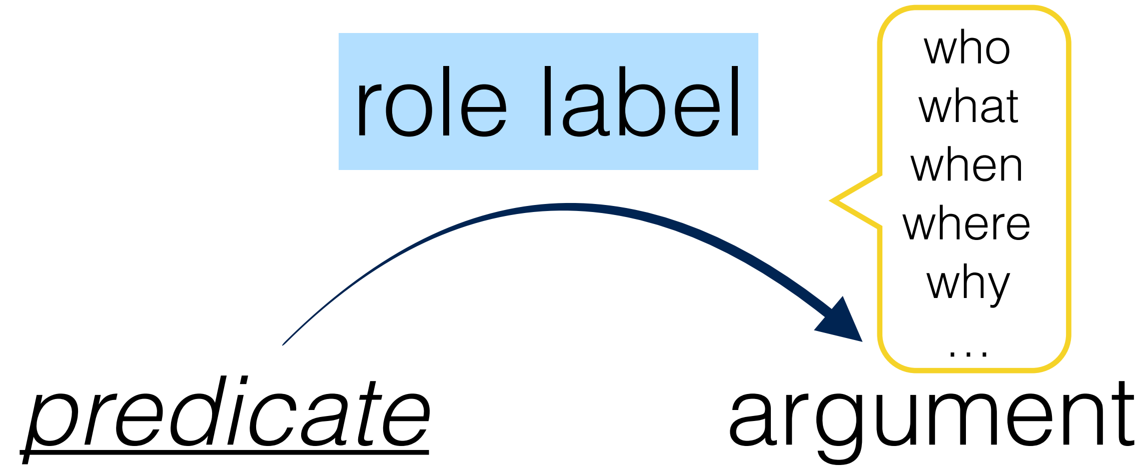


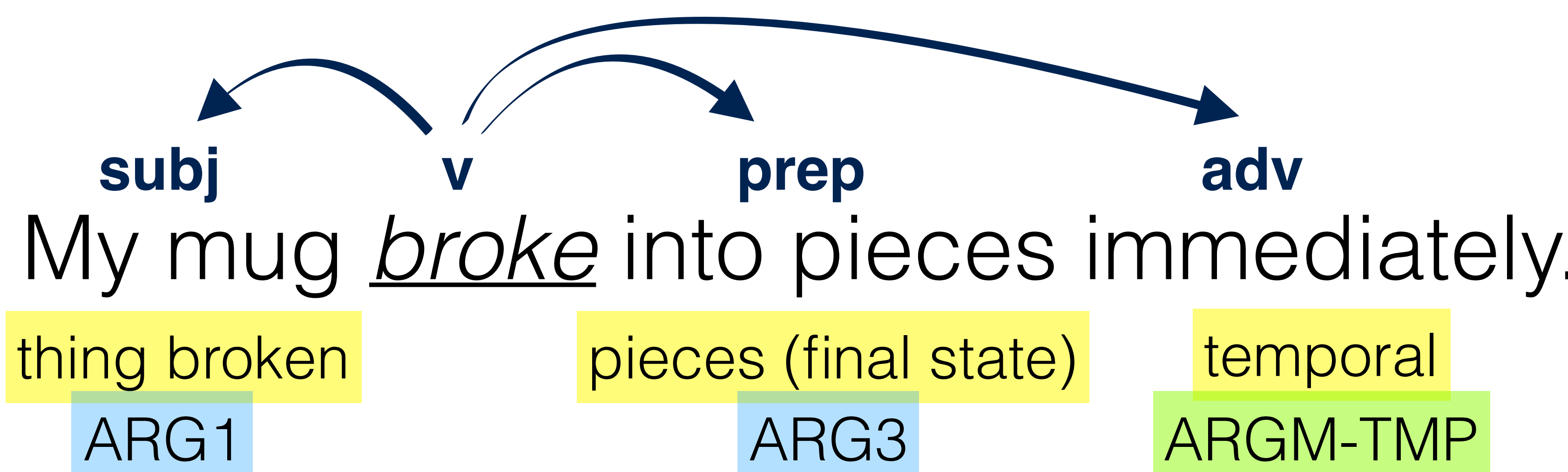


Frame: *break.01*

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

Semantic Role Labeling (SRL)





Frame: *break.01*

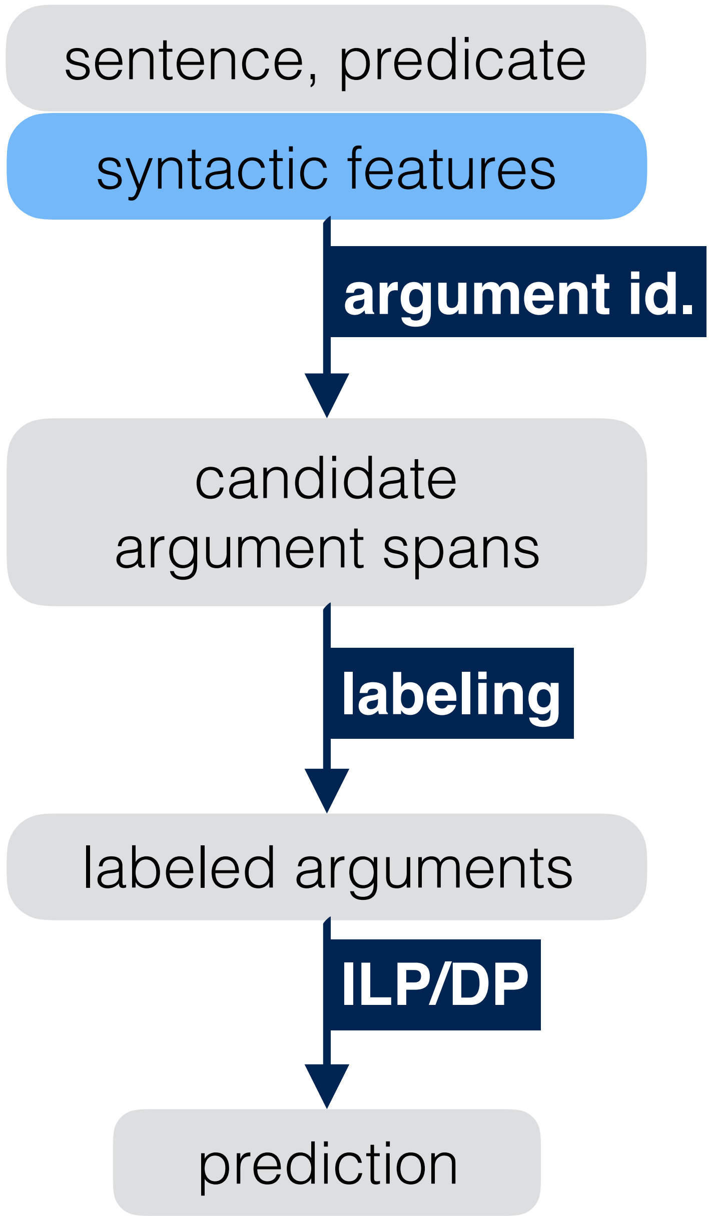
role	description
ARG0	breaker
ARG1	thing broken
ARG2	instrument
ARG3	pieces
ARG4	broken away from what?

SRL is a hard problem …

- Over 10 years, F1 on PropBank:
  80.3 (Toutanova et al, 2005) — **80.3** (FitzGerald et al, 2015)
- Many interesting challenges:
  Syntactic alternation
  Prepositional phrase attachment
  Long-range dependencies and common sense

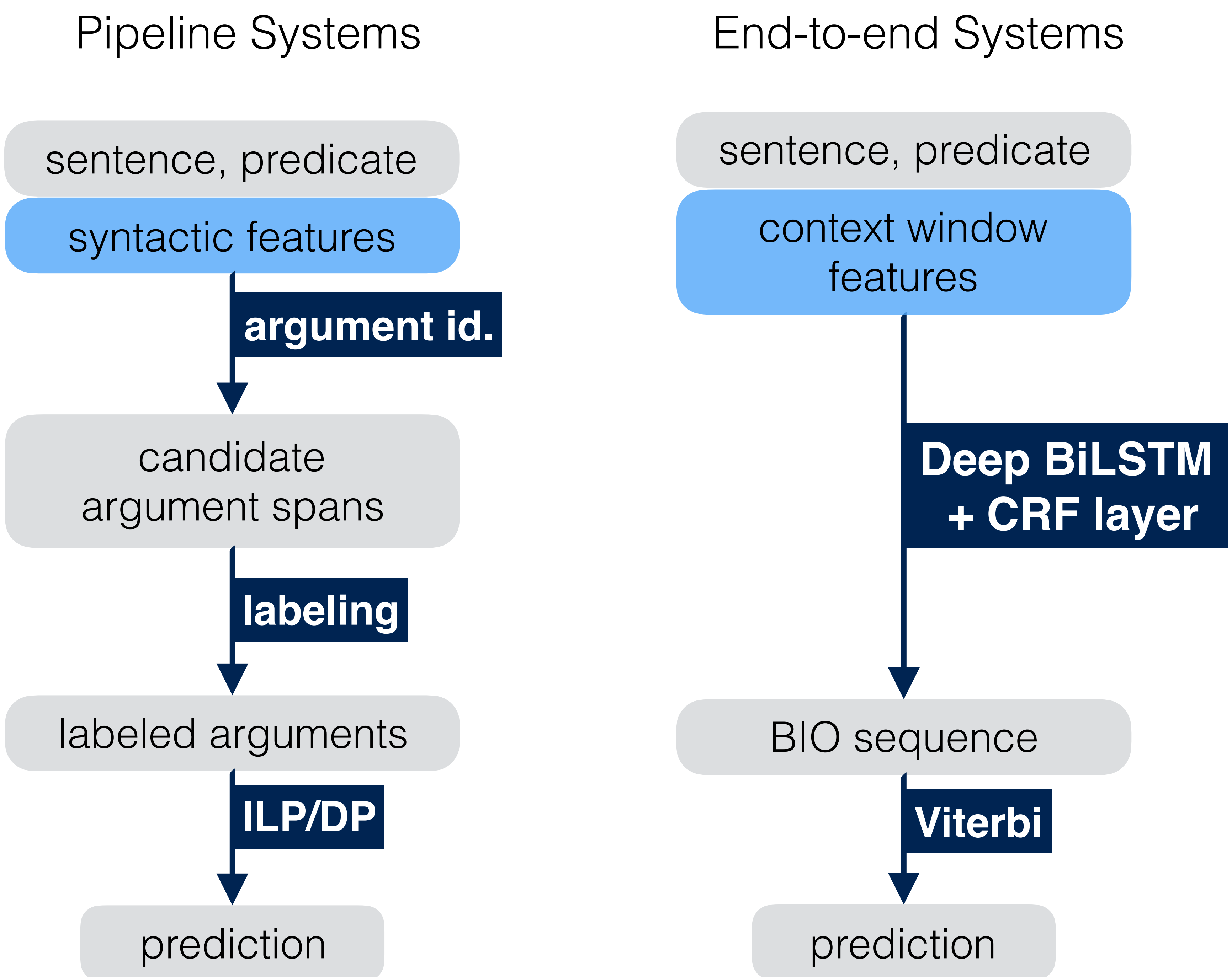
SRL Systems

Pipeline Systems



Punyakanok et al., 2008
Täckström et al., 2015
FitzGerald et al., 2015

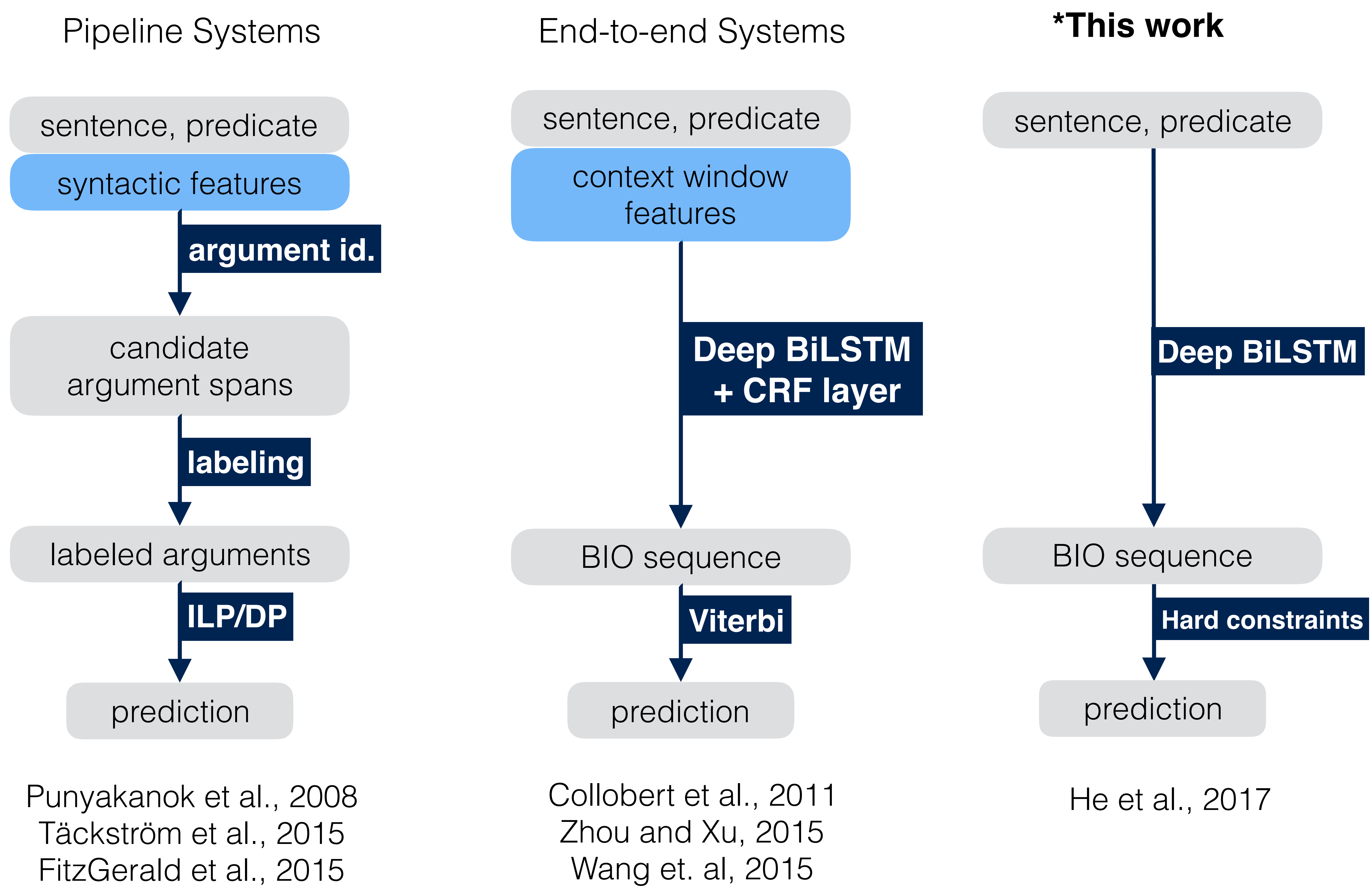
SRL Systems



Punyakanok et al., 2008
Täckström et al., 2015
FitzGerald et al., 2015

Collobert et al., 2011
Zhou and Xu, 2015
Wang et. al, 2015

SRL Systems


Pipeline Systems
sentence, predicate
syntactic features
argument id.
candidate argument spans
labeling
labeled arguments
ILP/DP
prediction
Punyakanok et al., 2008
Täckström et al., 2015
FitzGerald et al., 2015
End-to-end Systems
sentence, predicate
context window features
Deep BiLSTM + CRF layer
BIO sequence
Viterbi
prediction
Collobert et al., 2011
Zhou and Xu, 2015
Wang et. al, 2015
*This work
sentence, predicate
Deep BiLSTM
BIO sequence
Hard constraints
prediction
He et al., 2017

SRL as BIO Tagging Problem

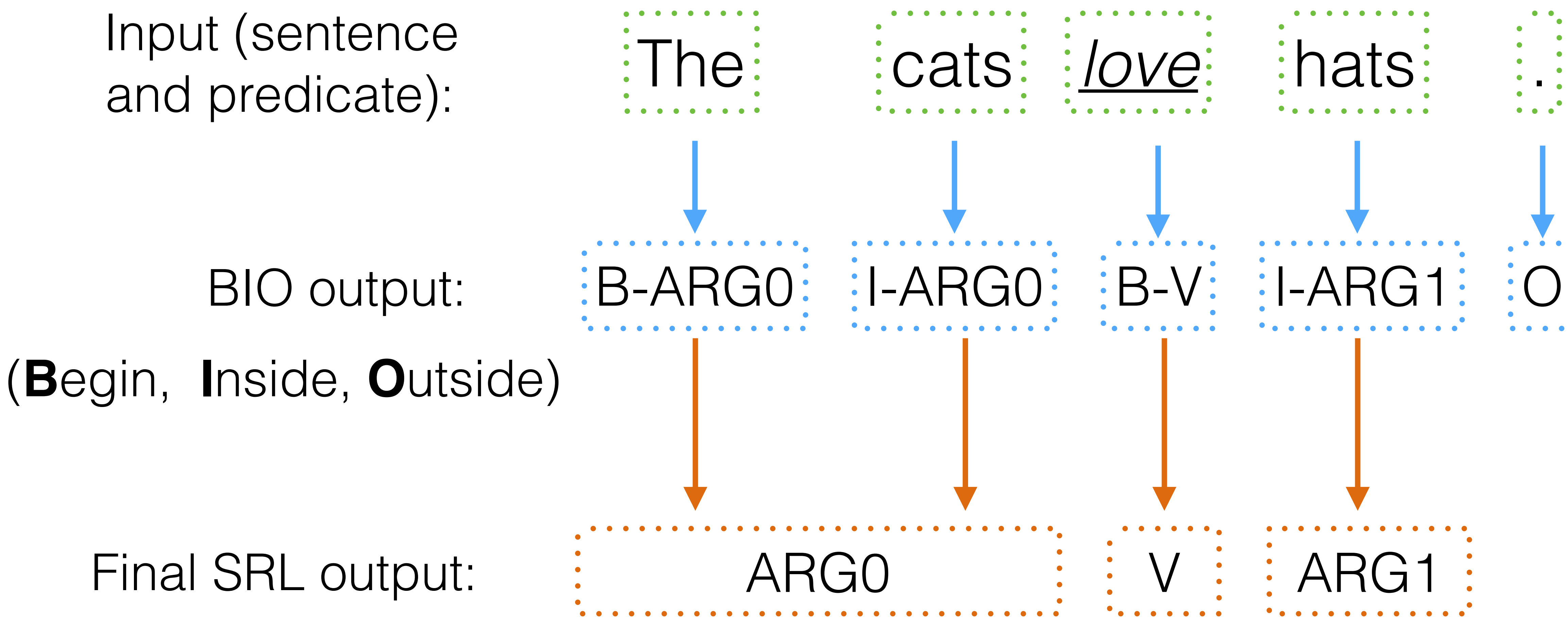
Input (sentence and predicate): The cats <u>*love*</u> hats .

