

A Mention-Ranking Model for Abstract Anaphora Resolution

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Abstract Anaphora Resolution

Resolution of (unrestricted) anaphors – nominal or pronominal – that refer to **abstract objects**: propositions, facts, events or properties.

The research of Iran Human Rights shows 34 people were hanged in public in Iran in 2016, and **an audience of hundreds of people, including children, were present for most of these hangings**. Human rights activists and informed members of civil society have always severely *criticized* this issue. / this.



unrestricted abstract anaphora resolution

Abstract Anaphora Resolution

ENTITY ANAPHORA RESOLUTION (COREFERENCE RESOLUTION)	ABSTRACT ANAPHORA RESOLUTION
resolving multiple ambiguous mentions of a single entity representing a person, a location or an organization	resolution of anaphoric expressions that refer to propositions, facts, events or properties
standard features: agreement, apposition, saliency, etc.	standard features for resolution of entity anaphora do not apply
considerable amounts of annotated training data	lack of sufficient amounts of annotated training data

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**NEURAL
MODEL**



**GENERATE
TRAINING
DATA**

We address resolution of **unrestricted** abstract anaphora with **artificially created training data** and a **neural model**.

Related work

task	example	data size	neural	note
event coreference (Lu and Ng, 2017)	Police said Lo Presti <u>had hanged</u> himself. His <u>suicide</u> appeared to be related to clan feuds.	9955 event coreference chains (KBP, Eng)	YES	coreference between VP and NP mentions of similar abstractness

Related work

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sluicing (Anand and Hardt, 2016)	Harry traveled to southern Denmark <u>to study botany.</u> I want to know <u>why.</u>	4100 examples	NO	small data, not published

Related work

– shell noun resolution (Kolhatkar et al., 2013)

Environmental Defense notes that **mowing the lawn with a gas mower produces as much pollution as driving a car 172 miles**. **This fact** may explain the recent surge in the sales of old-fashioned push mowers.

Anaphoric
Shell Noun
(ASN)


*(fact, reason, issue,
question, ...)*

Related work

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event coreference (Lu and Ng, 2017)	Police said Lo Presti <u>had hanged</u> himself. His <u>suicide</u> appeared to be related to clan feuds.	9955 event coreference chains (Eng)	YES	coreference between VP and NP mentions of similar abstractness
sluicing (Anand and Hardt, 2016)	Harry traveled to southern Denmark to study botany. I want to know <u>why</u> .	4100 examples	NO	small data, not published
anaphoric connectives (Stede and Grishina, 2016)	Peter was the best goal scorer. <u>Therefore</u> he received the trophy.	140 instances (therefore)	NO	restricted in type, ambiguous and require WSD


Related work

– shell noun resolution (Kolhatkar et al., 2013)



Environmental Defense notes that **mowing the lawn with a gas mower produces as much pollution as driving a car 172 miles**. **This fact** may explain the recent surge in the sales of old-fashioned push mowers.

**Anaphoric
Shell Noun
(ASN)**



Congress has focused almost solely on **the fact** that **special education is expensive - and that it takes away money from regular education**.

**Cataphoric
Shell Noun
(CSN)**



syntactic rules: N-to, N-to-be, N-that, etc.