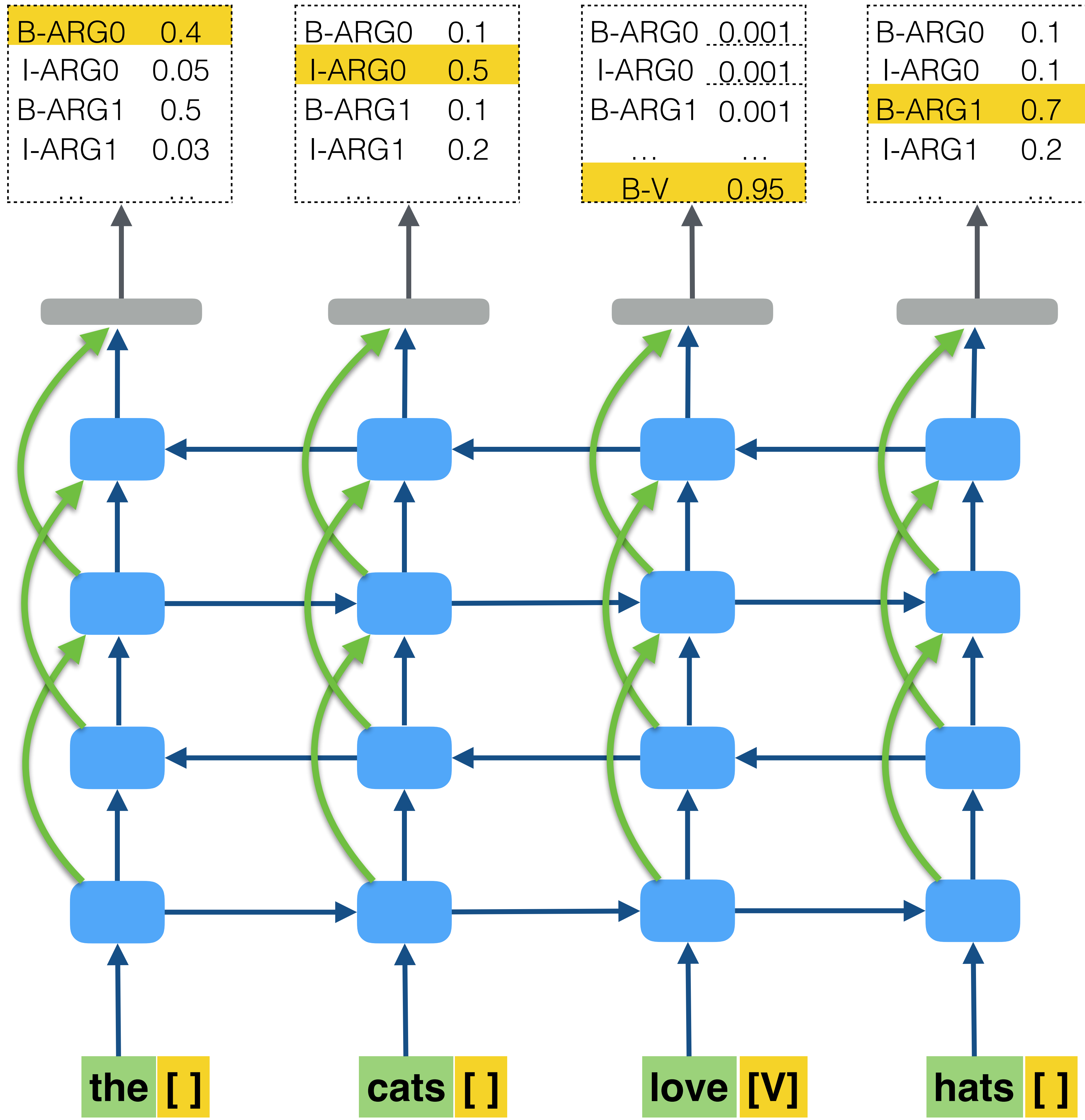
SRL as BIO Tagging Problem

Input (sentence and predicate):	The	cats	<u>*love*</u>	hats	.
BIO output:	B-ARG0	I-ARG0	B-V	I-ARG1	O

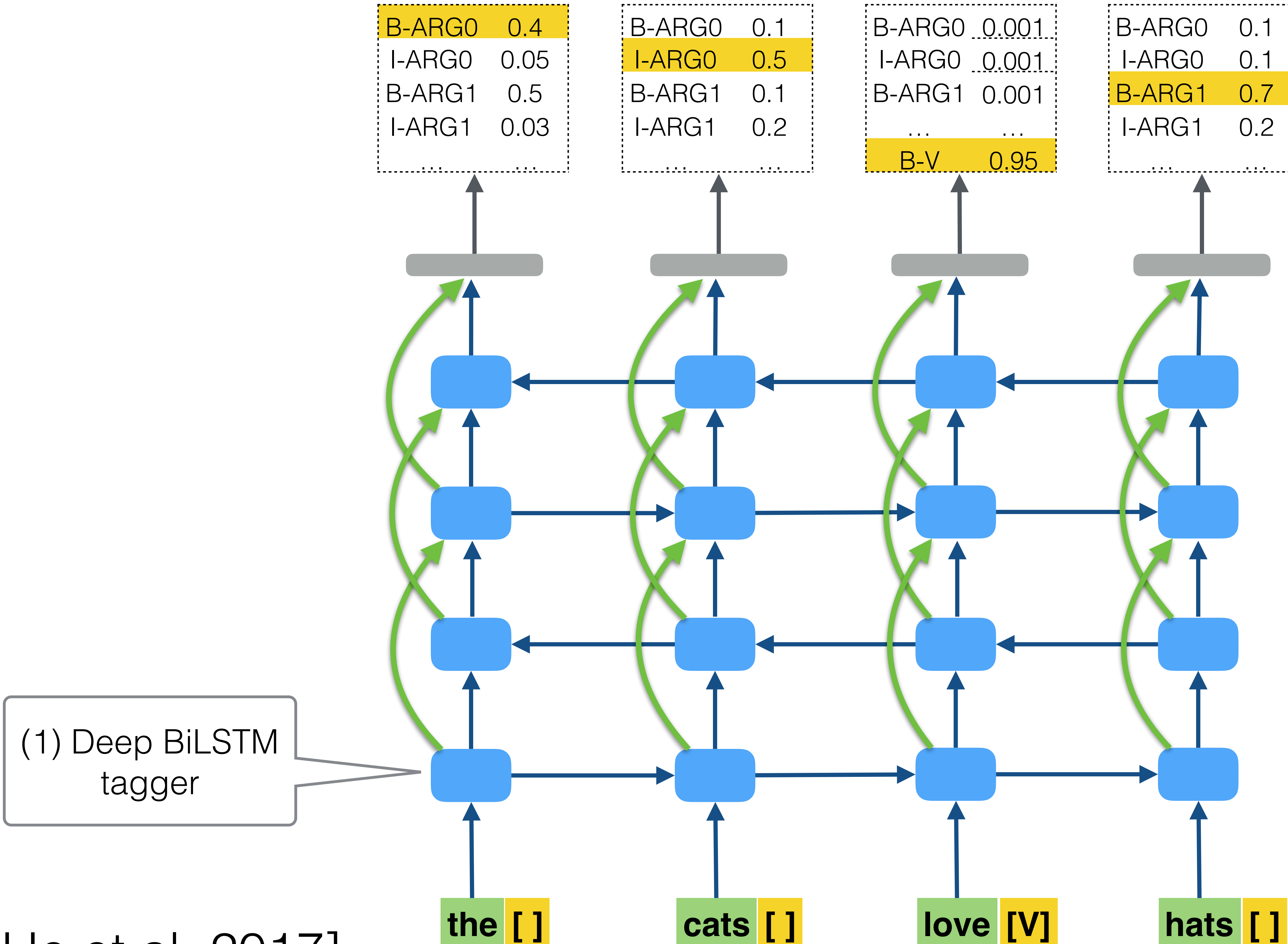
(**B**egin, **I**nside, **O**utside)

SRL as BIO Tagging Problem



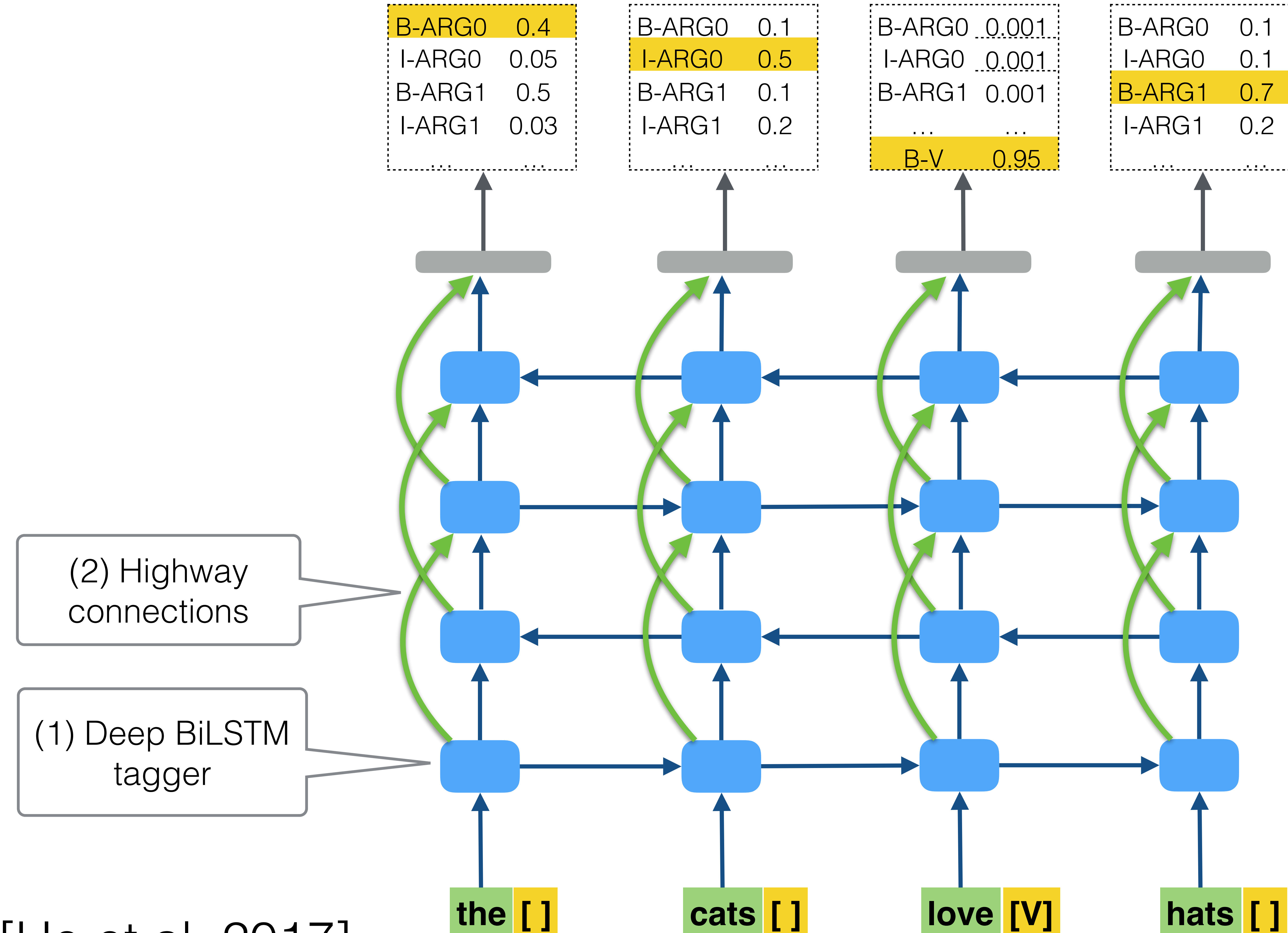

B-ARG0 0.4
I-ARG0 0.05
B-ARG1 0.5
I-ARG1 0.03
... ...
B-ARG0 0.1
I-ARG0 0.5
B-ARG1 0.1
I-ARG1 0.2
... ...
B-ARG0 0.001
I-ARG0 0.001
B-ARG1 0.001
... ...
B-V 0.95
B-ARG0 0.1
I-ARG0 0.1
B-ARG1 0.7
I-ARG1 0.2
... ...
the [ ]
cats [ ]
love [V]
hats [ ]

[He et al, 2017]

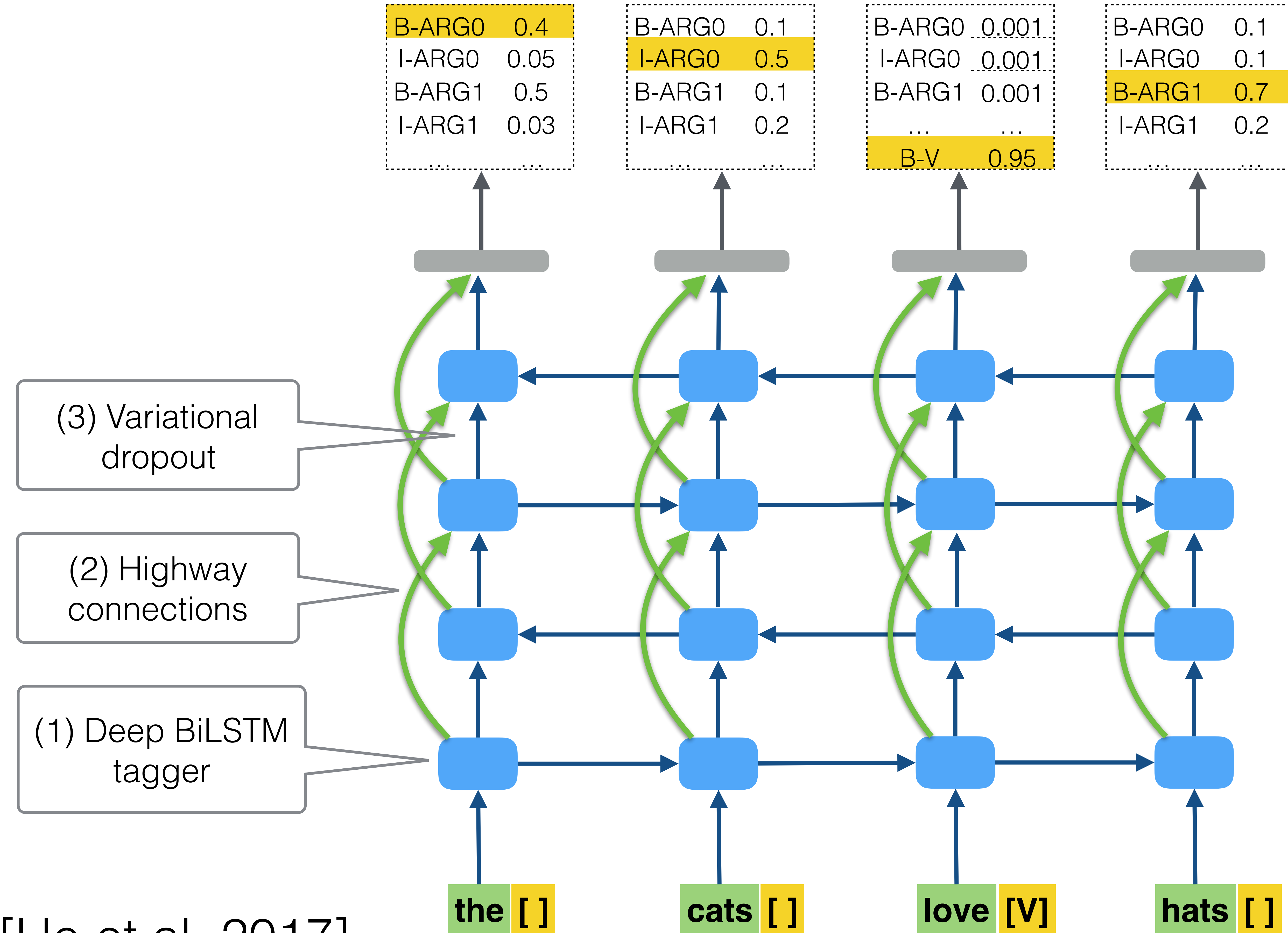


B-ARG0 0.4
I-ARG0 0.05
B-ARG1 0.5
I-ARG1 0.03
... ...
B-ARG0 0.1
I-ARG0 0.5
B-ARG1 0.1
I-ARG1 0.2
... ...
B-ARG0 0.001
I-ARG0 0.001
B-ARG1 0.001
... ...
B-V 0.95
B-ARG0 0.1
I-ARG0 0.1
B-ARG1 0.7
I-ARG1 0.2
... ...
(1) Deep BiLSTM tagger
the [ ]
cats [ ]
love [V]
hats [ ]

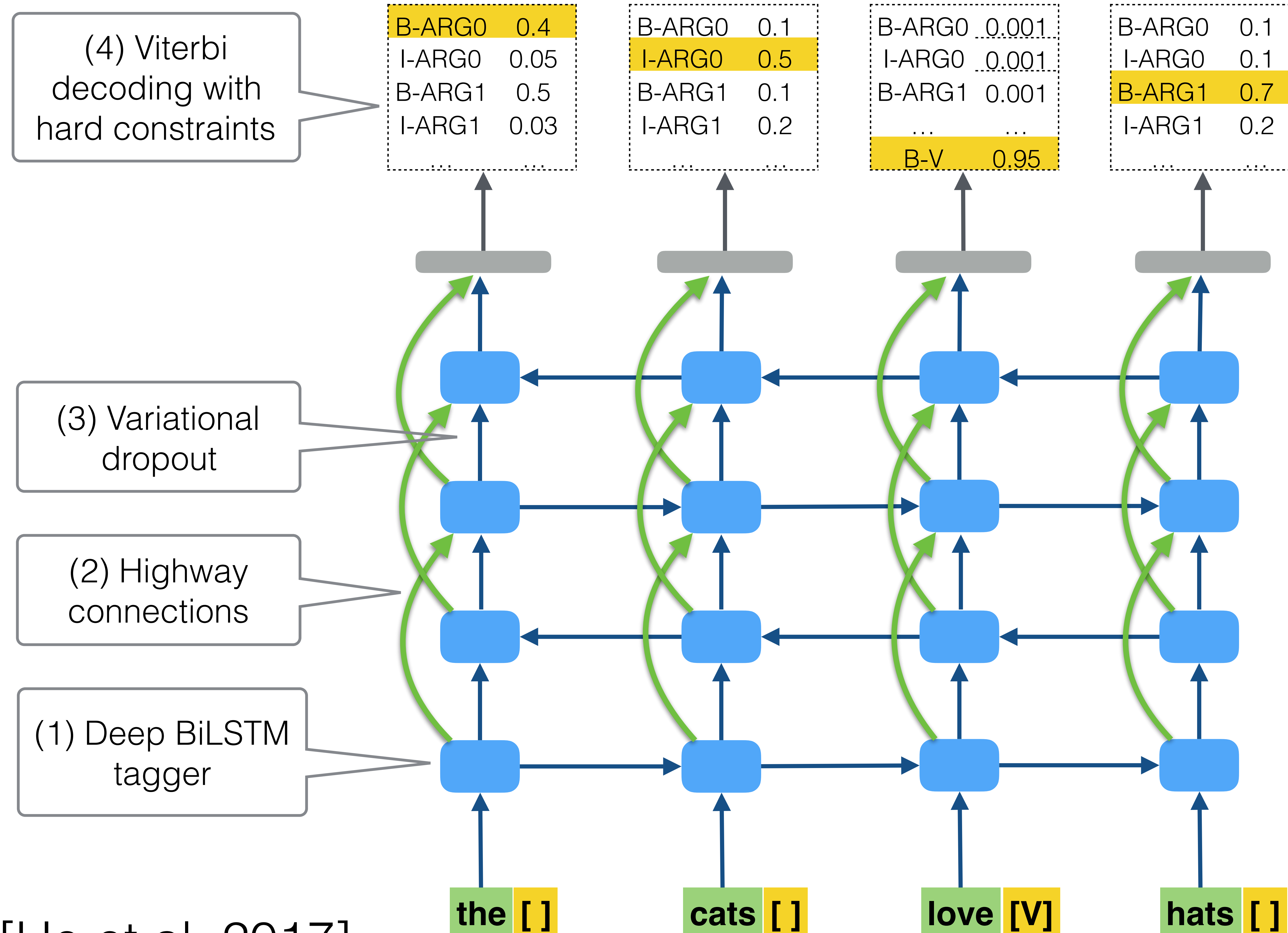
[He et al, 2017]


B-ARG0 0.4
I-ARG0 0.05
B-ARG1 0.5
I-ARG1 0.03
... ...
B-ARG0 0.1
I-ARG0 0.5
B-ARG1 0.1
I-ARG1 0.2
... ...
B-ARG0 0.001
I-ARG0 0.001
B-ARG1 0.001
... ...
B-V 0.95
B-ARG0 0.1
I-ARG0 0.1
B-ARG1 0.7
I-ARG1 0.2
... ...
(2) Highway connections
(1) Deep BiLSTM tagger
the [ ]
cats [ ]
love [V]
hats [ ]

[He et al, 2017]


B-ARG0 0.4
I-ARG0 0.05
B-ARG1 0.5
I-ARG1 0.03
... ...
B-ARG0 0.1
I-ARG0 0.5
B-ARG1 0.1
I-ARG1 0.2
... ...
B-ARG0 0.001
I-ARG0 0.001
B-ARG1 0.001
... ...
B-V 0.95
B-ARG0 0.1
I-ARG0 0.1
B-ARG1 0.7
I-ARG1 0.2
... ...
(3) Variational dropout
(2) Highway connections
(1) Deep BiLSTM tagger
the [ ]
cats [ ]
love [V]
hats [ ]

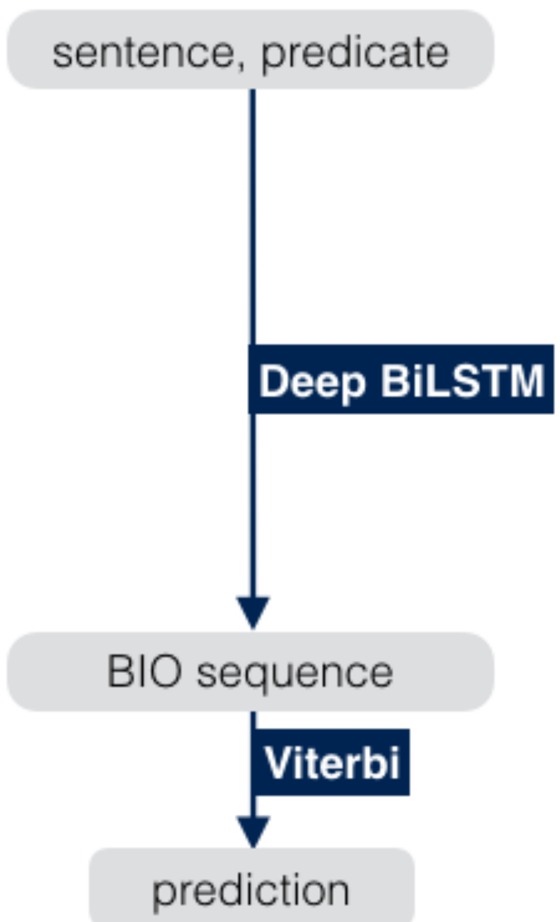
[He et al, 2017]



(4) Viterbi decoding with hard constraints
(3) Variational dropout
(2) Highway connections
(1) Deep BiLSTM tagger
B-ARG0 0.4
I-ARG0 0.05
B-ARG1 0.5
I-ARG1 0.03
... ...
B-ARG0 0.1
I-ARG0 0.5
B-ARG1 0.1
I-ARG1 0.2
... ...
B-ARG0 0.001
I-ARG0 0.001
B-ARG1 0.001
... ...
B-V 0.95
B-ARG0 0.1
I-ARG0 0.1
B-ARG1 0.7
I-ARG1 0.2
... ...
the [ ]
cats [ ]
love [V]
hats [ ]

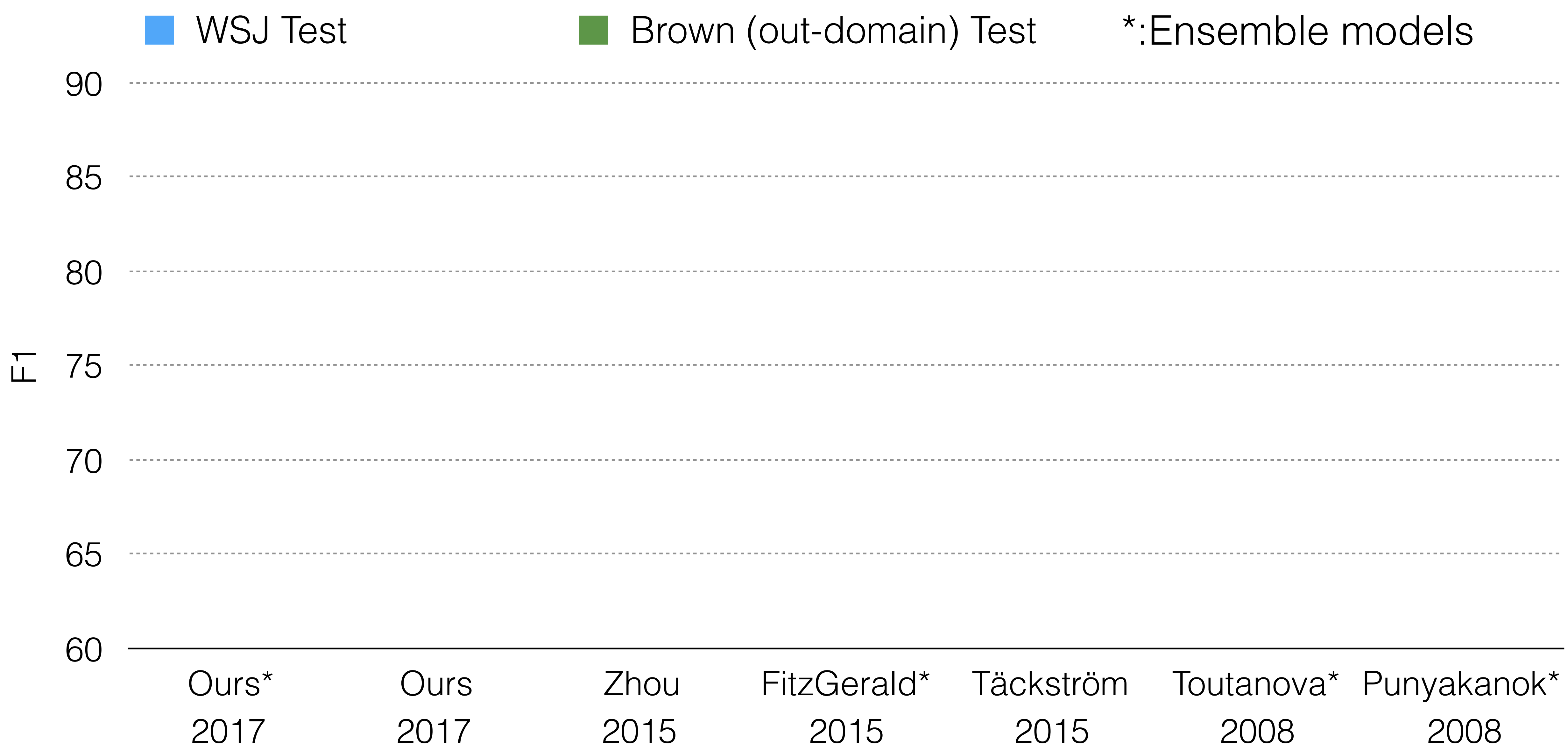
[He et al, 2017]

Other Implementation Details …

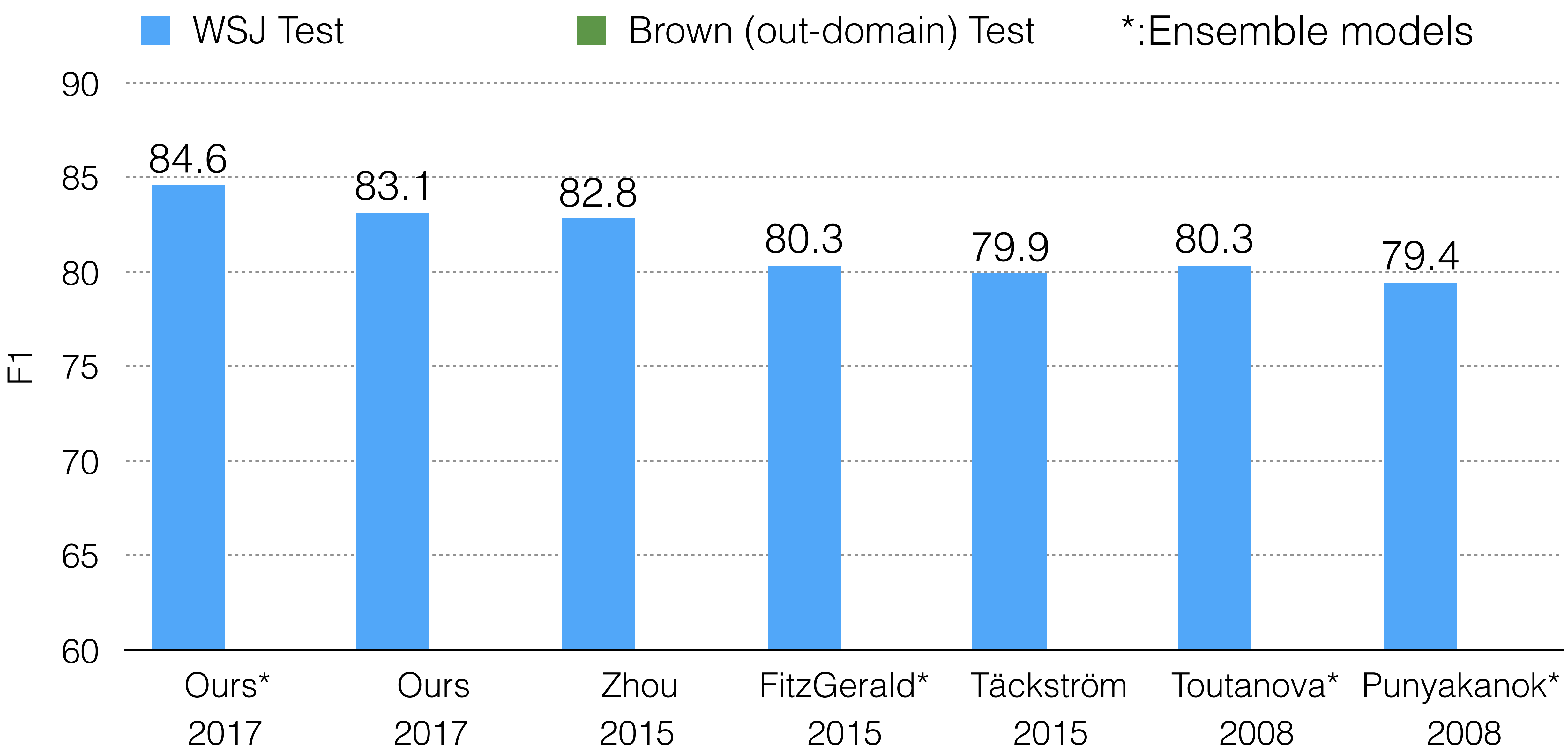


- 8 layer BiLSTMs with 300D hidden layers.
- 100D GloVe embeddings, updated during training.
- **Orthonormal initialization** for LSTM weight matrices (Saxe et al., 2013)
- 5 model ensemble with **product-of-experts** (Hinton 2002)
- Trained for 500 epochs.