**special education is expensive - and that
it takes away money from regular education**

antecedent

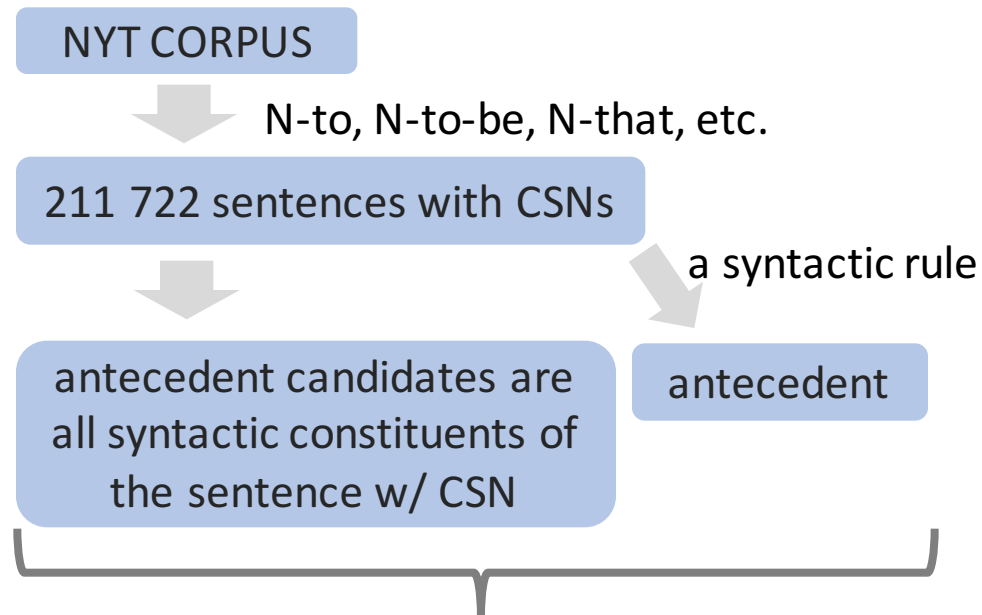


Congress has focused almost solely on **this fact**.

**sentence with
the shell noun**

Related work

- shell noun resolution (Kolhatkar et al., 2013)



CSN:

... the fact that S ...

trained SVM-rank

ASN:

... pointed to this fact...



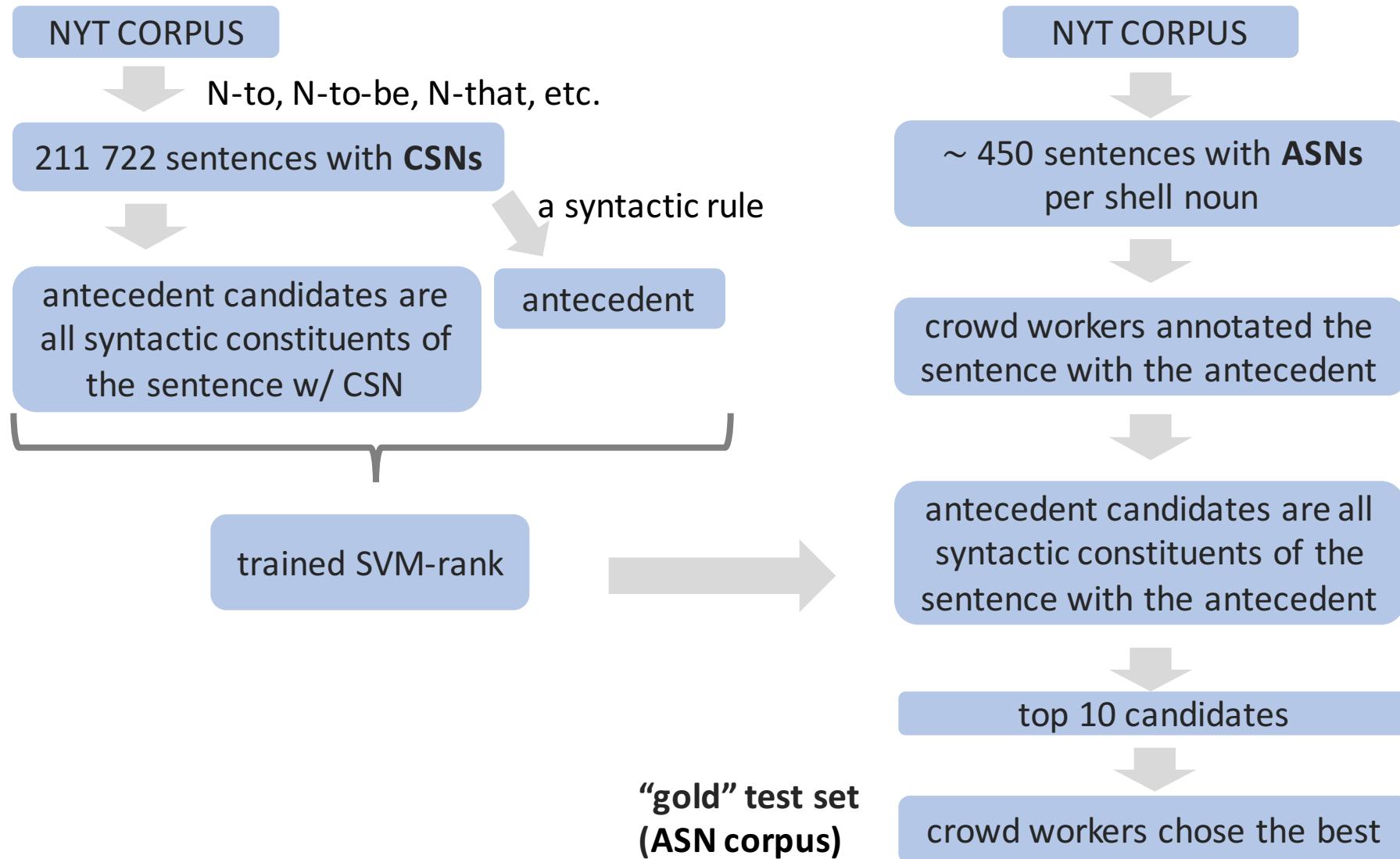
assumption: linguistic knowledge encoded in CSN antecedents will help in interpreting ASNs

=>

apply the SVM-rank model trained on CSN data to **predict ASN antecedents** as well

Related work

- shell noun resolution (Kolhatkar et al., 2013)



Related work

KOLHAKTAR ET AL. (2013)	OUR WORK
shell noun resolution	Unrestricted abstract anaphora (AA) resolution (nominal and pronominal)
data generation method depends on properties and categorization of shell nouns	a common syntactic construction
feature-based ranking model	neural ranking model

Intuitions – for our model



How can we learn what is the **correct** antecedent for a given AA?

Our intuition: by **learning the relation** between

Anaphoric Sentence w/ AA

&

Antecedent

Human rights activists ... criticized AA

*... **hundreds of people, including children, were present for these hangings.***

Intuitions – for training data generation




We can extract such Antecedent – Anaphoric Sentence pairs automatically from **constructions with embedded sentences**, by a simple transformation:

Human rights activists and informed members of civil society have always severely criticized [_S that [_S an audience of hundreds of people, including children, were present for most of these hangings]].



Human rights activists and informed members of civil society have always severely criticized this / this issue. **An audience of hundreds of people, including children, were present for most of these hangings.**

Training data generation



type	head of S'	possible anaphoric phrase
empty	∅	<u>this, that</u>
general	that, this	that, this
causal	because, as	therefore, because of this/that
temporal	while, since, etc.	during this/that
conditional	if, whether	if this/that is true


Complements

He **doubts** [**S'** ∅ [**S** ~~a Bismarckian super state will emerge that would dominate Europe~~], but warns of “a risk of profound change in the heart of the European Community from a Germany that is too strong, even if democratic”].



[**S** a Bismarckian super state will emerge that would dominate Europe]

Training data generation



type	head of S'	possible anaphoric phrase
empty	∅	<u>this, that</u>
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causal	because, as	therefore, because of this/that
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Complements

He **doubts** [S' ∅ [S this], but warns of “a risk of profound change in the heart of the European Community from a Germany that is too strong, even if democratic”].



[S a Bismarckian super state will emerge that would dominate Europe]

Training data generation

type	head of S'	possible anaphoric phrase
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Complements

He **doubts this**, but warns of “a risk of profound change in the heart of the European Community from a Germany that is too strong, even if democratic”.

Anaphoric
Sentence



A Bismarckian super state will emerge that would dominate Europe.

Antecedent

Training data generation

type	head of S'	possible anaphoric phrase
empty	∅	this, that
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conditional	if, whether	if this/that is true

Adjuncts

There is speculation that property casualty firms will sell even more munis
[S' **as** [~~S~~ they scramble to raise cash to pay claims related to Hurrican Hugo
and the Northern California earthquake]].

[S they scramble to raise cash to pay claims related to Hurrican Hugo and
the Northern California earthquake]

Training data generation

type	head of S'	possible anaphoric phrase
empty	∅	this, that
general	that, this	that, this
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There is speculation that property casualty firms will sell even more munis
[S' ***because of this***].

[S they scramble to raise cash to pay claims related to Hurrican Hugo and
the Northern California earthquake]

Training data generation

type	head of S'	possible anaphoric phrase
empty	∅	this, that
general	that, this	that, this
causal	because, as	therefore, because of this/that
temporal	while, since, etc.	during this/that
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Adjuncts

There is speculation that property casualty firms will sell even more munis ***because of this***.