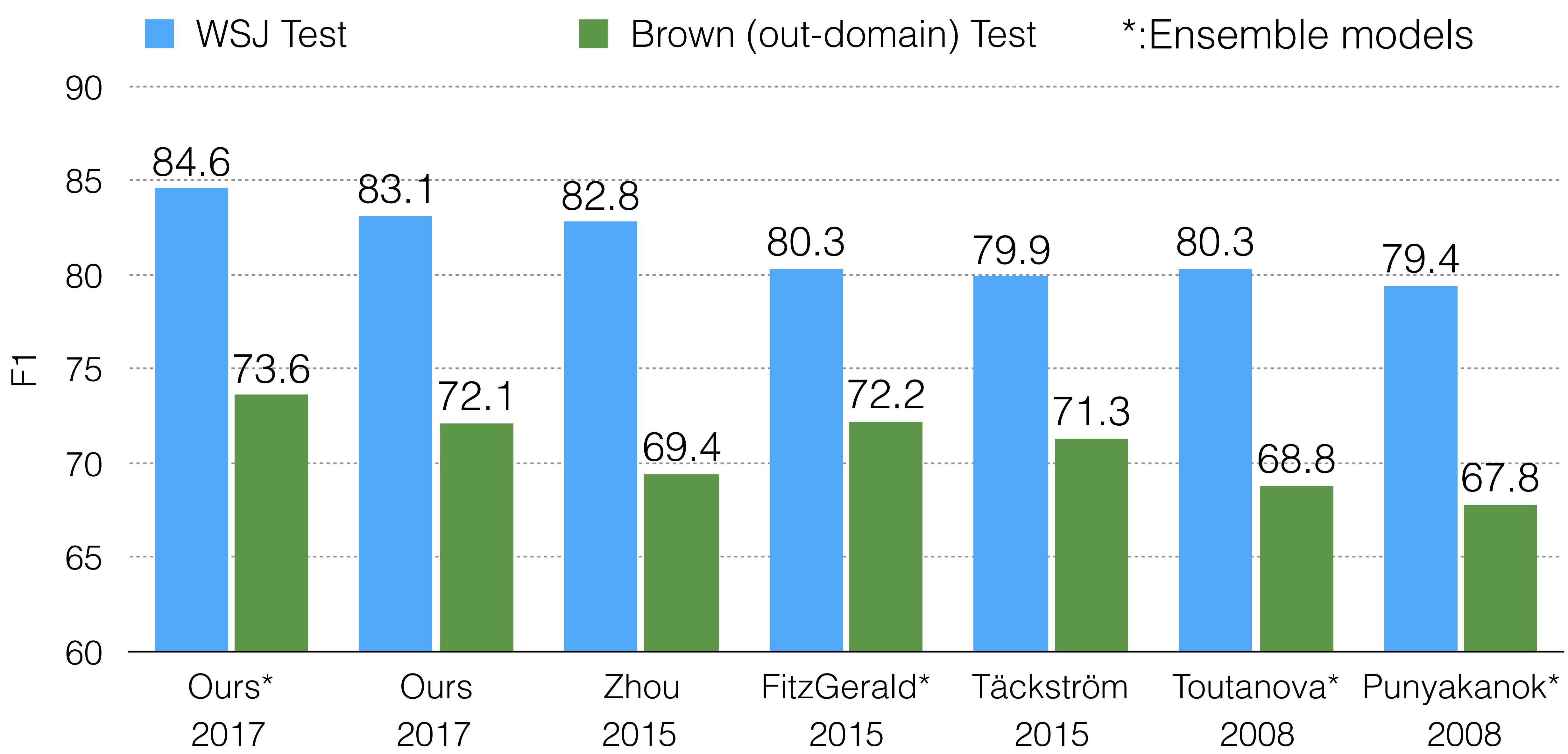
CoNLL 2005 Results



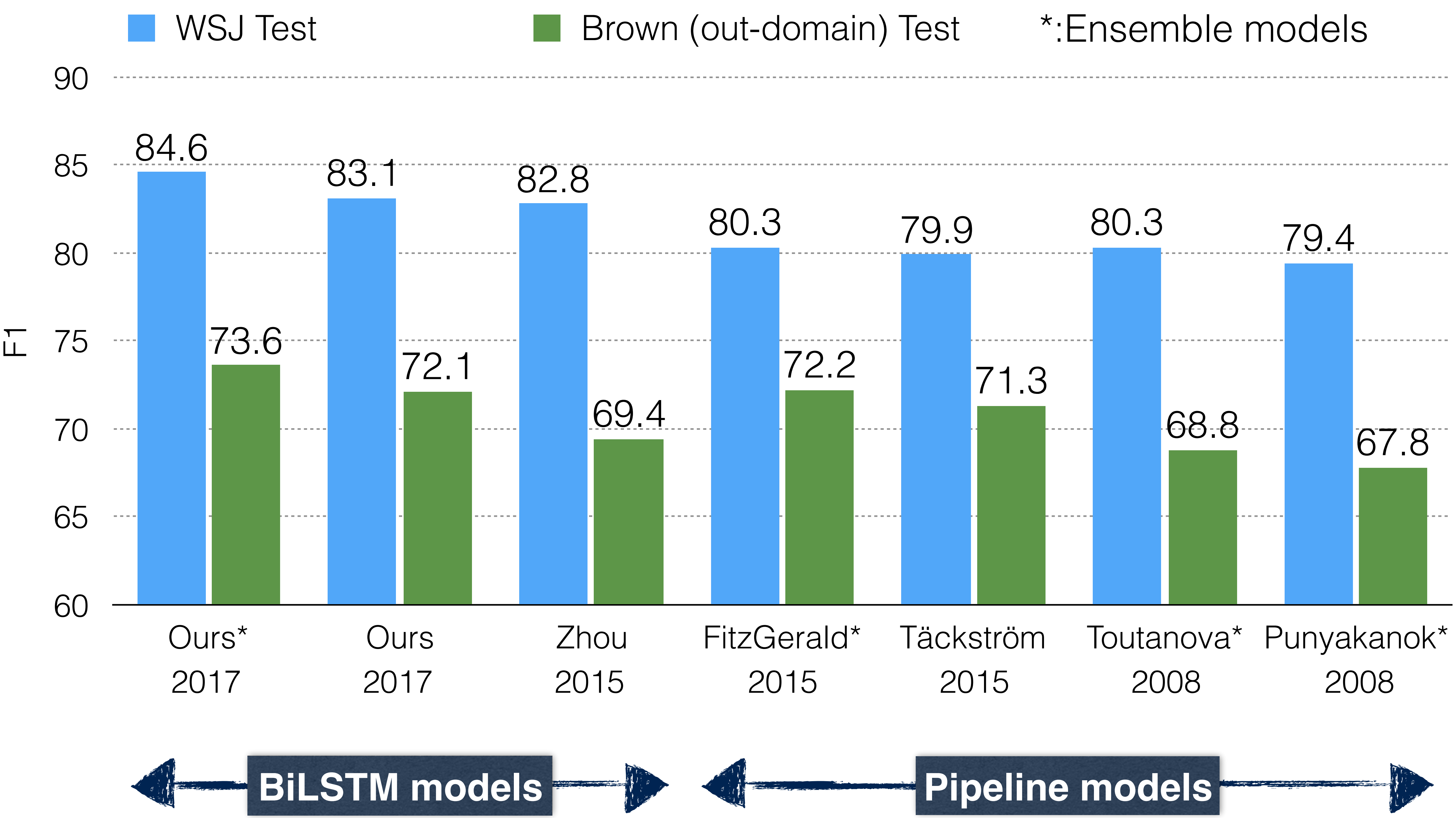
CoNLL 2005 Results



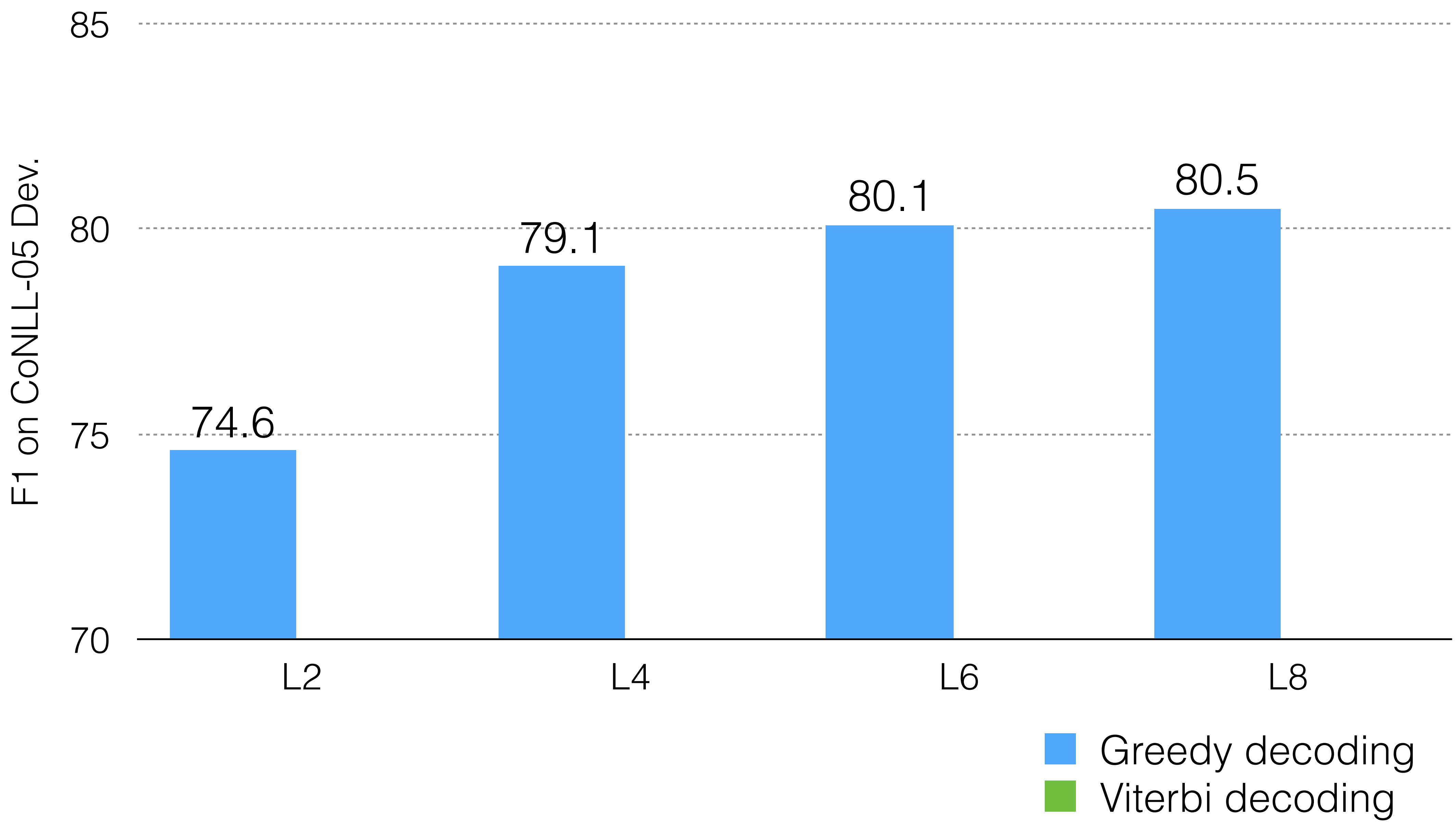
CoNLL 2005 Results



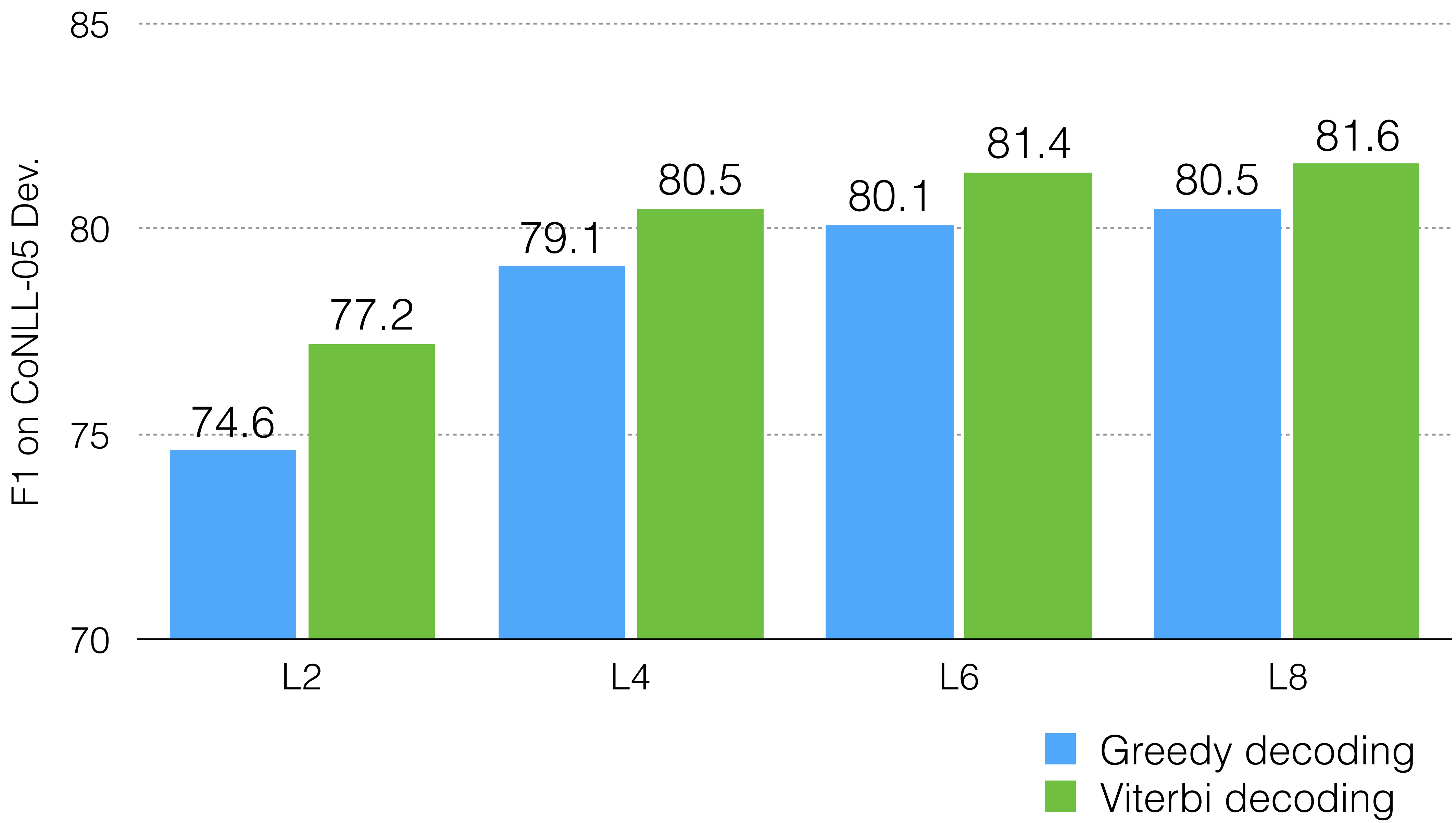
CoNLL 2005 Results



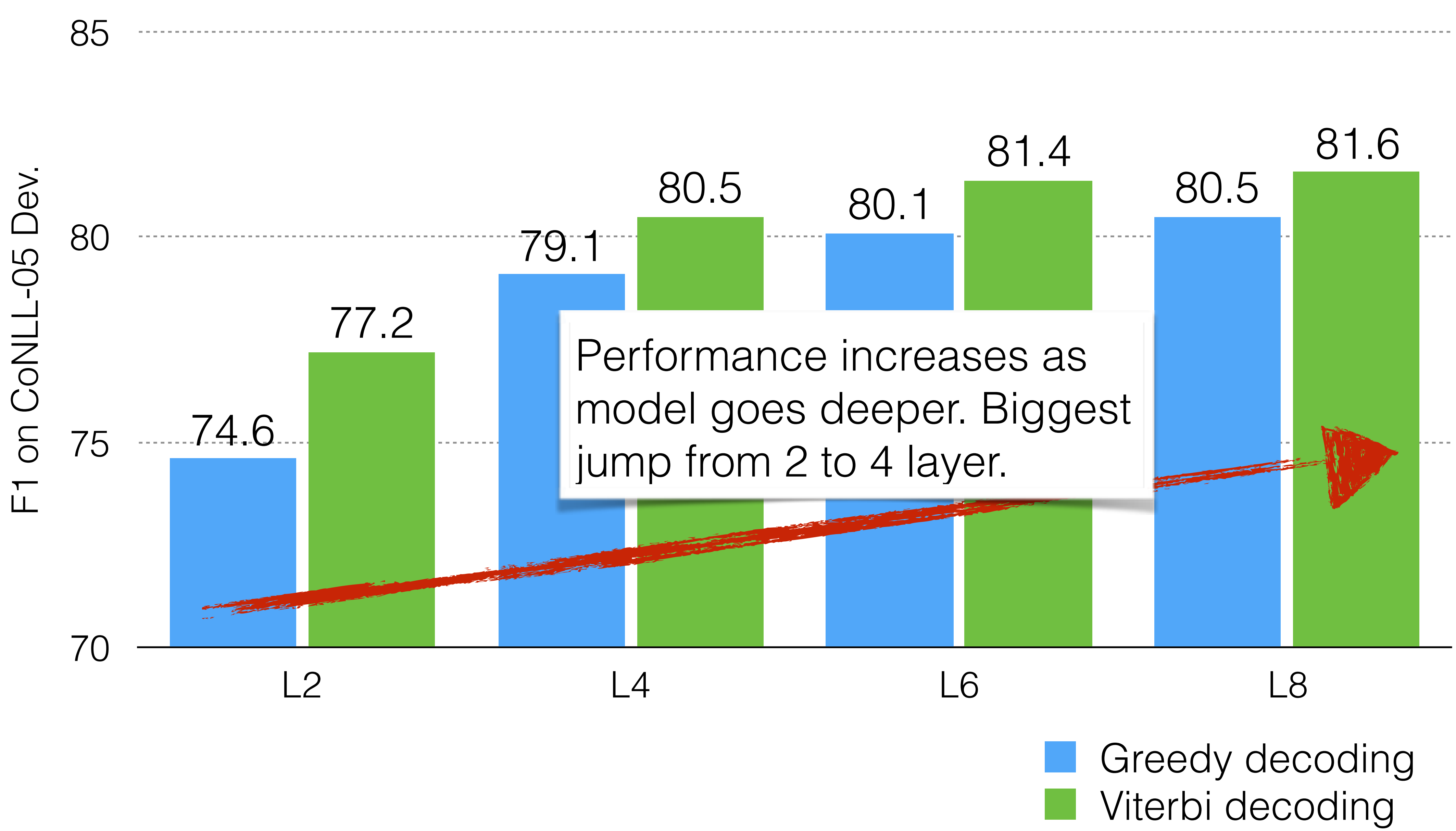
Ablations on Number of Layers (2,4,6 and 8)



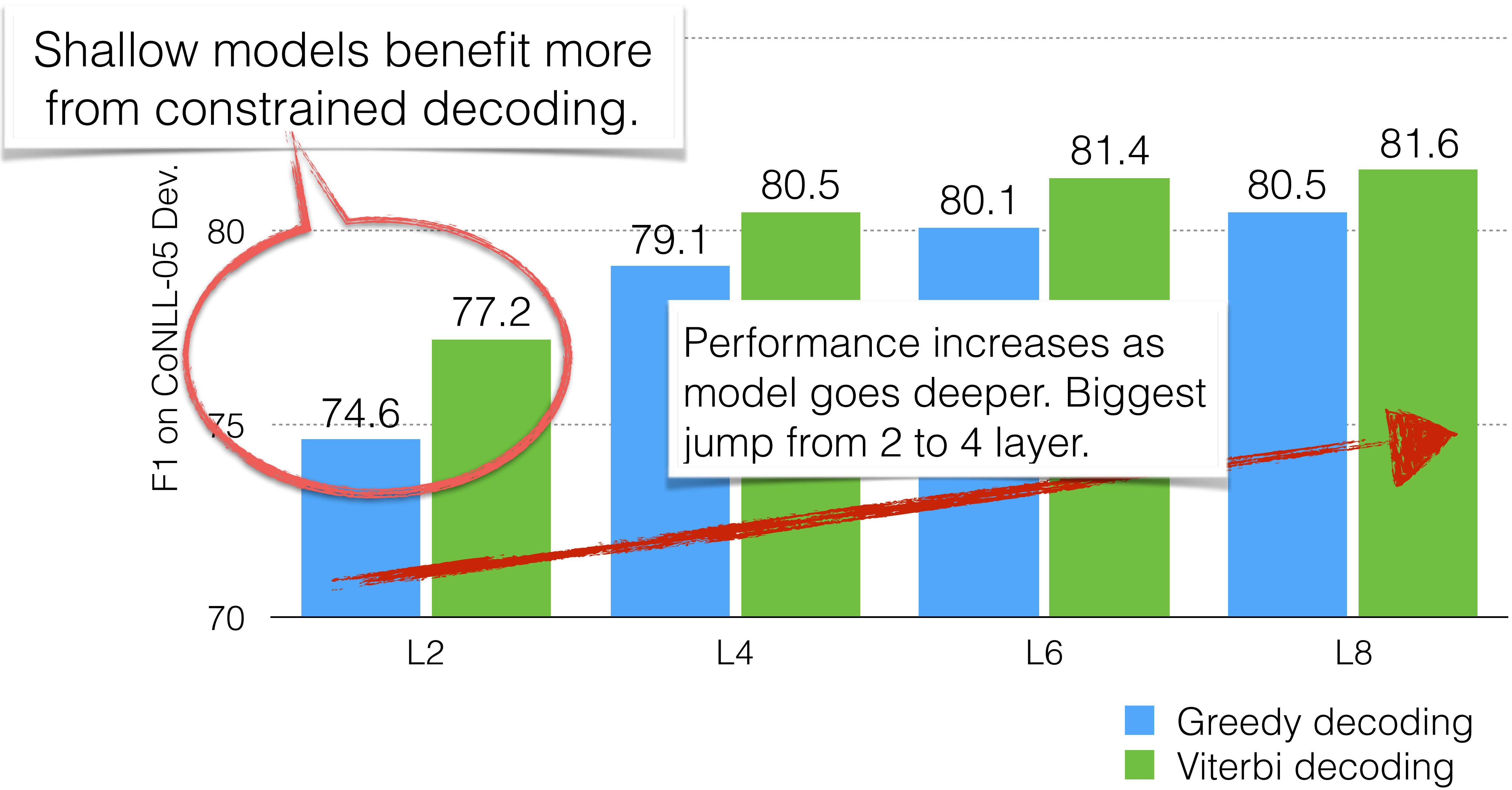
Ablations on Number of Layers (2,4,6 and 8)



Ablations on Number of Layers (2,4,6 and 8)



Ablations on Number of Layers (2,4,6 and 8)



New Learning Approaches

New state-of-the-art results for two tasks:

Coreference:

A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Semantic Role Labeling:

ARG0	NASA
PRED	*observe*
ARG1	an X-ray flare 400 times brighter than usual
TMP	On January 5, 2015

Common themes:

- End-to-end training of deep neural networks
- No preprocessing (e.g., no POS, no parser, etc.)
- Large gains in accuracy with simpler models and no extra training data

Coreference Resolution

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Coreference Resolution

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Cluster #1	A fire in a Bangladeshi garment factory	the blaze in the four-story building

Coreference Resolution

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Cluster #1	A fire in a Bangladeshi garment factory	the blaze in the four-story building
Cluster #2	a Bangladeshi garment factory	the four-story building

Coreference Resolution

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Cluster #1	A fire in a Bangladeshi garment factory	the blaze in the four-story building
Cluster #2	a Bangladeshi garment factory	the four-story building
Cluster #3	at least 37 people	the deceased

Two Subproblems

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Mention detection

A fire in a Bangladeshi garment factory
at least 37 people
…
the four-story building

Mention clustering

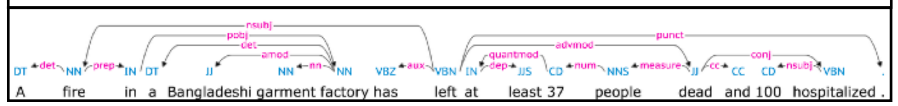
Cluster #1	A fire in a Bangladeshi garment factory	the blaze in the four-story building
Cluster #2	a Bangladeshi garment factory	the four-story building
Cluster #3	at least 37 people	the deceased

Previous Approach: Rule-based pipeline

Input document

A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized.

Syntactic parser



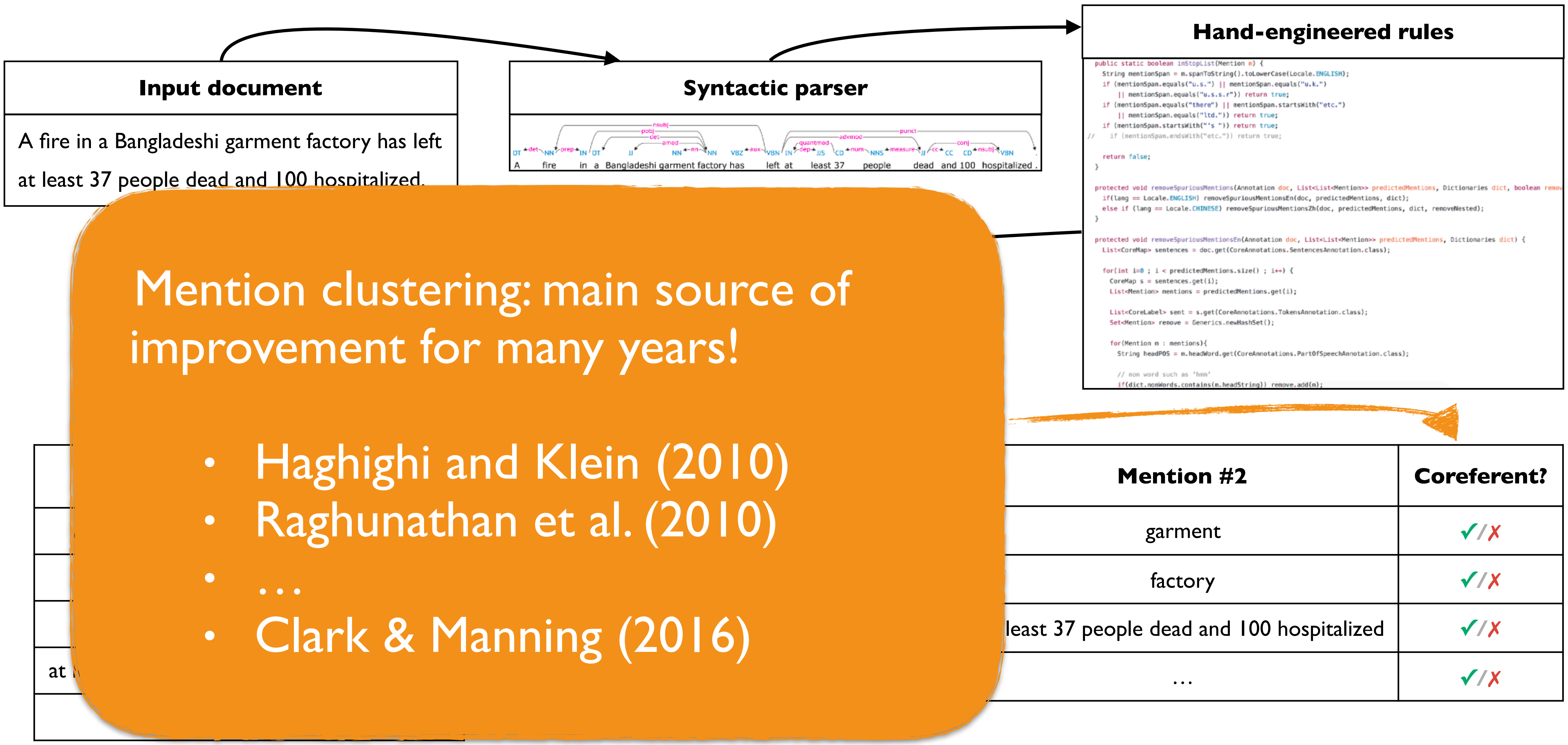
Hand-engineered rules

```
public static boolean inStopList(Mention m) {
  String mentionSpan = m.spanToString().toLowerCase(Locale.ENGLISH);
  if (mentionSpan.equals("u.s.") || mentionSpan.equals("u.k.")
      || mentionSpan.equals("u.s.s.r")) return true;
  if (mentionSpan.equals("there") || mentionSpan.startsWith("etc.")
      || mentionSpan.equals("ltd.")) return true;
  if (mentionSpan.startsWith("'s ")) return true;
//    if (mentionSpan.endsWith("etc.")) return true;

  return false;
}

protected void removeSpuriousMentions(Annotation doc, List<List<Mention>> predictedMentions, Dictionaries dict, boolean remov
  if(lang == Locale.ENGLISH) removeSpuriousMentionsEn(doc, predictedMentions, dict);
  else if (lang == Locale.CHINESE) removeSpuriousMentionsZh(doc, predictedMentions, dict, removeNested);
}

protected void removeSpuriousMentionsEn(Annotation doc, List<List<Mention>> predictedMentions, Dictionaries dict) {
  List<CoreMap> sentences = doc.get(CoreAnnotations.SentencesAnnotation.class);

  for(int i=0 ; i < predictedMentions.size() ; i++) {
    CoreMap s = sentences.get(i);
    List<Mention> mentions = predictedMentions.get(i);

    List<CoreLabel> sent = s.get(CoreAnnotations.TokensAnnotation.class);
    Set<Mention> remove = Generics.newHashSet();

    for(Mention m : mentions){
      String headPOS = m.headWord.get(CoreAnnotations.PartOfSpeechAnnotation.class);

      // non word such as 'hmm'
      if(dict.nonWords.contains(m.headString)) remove.add(m);
```

Candidate mentions
A fire in a Bangladeshi garment factory
garment
factory
at least 37 people dead and 100 hospitalized
…

Mention #1	**Mention #2**	**Coreferent?**
A fire in a Bangladeshi garment factory	garment	✓/✗
garment	factory	✓/✗
factory	at least 37 people dead and 100 hospitalized	✓/✗
…	…	✓/✗

Previous Approach: Rule-based pipeline



Mention clustering: main source of improvement for many years!

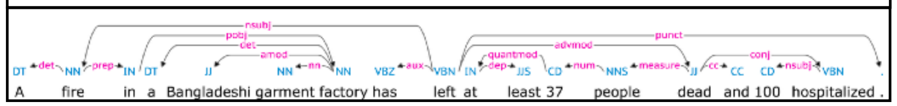
- Haghighi and Klein (2010)
- Raghunathan et al. (2010)
- …
- Clark & Manning (2016)

Previous Approach: Rule-based pipeline

Input document

A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized.