Anaphoric
Sentence

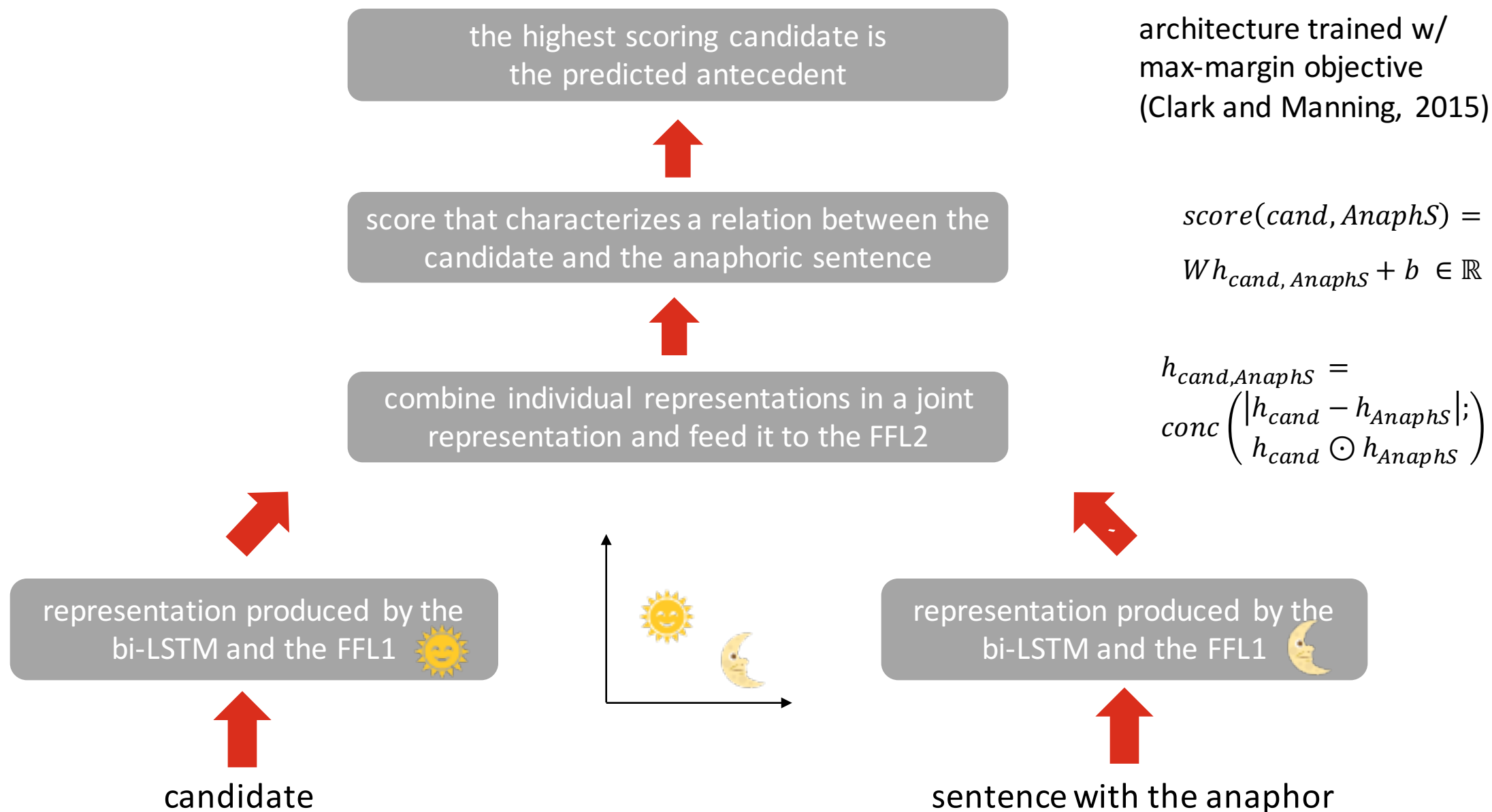
→ They scramble to raise cash to pay claims related to Hurrican Hugo and the Northern California earthquake.