Syntactic parser



Hand-engineered rules

Relies on parser for:

- mention detection
- syntactic features for clustering (e.g. head words)

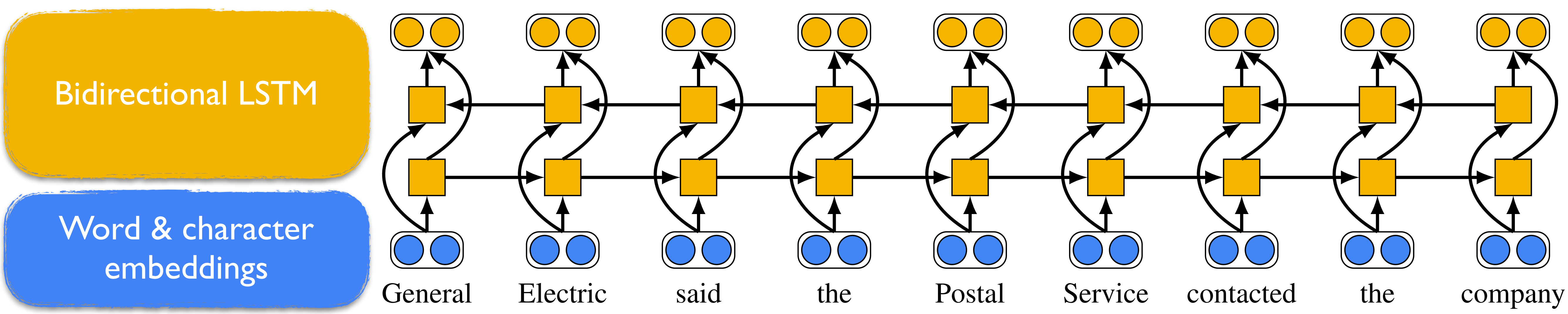
A fire in a Bangladeshi garment factory
garment
factory
at least 37 people dead and 100 hospitalized
…

		Coreferent?
A fire in a Bangladeshi garment factory	garment	✓/✗
garment	factory	✓/✗
factory	at least 37 people dead and 100 hospitalized	✓/✗
…	…	✓/✗

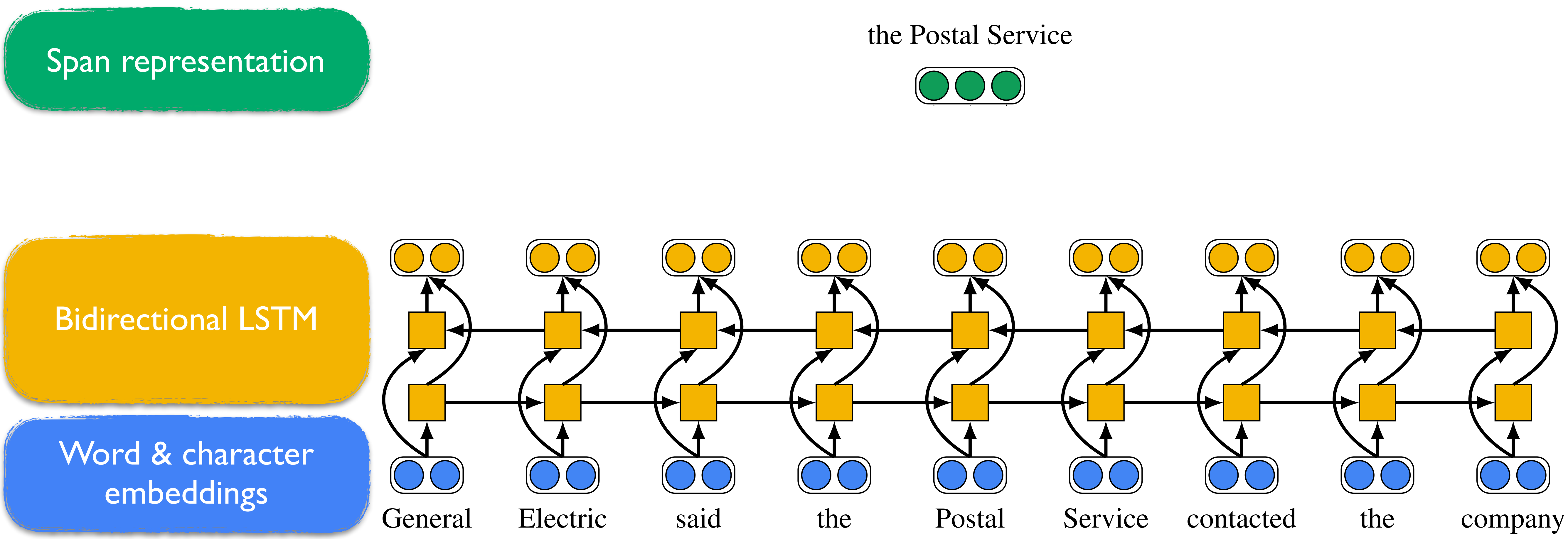
End-to-end Approach

- Consider all possible spans
- Learn to rank antecedent spans
- Factored model to prune search space

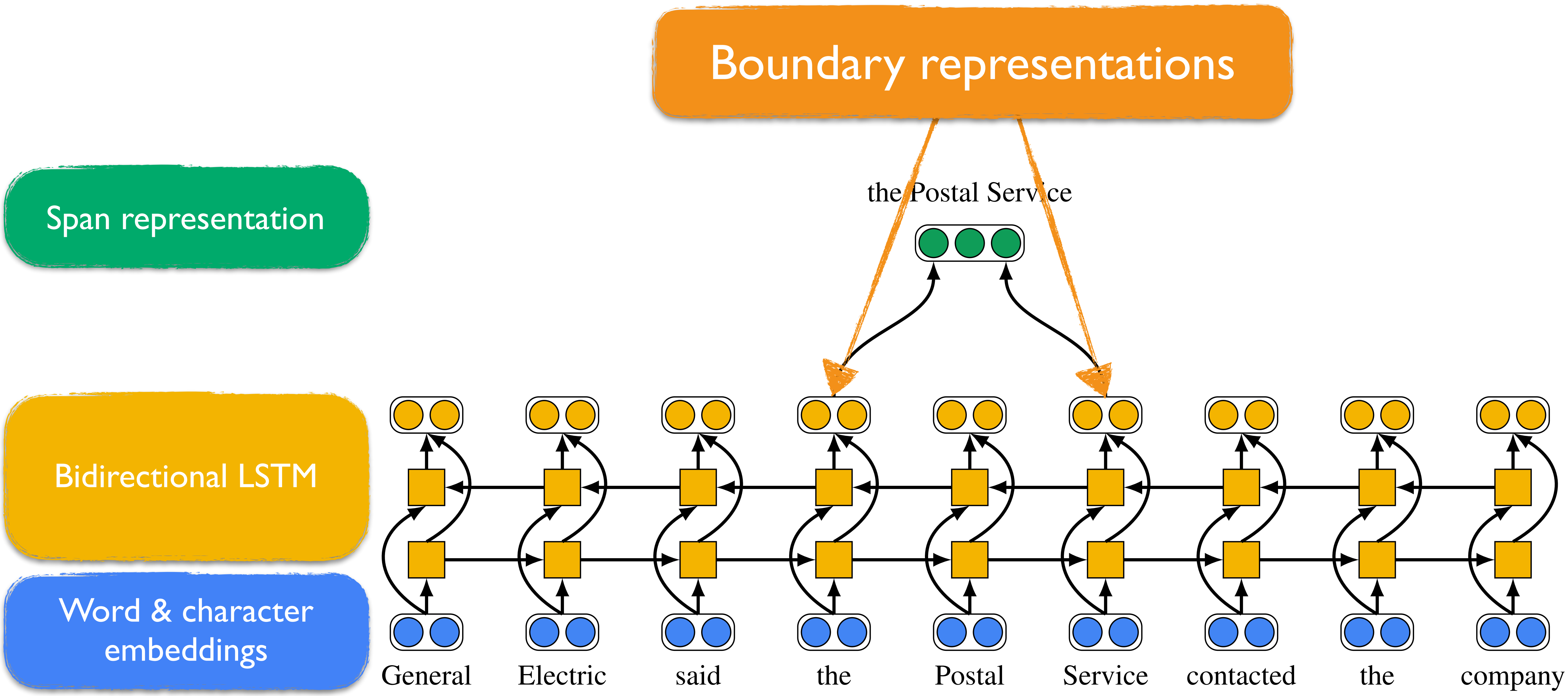
Key Idea: Span Representations



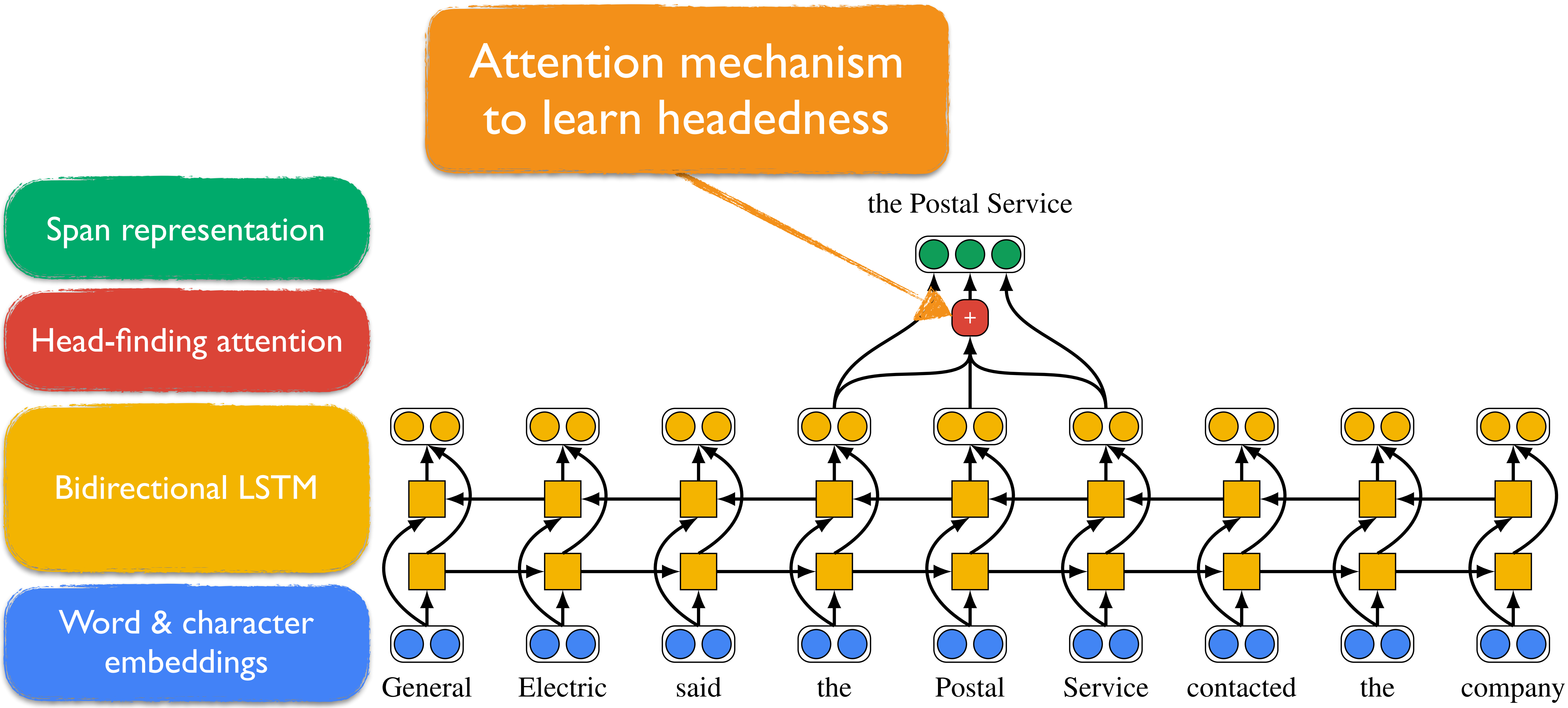
Key Idea: Span Representations



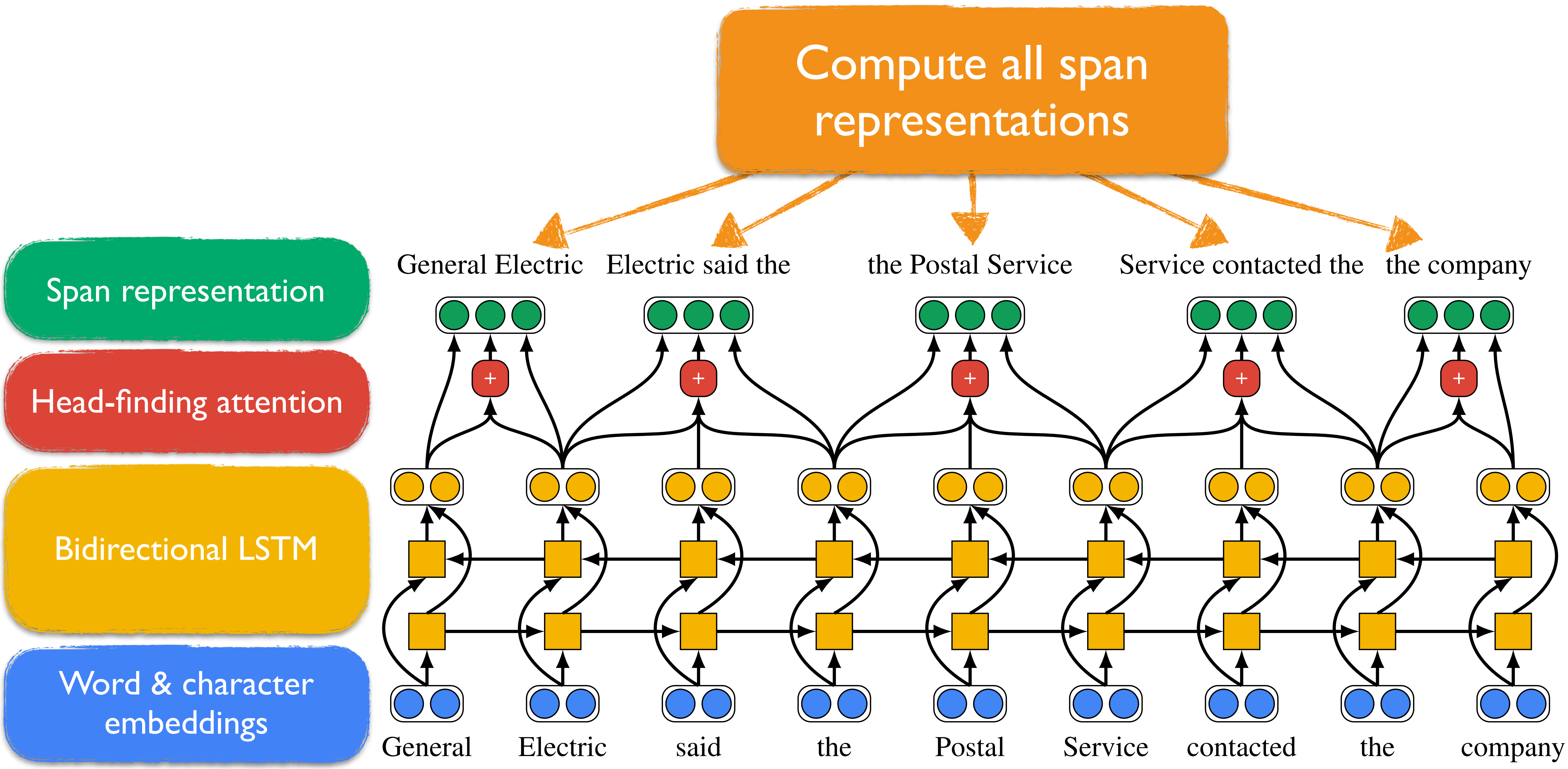
Key Idea: Span Representations



Key Idea: Span Representations



Key Idea: Span Representations



Mention Ranking

Every span independently chooses an antecedent

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building. Witnesses say the only exit door was on the ground floor, and that it was locked when the fire broke out.

Mention Ranking

- Reason over all possible spans

- Assign an antecedent to every span

$$y_3 \in \{\epsilon, 1, 2\}$$

	Span	**Antecedent**
1	A	y_1
2	A fire	y_2
3	A fire in	y_3
…	…	…
M	out	y_M

Example Clustering

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building. Witnesses say the only exit door was on the ground floor, and that it was locked when the fire broke out.

Span	**Antecedent (y_i)**
A	ϵ
A fire	ϵ
...	...
a Bangladeshi garment factory	ϵ
...	...
the four-story building	a Bangladeshi garment factory
...	...
out	ϵ

Example Clustering

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building. Witnesses ... d floor, and that it was locked when the fire broke out.

Not a mention

Span	Antecedent (y_i)
A	ϵ
A fire	ϵ
…	…
a Bangladeshi garment factory	ϵ
…	…
the four-story building	a Bangladeshi garment factory
…	…
out	ϵ

Example Clustering

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building. Witnesses say the only exit door was on the ground floor, and that it was locked when the fire broke out.

No link with previously occurring span

Span	Antecedent (y_i)
…	…
a Bangladeshi garment factory	ϵ
…	…
the four-story building	a Bangladeshi garment factory
…	…
out	ϵ

Example Clustering

Input document
A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building. Witnesses say the only exit door was on the ground floor, and that it was locked when the fire broke out.

Predicted coreference link

Span	**Antecedent (y_i)**
A	ϵ
A fire	ϵ
	$\dots$
	ϵ
$\dots$	$\dots$
the four-story building	a Bangladeshi garment factory
$\dots$	$\dots$
out	ϵ

Span Ranking Model

$$P(y_1, \ldots, y_M \mid D) = \prod_{i=1}^{M} P(y_i \mid D)$$

$$= \prod_{i=1}^{M} \frac{e^{s(i, y_i)}}{\sum_{y' \in \mathcal{Y}(i)} e^{s(i, y')}}$$

Factor coreference score $s(i, j)$ to enable span pruning:

$$s(i,j) = \begin{cases} s_{\mathrm{m}}(i) + s_{\mathrm{m}}(j) + s_{\mathrm{a}}(i,j) & j \neq \epsilon \\ 0 & j = \epsilon \end{cases}$$

Span Ranking Model

$$P(y_1, \ldots, y_M \mid D) = \prod_{i=1}^{M} P(y_i \mid D)$$

$$\prod_{i=1}^{M} \frac{e^{s(i,y_i)}}{\sum_{y' \in \mathcal{Y}(i)} e^{s(i,y')}}$$

Is this span a mention?

Factor coreference score $s(i,j)$ to enable span pruning:

$$s(i,j) = \begin{cases} s_{\mathrm{m}}(i) + s_{\mathrm{m}}(j) + s_{\mathrm{a}}(i,j) & j \neq \epsilon \\ 0 & j = \epsilon \end{cases}$$

Span Ranking Model

$$P(y_1, \ldots, y_M \mid D) = \prod_{i=1}^{M} P(y_i \mid D)$$

$$= \prod_{i=1}^{M} \frac{e^{s(i,y_i)}}{\cdots}$$

Is span j an antecedent of span i?

Factor coreference score $s(i,j)$ to enable span pruning:

$$s(i,j) = \begin{cases} s_{\mathrm{m}}(i) + s_{\mathrm{m}}(j) + s_{\mathrm{a}}(i,j) & j \neq \epsilon \\ 0 & j = \epsilon \end{cases}$$

Span Ranking Model

$$P(y_1, \ldots, y_M \mid D) = \prod_{i=1}^{M} P(y_i \mid D)$$

$$= \prod_{i=1}^{M} \frac{e^{s(i, y_i)}}{\sum_{y' \in \mathcal{Y}(i)} e^{s(i, y')}}$$

Factor coreference score $s(i, j)$ to enable span pruning:

$$s(i, j) = \begin{cases} s_{\mathrm{m}}(i) + s_{\mathrm{m}}(j) + s_{\mathrm{a}}(i, j) & j \neq \epsilon \\ 0 & j = \epsilon \end{cases}$$

Dummy antecedent has a fixed zero score

Experimental Setup

Dataset: English OntoNotes (CoNLL-2012)

Genres: Telephone conversations, newswire, newsgroups, broadcast conversation, broadcast news, weblogs

Documents: 2802 training, 343 development, 348 test

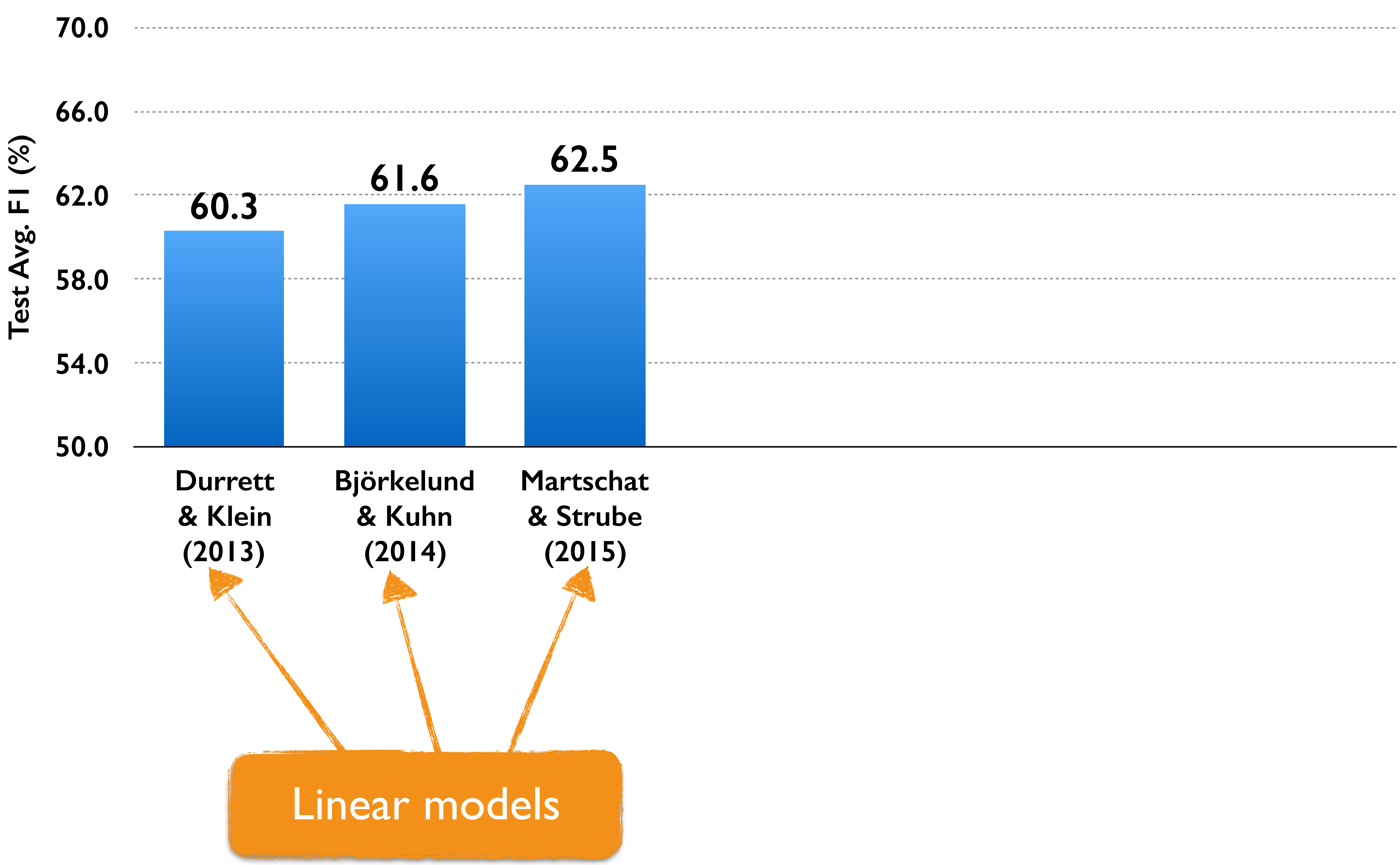
Longest document has 4009 words!