Antecedent

Training data generation

- training data for **unrestricted** abstract anaphora resolution
- obtained using a **common** construction – a verb with an embedded sentence
- **large-scale training data**
 - 15,282 instances from the WSJ part of the PTB corpus for initial experiments
 - but much more can be extracted

Siamese-LSTM Mention-ranking model



Siamese-LSTM Mention-ranking model

– input

an audience of hundreds of people, including children, were present for most of these hangings

candidate

input to LSTM

emb(token)

Human rights activists and informed members of civil society have always severely criticized **this issue**.

sentence with
the anaphor
(AnaphS)

input to LSTM

emb(token)

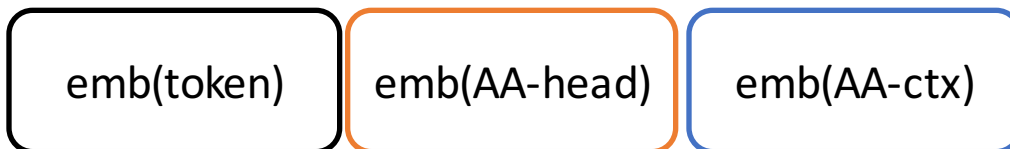
Siamese-LSTM Mention-ranking model

– input

an audience of hundreds of people, including children, were present for most of these hangings

candidate

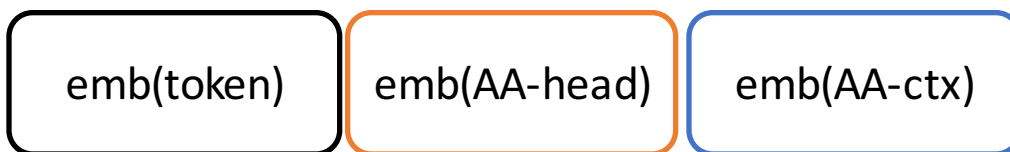
input to LSTM



Human rights activists and informed members of civil society have always severely criticized **this issue**.

sentence with
the anaphor
(AnaphS)

input to LSTM



The anaphoric sentence may have more than one abstract anaphor (AA)

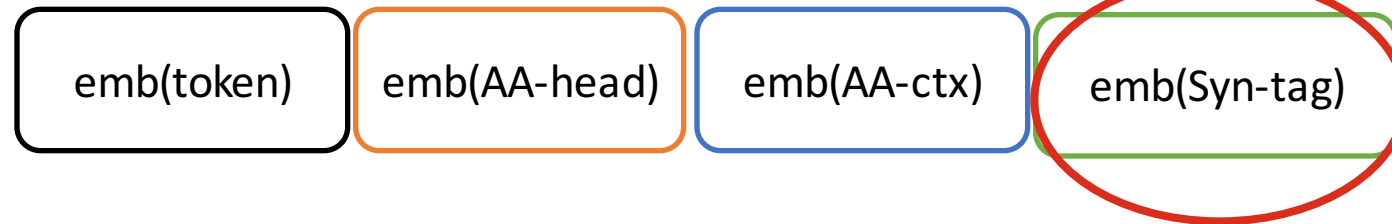
Siamese-LSTM Mention-ranking model

– input

an audience of hundreds of people, including children, were present for most of these hangings

candidate

input to LSTM

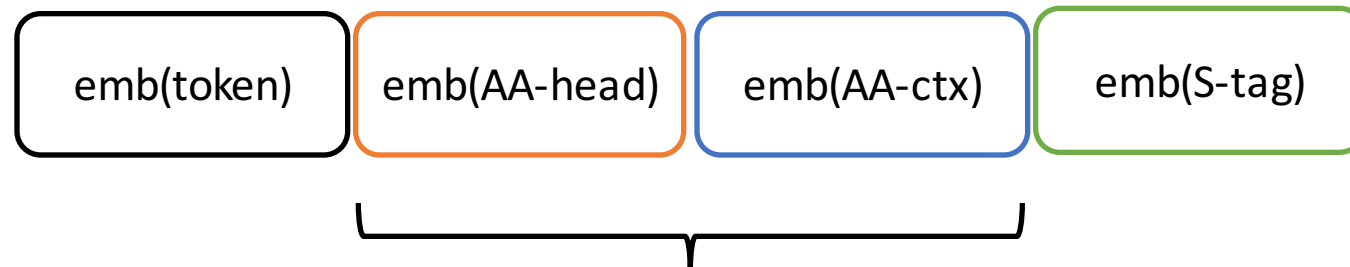


a constituent tag label is a good signal of worthy candidates

Human rights activists and informed members of civil society have always severely criticized **this issue**.