Aggressive pruning: Maximum span width, maximum sentence training, suppress spans with inconsistent bracketing, maximum number of antecedents

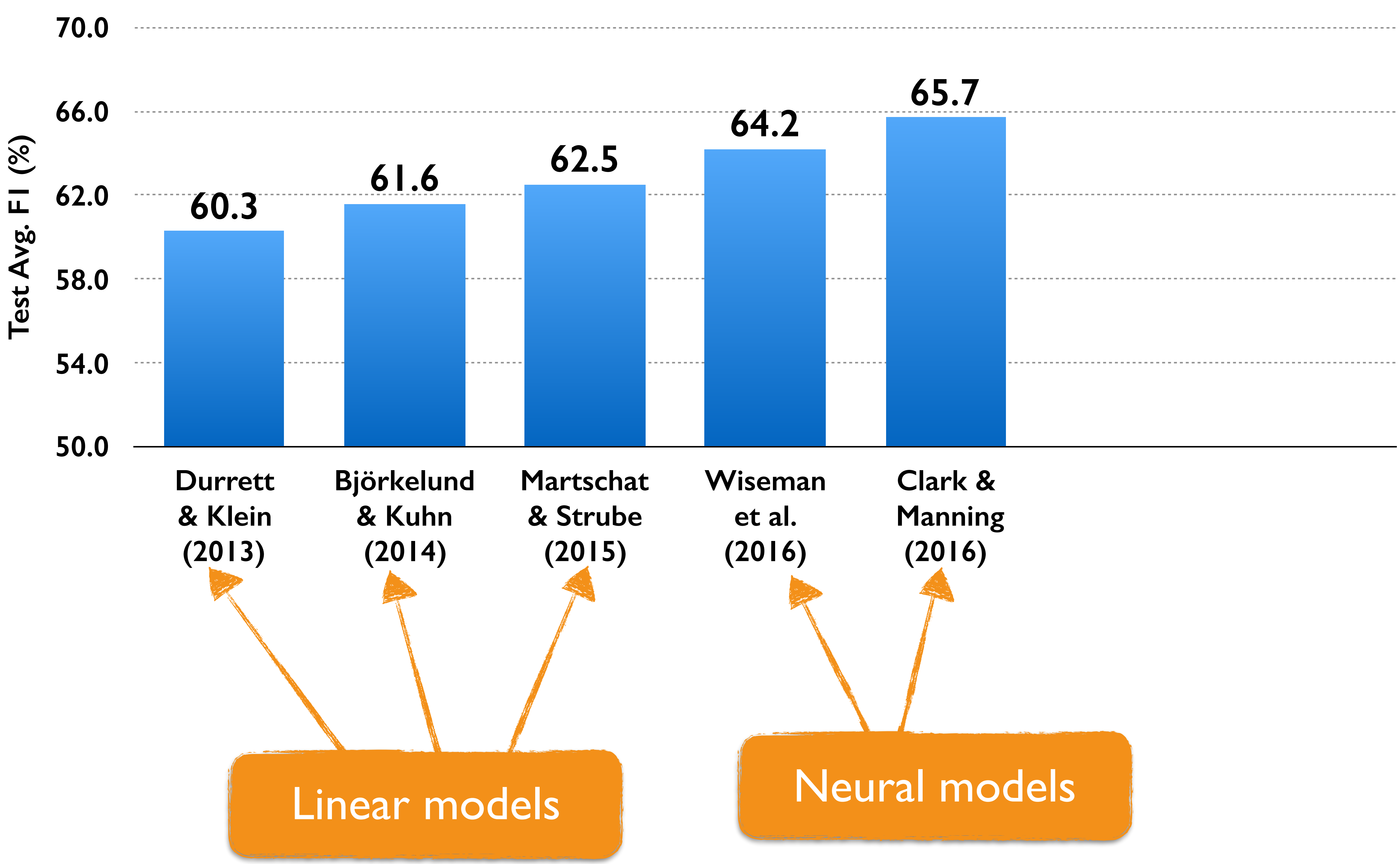
Features: distance between spans, span width

Metadata: speaker information, genre

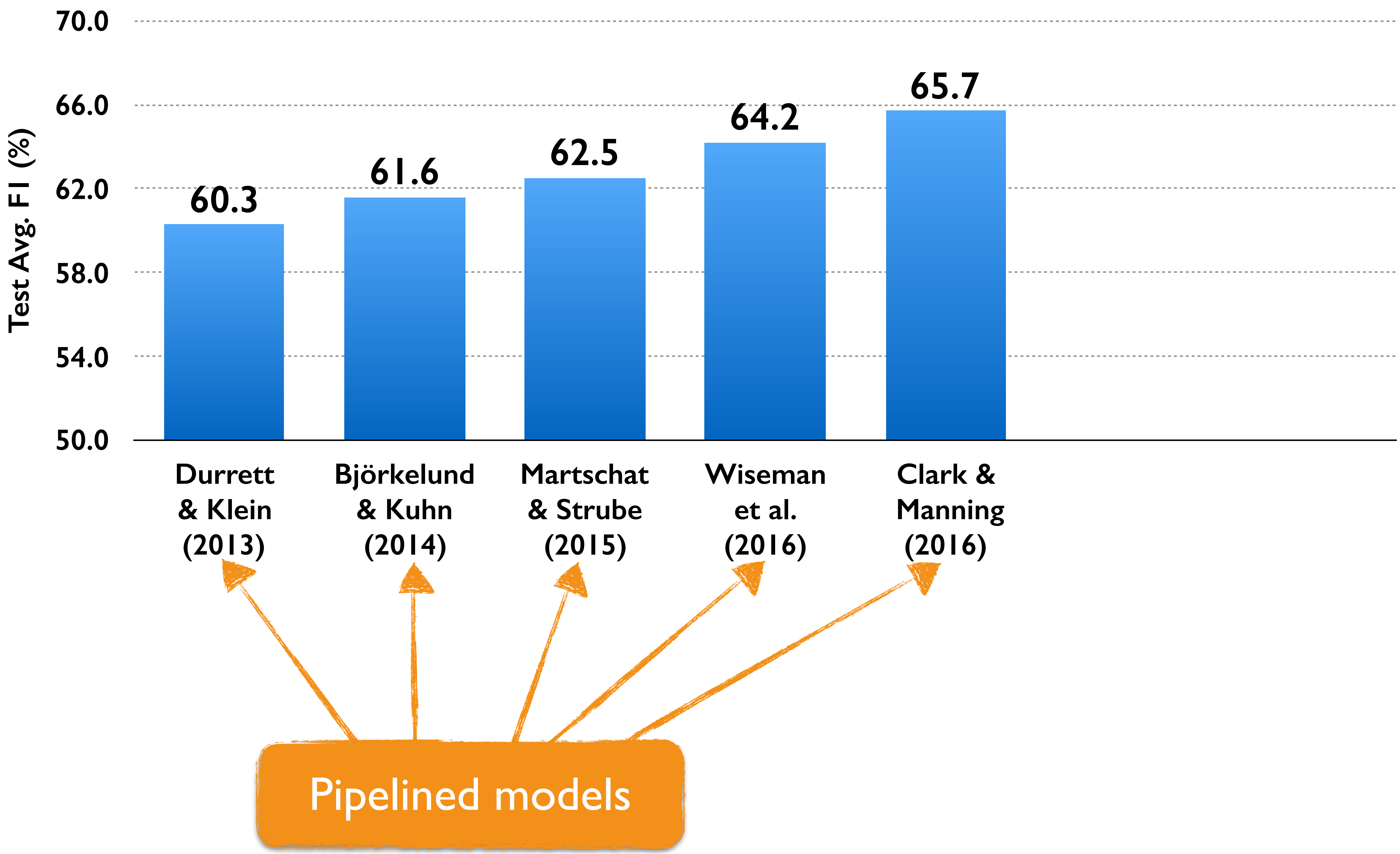
Coreference Results



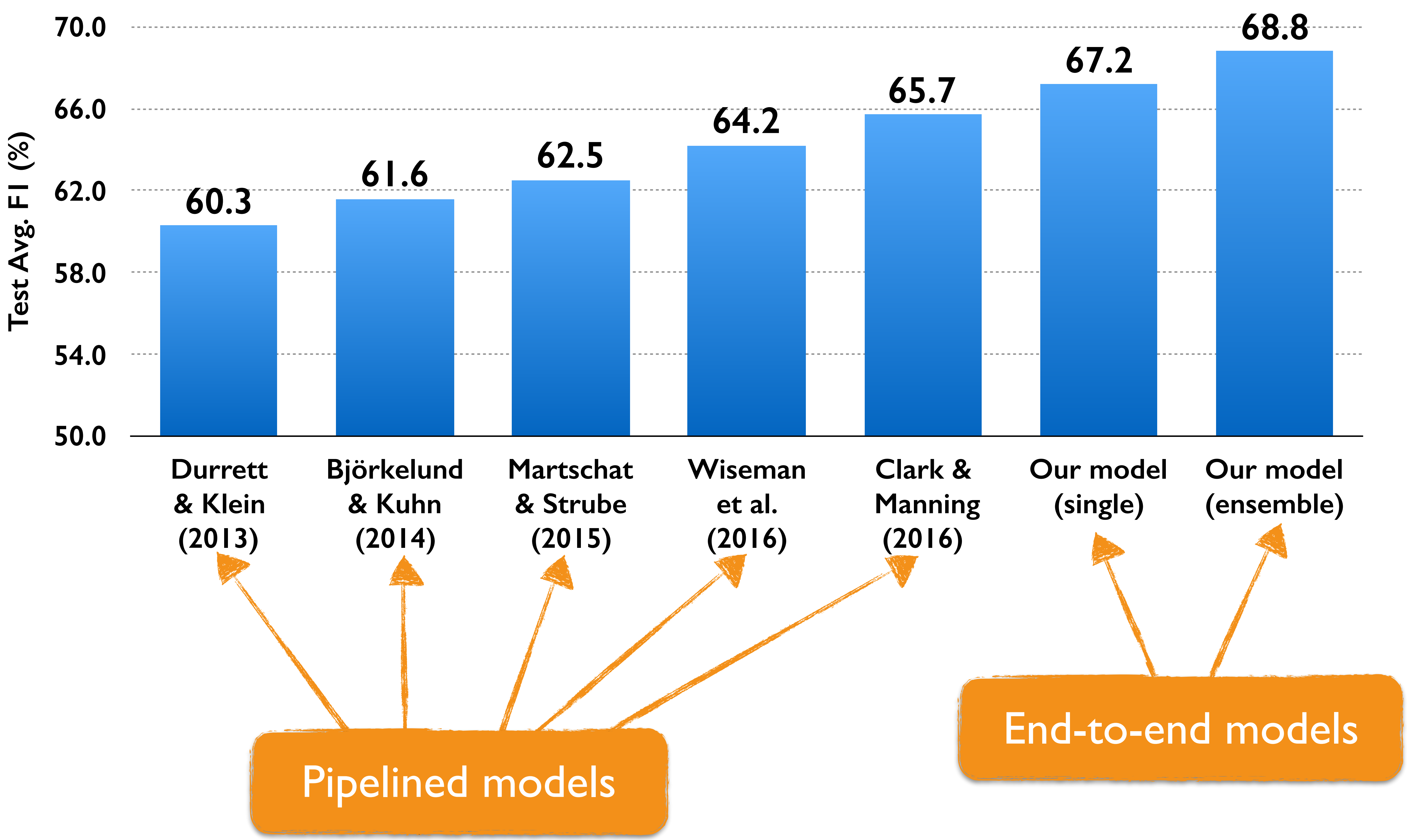
Coreference Results



Coreference Results



Coreference Results



Qualitative Analysis

: Mention in a predicted cluster

: Head-finding attention weight

A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Qualitative Analysis

: Mention in

: Head-findin

Attention-based head finder facilitates soft similarity cues

A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Qualitative Analysis

: Mention in a predicted cluster

: Hea

Good head-finding requires word-order information!

A fire in a Bangladeshi garment factory has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee the blaze in the four-story building.

Common Error Case

: Mention in a predicted cluster

: Head-finding attention weight

The flight attendants have until 6:00 today to ratify labor concessions. The pilots' union and ground crew did so yesterday.

Common Error Case

: Mention in a predicted cluster

: Head-finding attention weight

The flight attendants have until 6:00 today to ratify labor concessions. The pilots' union and ground crew did so yesterday.

Conflating **relatedness** with **paraphrasing**

Does the Recipe Work for Broad Coverage Semantics?

Step 1: Gather lots of training data!

Challenge 1: Data is costly and limited (e.g. linguists required to label PennTreebank / OntoNotes)

Step 2: Apply Deep Learning!!

Challenge 2: Pipeline of structured prediction problems with cascading errors (e.g. POS->Parsing->SRL->Coref)

Step 3: Observe Impressive Gains!!!

Where Will the Data Come From???

Where Will the Data Come From???

Option 1: Semi-supervised learning

- E.g. word2vec and GloVe are in wide use
  [Mikolov et al., 2013; Pennington et al., 2014]

Where Will the Data Come From???

Option 1: Semi-supervised learning

- E.g. word2vec and GloVe are in wide use
  [Mikolov et al., 2013; Pennington et al., 2014]
- Can we learn better word representations?

Where Will the Data Come From???

Option 1: Semi-supervised learning

- E.g. word2vec and GloVe are in wide use
  [Mikolov et al., 2013; Pennington et al., 2014]
- Can we learn better word representations?

Option 2: Supervised learning

Where Will the Data Come From???

Option 1: Semi-supervised learning

- E.g. word2vec and GloVe are in wide use
  [Mikolov et al., 2013; Pennington et al., 2014]
- Can we learn better word representations?

Option 2: Supervised learning

- Can we gather more direct forms of supervision?

Learning Better Word Representations

Goal: Model contextualized syntax and semantics

$$R(w_i, w_1 \ldots w_n) \in \mathbb{R}^n$$

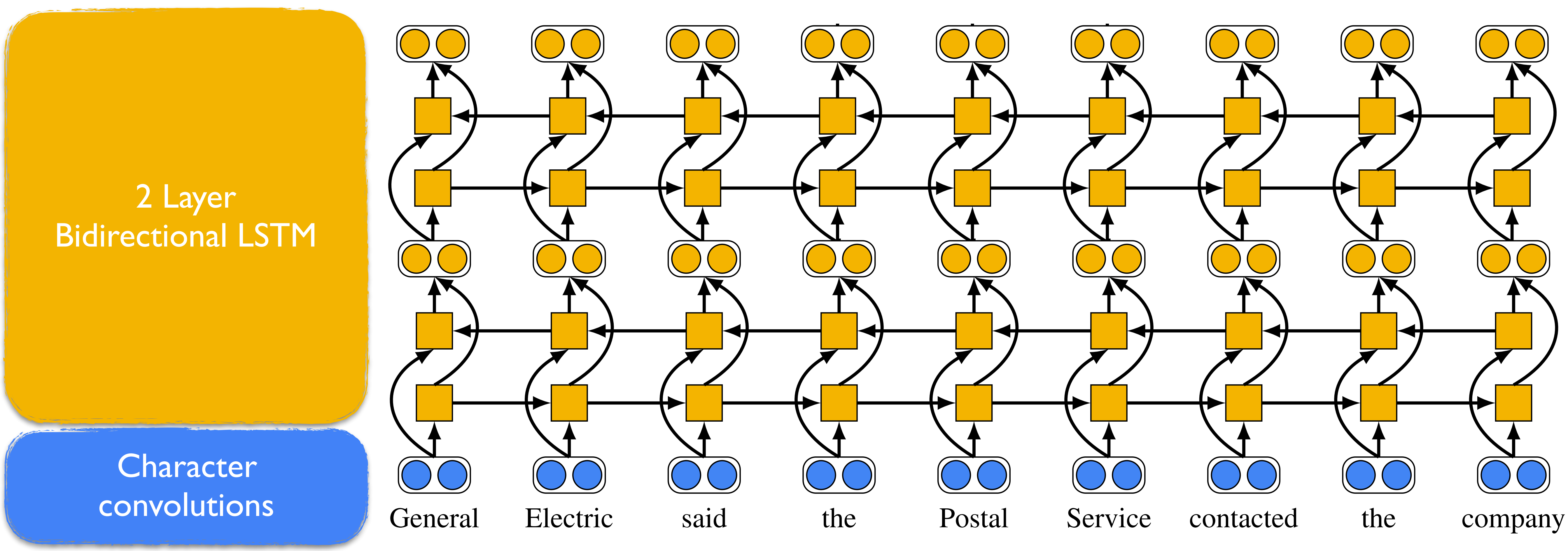
R(plays, “The robot plays piano.”)

$$\neq$$

R(plays, “The robot starred in many plays.”)