sentence with the anaphor (AnaphS)

input to LSTM



The anaphoric sentence may have more than one abstract anaphor (AA)

Experiment 1: Shell noun resolution

	train	test
fact	43 809	472
reason	4 529	442
issue	2 664	303
decision	42 289	389
question	9 327	440
possibility	11 874	277

Datasets

- train data*: generated with resolution of CSNs
- test data*: anaphoric shell noun dataset annotated with crowd workers (the ASN corpus)
- dev data: a small-scaled subset of the ARRAU corpus (Uryupina et al., 2016) restricted to unconstrained abstract anaphors (ARRAU-AA)

* Obtained from Kolhatkar et al. 2013

Exp1: Shell noun resolution

	train	test	model
fact	43 809	472	MR-LSTM
	-	-	KZH13
	-	-	TAG-BL
reason	4 529	442	MR-LSTM
	4 529	442	MR-LSTM-tune
	-	-	KZH13
	-	-	TAG-BL
issue	2 664	303	MR-LSTM
	-	-	KZH13
	-	-	TAG-BL
decision	42 289	389	MR-LSTM
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question	9 327	440	MR-LSTM
	-	-	KZH13
	-	-	TAG-BL
possibility	11 874	277	MR-LSTM
	-	-	KZH13
	-	-	TAG-BL

Baselines

- Kolhatkar et al. (2013) – **KZH13**

Exp1: Shell noun resolution

	train	test	model
fact	43 809	472	MR-LSTM
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	-	-	KZH13
	-	-	TAG-BL

Baselines

- Kolhatkar et al. (2013) – KZH13
- the **TAG baseline** randomly chooses a candidate with the tag in {S, VP, ROOT, SBAR}

Exp1: Shell noun resolution

	train	test	model	s@1	s@2	s@3	s@4
fact	43 809	472	MR-LSTM				
	-	-	KZH13				
	-	-	TAG-BL				
reason	4 529	442	MR-LSTM				
	4 529	442	MR-LSTM-tune				
	-	-	KZH13				
	-	-	TAG-BL				
issue	2 664	303	MR-LSTM				
	-	-	KZH13				
	-	-	TAG-BL				
decision	42 289	389	MR-LSTM				
	-	-	KZH13				
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	-	-	KZH13				
	-	-	TAG-BL				
possibility	11 874	277	MR-LSTM				
	-	-	KZH13				
	-	-	TAG-BL				

Evaluation metrics:

success@n (s@n) :

the antecedent or a

candidate that differs in

one word or *one word*

and punctuation is in the

first n ranked candidates,

$n \in \{1, 2, 3, 4\}$

Exp1: Shell noun resolution

	train	test	model	s@1	s@2	s@3	s@4
fact	43 809	472	MR-LSTM	83.47	85.38	86.44	87.08
	-	-	KZH13	70.00	86.00	92.00	95.00
	-	-	TAG-BL	46.99	-	-	-
reason	4 529	442	MR-LSTM	71.27	77.38	80.09	80.54
	4 529	442	MR-LSTM-tune	87.78	91.63	93.44	93.89
	-	-	KZH13	72.00	86.90	90.00	94.00
	-	-	TAG-BL	42.40	-	-	-
issue	2 664	303	MR-LSTM	88.12	91.09	93.07	93.40
	-	-	KZH13	47.00	61.00	72.00	81.00
	-	-	TAG-BL	44.92	-	-	-
decision	42 289	389	MR-LSTM	76.09	85.86	91.00	93.06
	-	-	KZH13	35.00	53.00	67.00	76.00
	-	-	TAG-BL	45.55	-	-	-
question	9 327	440	MR-LSTM	89.77	94.09	95.00	95.68
	-	-	KZH13	70.00	83.00	88.00	91.00
	-	-	TAG-BL	42.02	-	-	-
possibility	11 874	277	MR-LSTM	93.14	94.58	95.31	95.67
	-	-	KZH13	56.00	76.00	87.00	92.00
	-	-	TAG-BL	48.66	-	-	-

- MR-LSTM outperforms KZH13's and TAG-BL for 5/6 shell nouns without HP tuning!