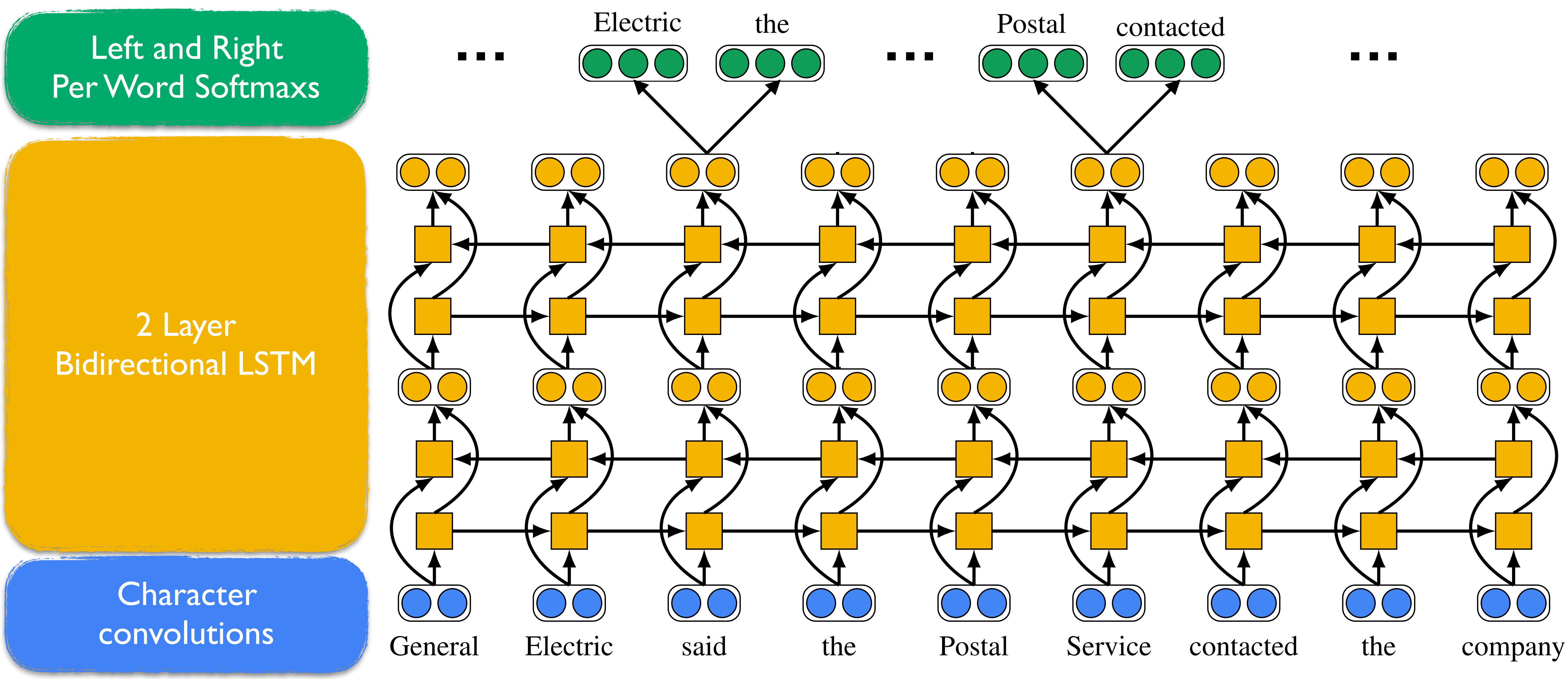
Word Embeddings from a Language Model

Step 1: Train a large BiLM on unlabeled data



Word Embeddings from a Language Model

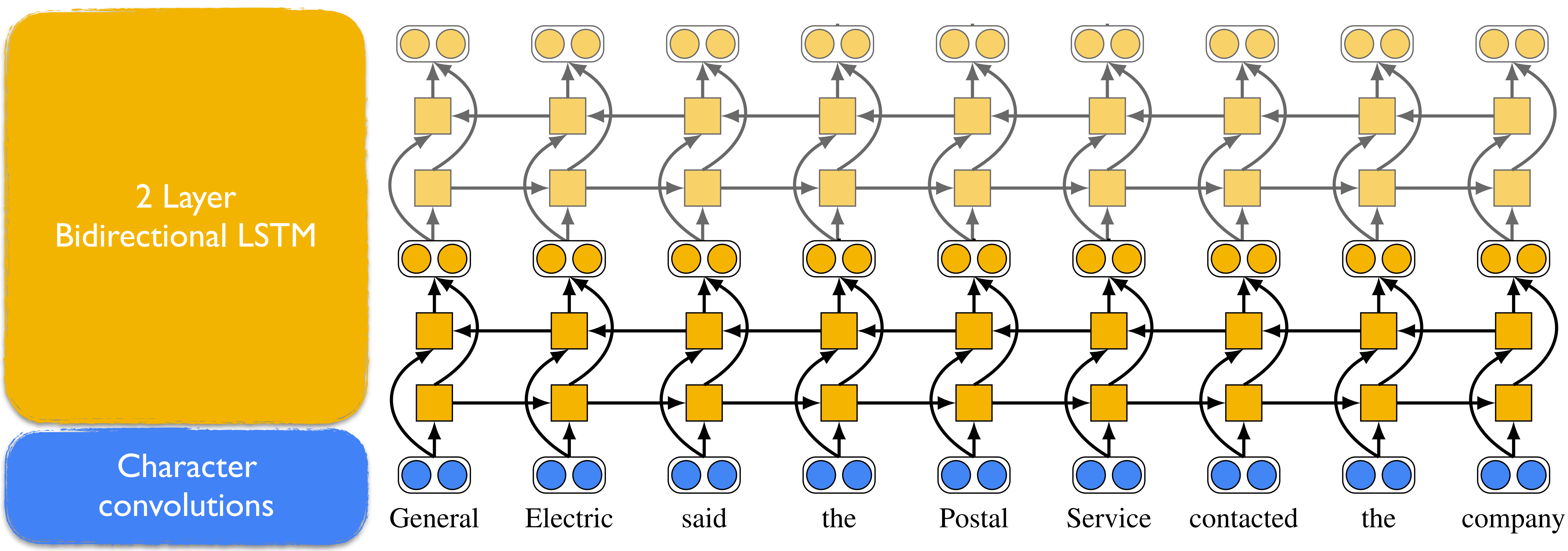
Step 1: Train a large BiLM on unlabeled data



Word Embeddings from a Language Model

Step 1: Train a large BiLM on unlabeled data

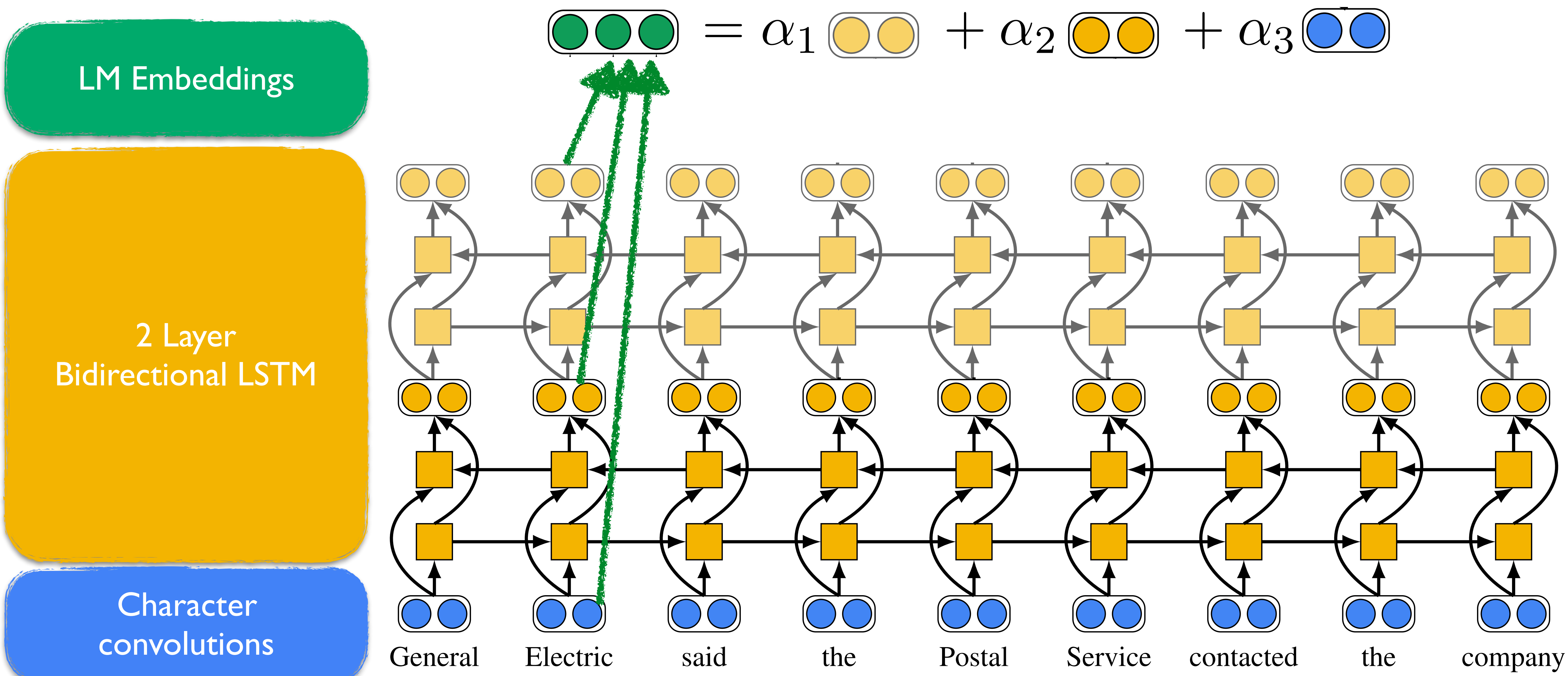
Step 2: Compute linear function of pre-trained model



Word Embeddings from a Language Model

Step 1: Train a large BiLM on unlabeled data

Step 2: Compute linear function of pre-trained model

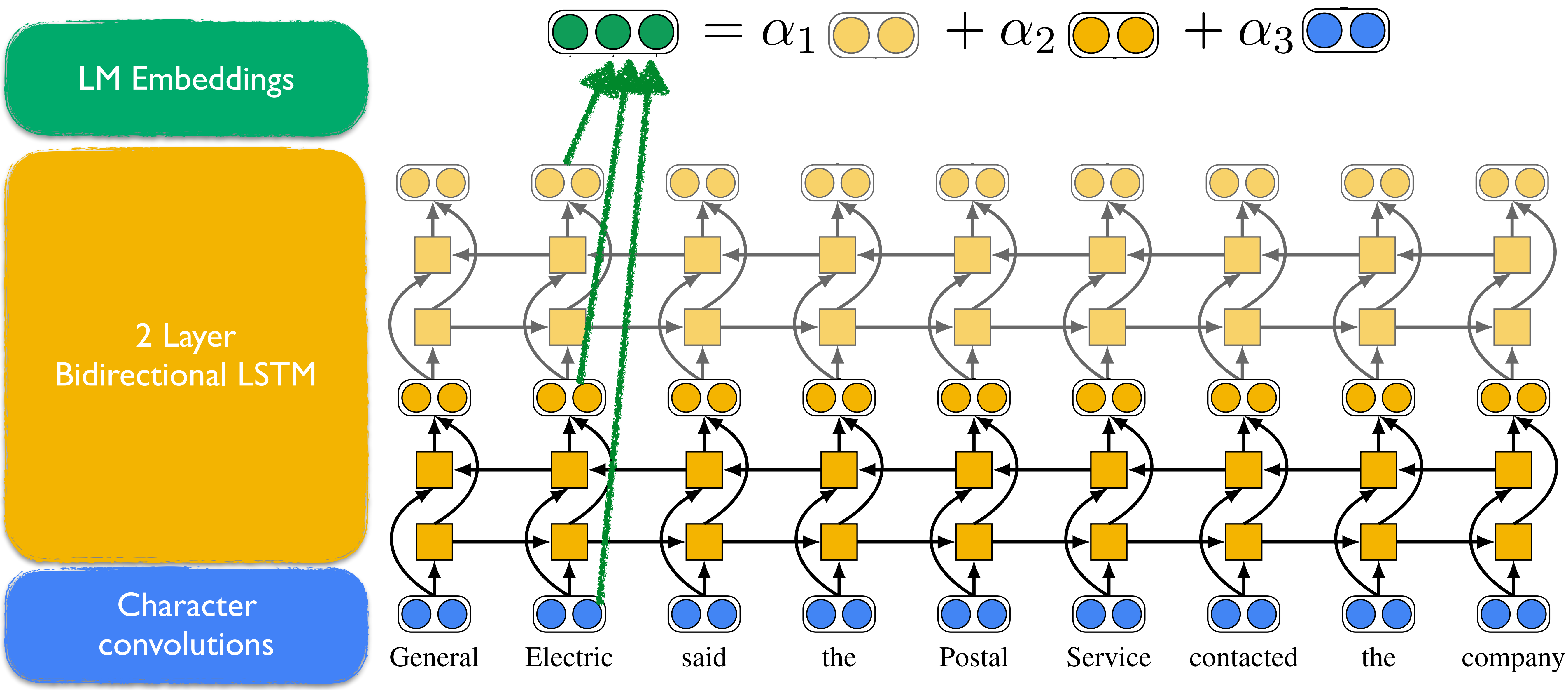


Word Embeddings from a Language Model

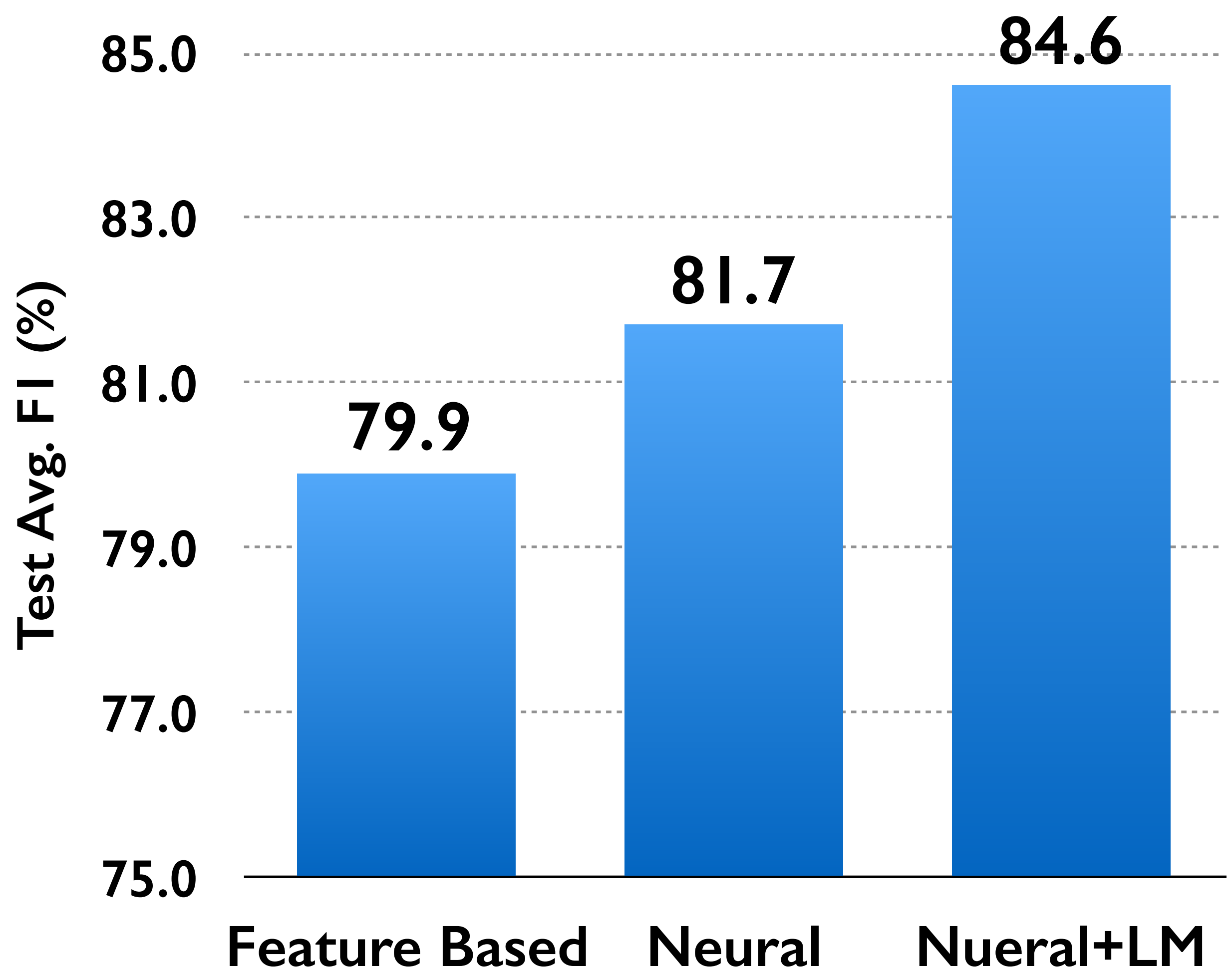
Step 1: Train a large BiLM on unlabeled data

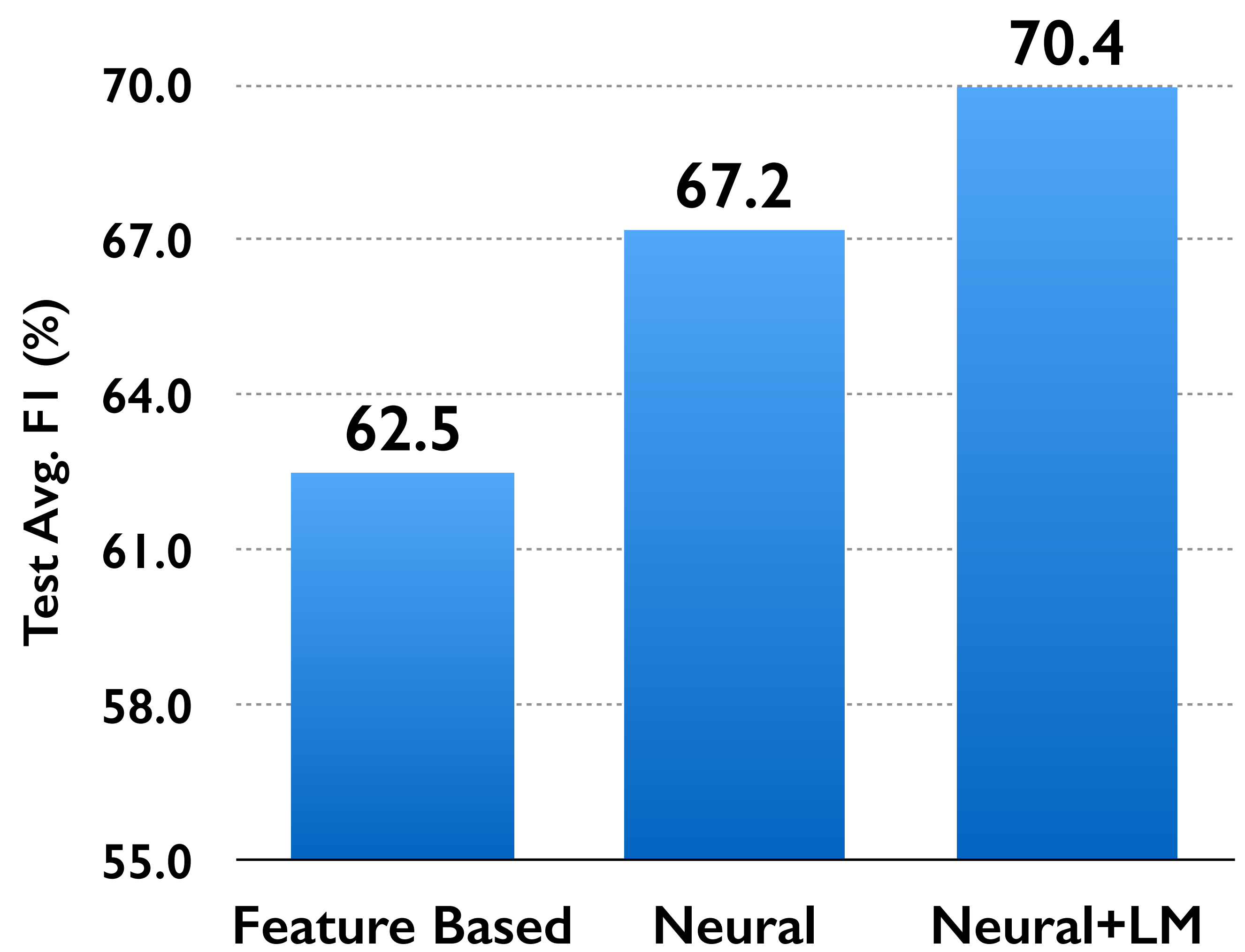
Step 2: Compute linear function of pre-trained model

Step 3: Learn weights for each end task



Best Single System Results

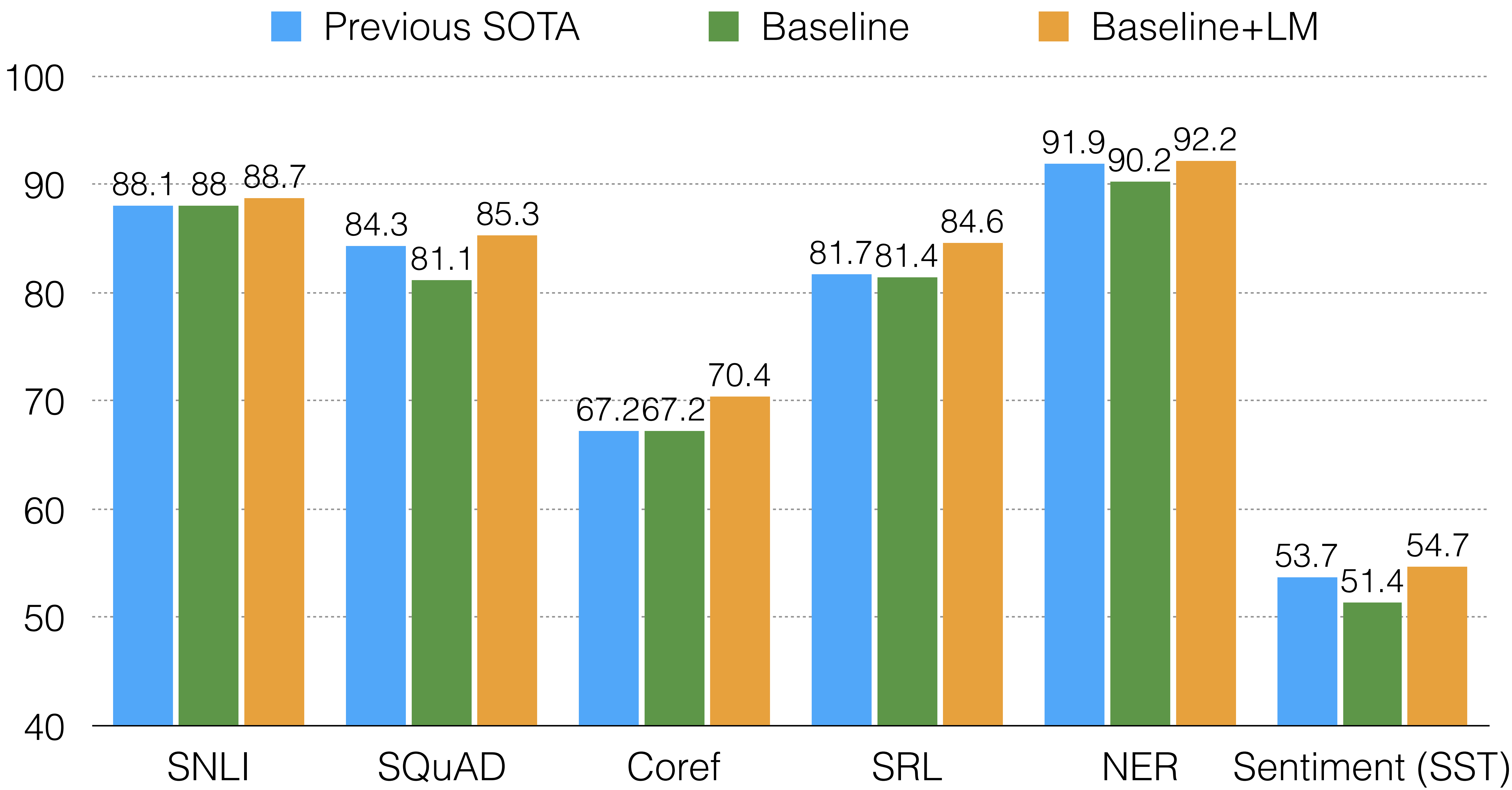




SRL
(+2.9 F1)

Coreference
(+3.2 F1)

SOTA For Many Others Tasks



What Does it Learn?

What Does it Learn?

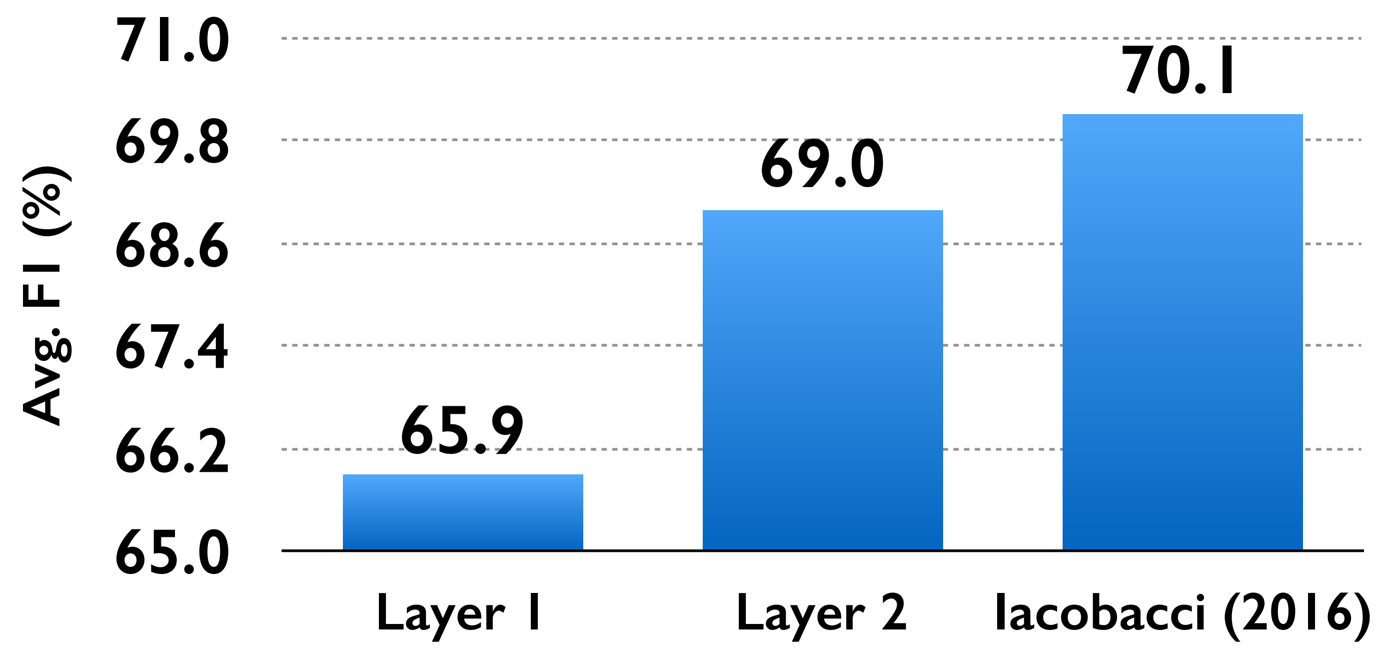
Semantics:

- Supervised WSD task [Miller et al.,1994]
- Use N-th layer in NN classifier

What Does it Learn?

Semantics:

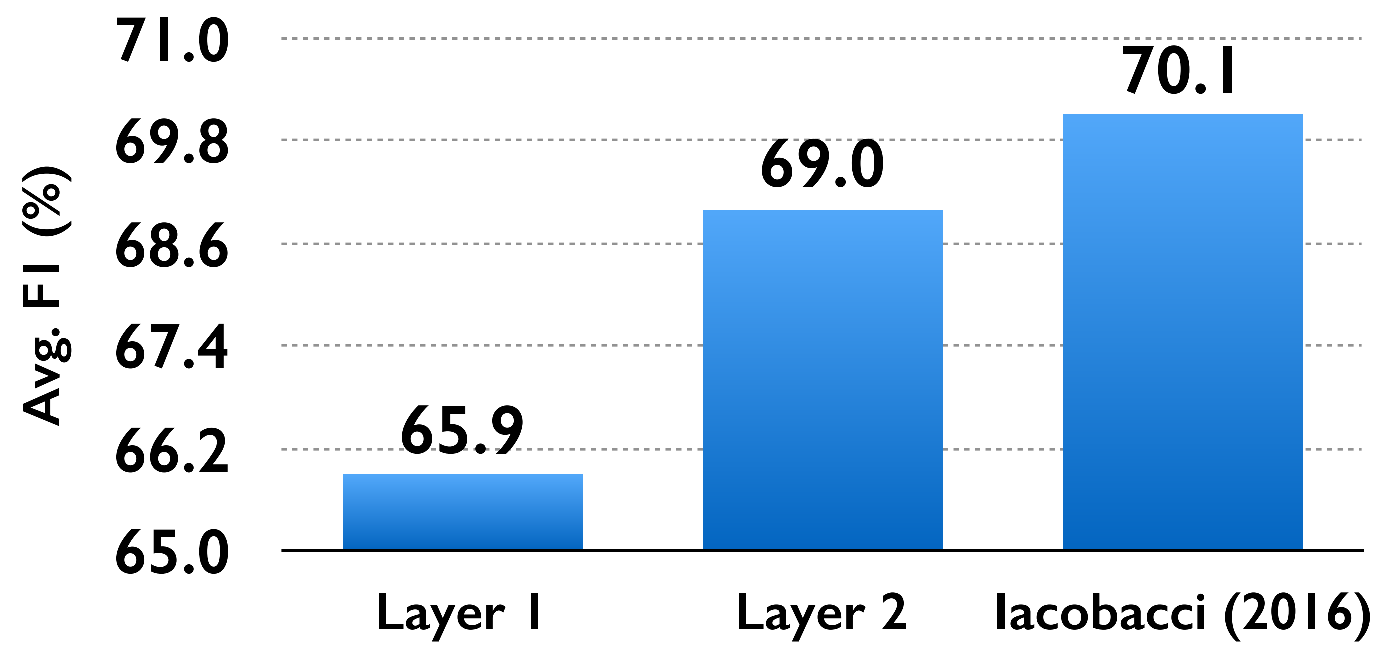
- Supervised WSD task [Miller et al.,1994]
- Use N-th layer in NN classifier



What Does it Learn?

Semantics:

- Supervised WSD task [Miller et al.,1994]
- Use N-th layer in NN classifier



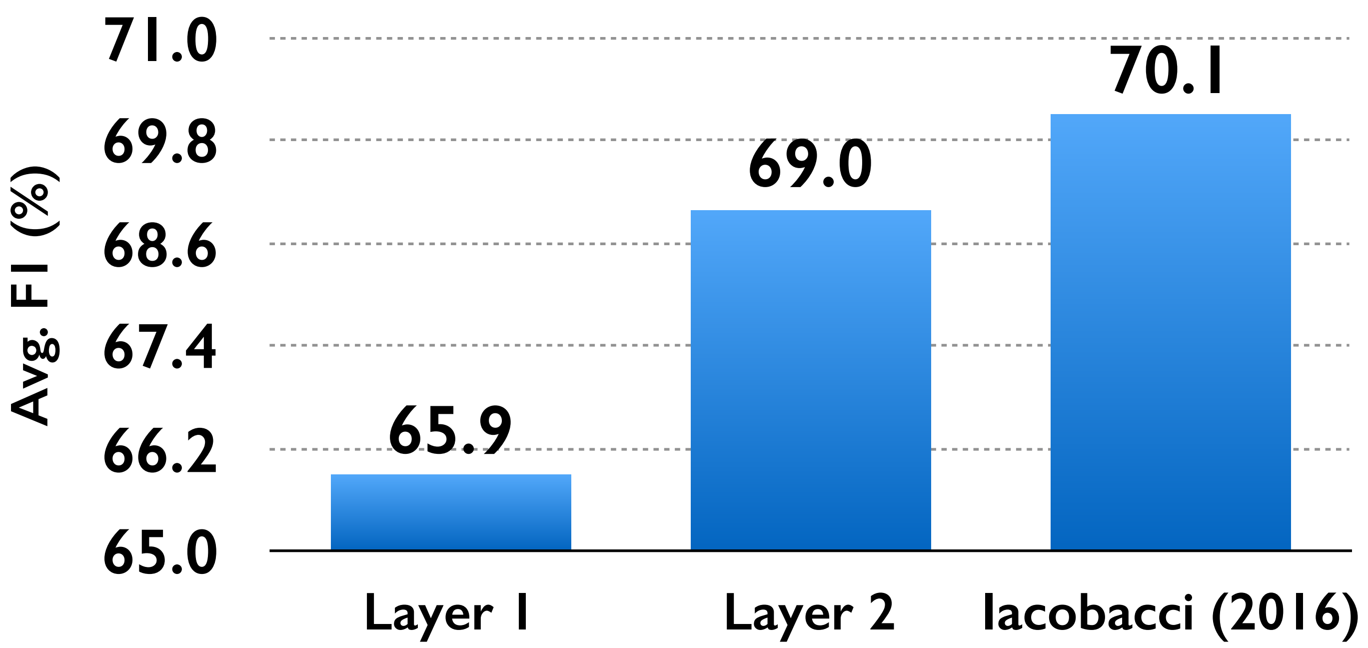
Syntax:

- Label POS corpus [Marcus et al., 1993]
- Learn classifier on N-th layer

What Does it Learn?

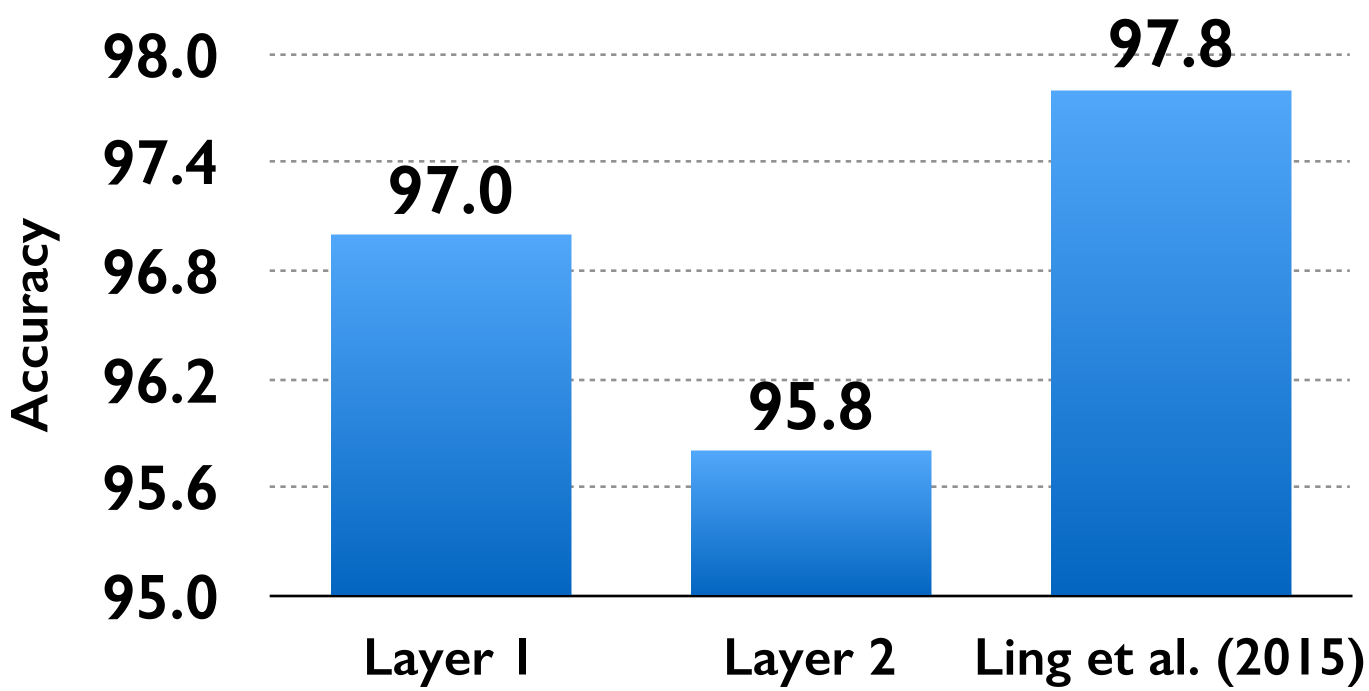
Semantics:

- Supervised WSD task [Miller et al.,1994]
- Use N-th layer in NN classifier



Syntax:

- Label POS corpus [Marcus et al., 1993]
- Learn classifier on N-th layer



Where Will the Data Come From???

Option 1: Semi-supervised learning

- E.g. word2vec and GloVe are in wide use [Mikolov et al., 2013; Pennington et al., 2014]
- Can we learn better word representations?

Option 2: Supervised learning

- Can we gather more direct forms of supervision?

A First Data Step: QA-SRL

- Introduce a **new SRL** formulation with **no frame or role inventory**
- Use **question-answer pairs** to model verbal predicate-argument relations
- Annotated **over 3,000 sentences in weeks** with **non-expert**, part-time annotators
- Showed that this data is **high-quality** and **learnable**

[He et al, 2015]

Previous Method: Annotation with Frames

ARG1 | ARG2 **amount risen** | ARG4 **end point**

The rent ***rose*** 10% from $3000 to $3300

ARG3 **start point**

> **Frameset: rise.01 , *go up***
>
> **Arg1-**: *Logical subject, patient, thing rising*
> **Arg2-EXT**: *EXT, amount risen*
> **Arg3-DIR**: *start point*
> **Arg4-LOC**: *end point*
> **Argm-LOC**: *medium*

- Depends on pre-defined frame inventory, requires syntactic parses
- Annotators need to:
  1) Identify the Frameset
  2) Find arguments in the parse
  3) Assign labels accordingly
- If frame doesn't exist, create new

The Proposition Bank: An Annotated Corpus of Semantic Roles, Palmer et al., 2005
http://verbs.colorado.edu/propbank/framesets-english/rise-v.html

Our Annotation Scheme

Given sentence and a verb:

They ***increased*** the rent this year .

Our Annotation Scheme

Given sentence and a verb:

They ***<u>increased</u>*** the rent this year .

<u>Step 1:</u> Ask a question about the verb:

Who increased something ?

Our Annotation Scheme

Given sentence and a verb:

They ***increased*** the rent this year .

Step 1: Ask a question about the verb:

Who increased something ?

Step 2: Answer with words in the sentence:

They

Our Annotation Scheme

Given sentence and a verb:

They ***increased*** the rent this year .

Step 1: **Ask a question about the verb:**

Who increased something ?

Step 2: **Answer with words in the sentence:**

They

Step 3: **Repeat, write as many QA pairs as possible …**

Our Annotation Scheme

Given sentence and a verb:

They ***<u>increased</u>*** the rent this year .

<u>Step 1:</u> Ask a question about the verb:

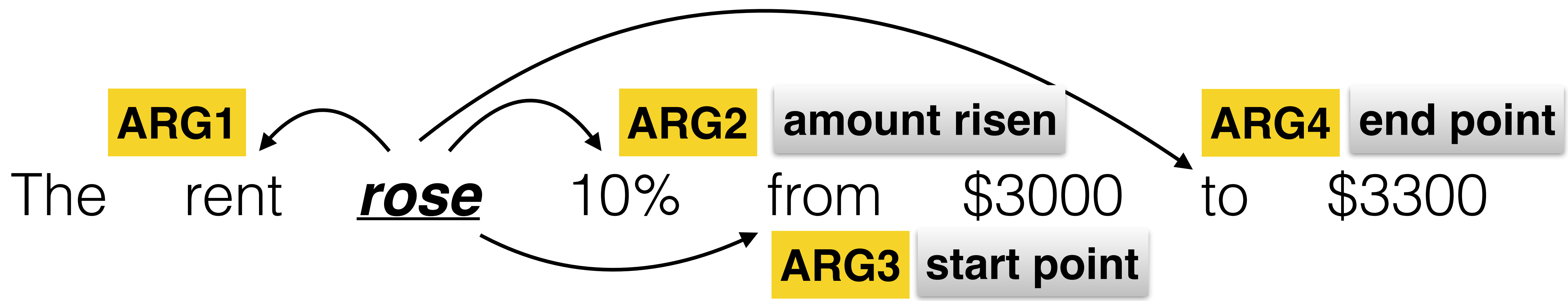
<u>Step 2:</u> Answer with words in the sentence:

Who increased something ?	They

<u>Step 3:</u> Repeat, write as many QA pairs as possible …

What is increased ?	the rent
When is something increased ?	this year

Our Method: Q/A Pairs for Semantic Relations



Wh-Question	**Answer**
What ***rose*** ?	the rent
How much did something ***rise*** ?	10%
What did something ***rise*** from ?	$3000
What did something ***rise*** to ?	$3300

Wh-words vs. PropBank Roles

	Who	What	When	Where	Why	How	HowMuch
ARG0	1575	414	3	5	17	28	2
ARG1	285	2481	4	25	20	23	95
ARG2	85	364	2	49	17	51	74
ARG3	11	62	7	8	4	16	31
ARG4	2	30	5	11	2	4	30
ARG5	0	0	0	1	0	2	0
AM-ADV	5	44	9	2	25	27	6
AM-CAU	0	3	1	0	23	1	0
AM-DIR	0	6	1	13	0	4	0
AM-EXT	0	4	0	0	0	5	5
AM-LOC	1	35	10	89	0	13	11
AM-MNR	5	47	2	8	4	108	14
AM-PNC	2	21	0	1	39	7	2
AM-PRD	1	1	0	0	0	1	0
AM-TMP	2	51	341	2	11	20	10

Advantages

- Easily explained
- No pre-defined roles, few syntactic assumption
- Can capture implicit arguments
- Generalizable across domains

Limitations

- Only modeling verbs (for now)
- Not annotating verb senses directly
- Can have multiple equivalent questions

Challenges

- What questions to ask?
- How much data do we need?
- Can we generalize to other tasks, such as coref?

Does the Recipe Work for Broad Coverage Semantics?

Step 1: Gather lots of training data!

Challenge 1: Data is costly and limited (e.g. linguists required to label PennTreebank / OntoNotes)

Step 2: Apply Deep Learning!!

Challenge 2: Pipeline of structured prediction problems with cascading errors (e.g. POS->Parsing->SRL->Coref)

Step 3: Observe Impressive Gains!!!

Contributions

Models

- End-to-end deep learning for SRL and coreference
- No preprocessing (e.g. no parser or POS tagger)

Data

- Contextualized word embeddings from a language model
- First steps towards scalable data annotation

PAUL G. ALLEN SCHOOL OF COMPUTER SCIENCE & ENGINEERING

ALLEN INSTITUTE for ARTIFICIAL INTELLIGENCE

The End: Questions?

Future Directions

- Multi-task learning, given architectural similarities
- Multi-lingual should work, in theory…
- Need to scale up data annotation efforts, and focus on out of domain performance

Recent Release

- AllenNLP: Deep Learning Semantic NLP toolkit
- See demos and code at AllenNLP.org

PAUL G. ALLEN SCHOOL OF COMPUTER SCIENCE & ENGINEERING

ALLEN INSTITUTE for ARTIFICIAL INTELLIGENCE