Exp1: Shell noun resolution

	train	test	model	s@1	s@2	s@3	s@4
fact	43 809	472	MR-LSTM	83.47	85.38	86.44	87.08
	-	-	KZH13	70.00	86.00	92.00	95.00
	-	-	TAG-BL	46.99	-	-	-
reason	4 529	442	MR-LSTM	71.27	77.38	80.09	80.54
	4 529	442	MR-LSTM-tune	87.78	91.63	93.44	93.89
	-	-	KZH13	72.00	86.90	90.00	94.00
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	-	-	TAG-BL	45.55	-	-	-
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	-	-	TAG-BL	48.66	-	-	-

← with HP tuning

- MR-LSTM outperforms KZH13's and TAG-BL for 5/6 shell nouns without HP tuning!
- tuned MR-LSTM results for *reason* well beyond KZH13

Exp1: Shell noun resolution

– tuning for *reason*

REASON									
CTX-AA	AA	TAG	SHORTCUT	FFL1	FFL2	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	87.78	91.63	93.44	93.89
✗						85.97	87.56	89.14	89.82
	✗					86.65	88.91	91.18	91.40
		→ ✗	✗			68.10	80.32	85.29	89.37
			✗			85.52	88.24	89.59	90.05
✗	✗	✗	✗			66.97	80.54	85.75	88.24
				✗		87.56	91.62	92.76	94.12
					✗	85.97	88.69	89.14	90.05

- a large performance drop when omitting syntactic info (tag, cut)
 - the model makes good use of syntactic info or it fits the bias in the tag distribution

Experiment2: unrestricted abstract anaphora VS. constrained shell noun resolution

		shell noun resolution		unrestricted AA resolution	
		CSN	ASN	ARTIFICIAL	ARRAU-AA
		train	test	train	test
# of shell nouns / anaphors		2 664 – 43 809	277 - 472	8 527	600
median # of tokens	Antec	12.75	13.87	11	20.5
	AnaphS	11.5	24	19	28
median #	Antec	2	→ 4.5	2	→ 1
	negatives	44.5	39	15	48
#	nominal	all	all	none	397
	pronominal	none	none	all	203

Exp2: unrestricted abstract anaphora VS. constrained shell noun resolution

		shell nouns resolution		unrestricted AA resolution	
		CSN	ASN	ARTIFICIAL	ARRAU-AA
		train	test	train	test
# of shell nouns / anaphors		2 664 – 43 809	277 - 472	8 527	600
median # of tokens	Antec	12.75	13.87	11	20.5
	AnaphS	11.5	24	19	28
median #	Antec	2	4.5	2	1
	negatives	44.5	39	15	48
#	nominal	all	all	none	→ 397
	pronominal	none	none	all	→ 203

Exp2: Unrestricted abstract anaphora resolution

	all				nominal				pronominal			
	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
PS-BL	27.67	-	-	-	30.48	-	-	-	22.17	-	-	-
TAG-BL	38.43	-	-	-	40.10	-	-	-	35.17	-	-	-

Baselines

- PS-BL: the preceding sentence baseline
- TAG-BL: randomly chooses a candidate with the tag in {S, VP, ROOT, SBAR}

Exp2: Unrestricted abstract anaphora resolution

						all				nominal				pronominal			
CTX	AA	TAG	CUT	FFL1	FFL2	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	24.17	43.67	54.50	63.00	29.47	50.63	62.47	72.04	13.79	30.05	38.92	45.32
PS-BL						27.67	-	-	-	30.48	-	-	-	22.17	-	-	-
TAG-BL						38.43	-	-	-	40.10	-	-	-	35.17	-	-	-

- the full architecture does not outperform baselines
- MR-LSTM resolves nominal anaphors better than pronominal

Exp2: Unrestricted abstract anaphora resolution

						all				nominal				pronominal			
CTX	AA	TAG	CUT	FFL1	FFL2	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	24.17	43.67	54.50	63.00	29.47	50.63	62.47	72.04	13.79	30.05	38.92	45.32
✗						29.67	52.50	66.00	75.00	33.50	58.19	72.04	80.86	22.17	41.38	54.19	63.55
	✗					22.83	39.00	52.00	61.33	22.42	41.31	54.66	64.48	23.65	34.48	46.80	55.17
			PS-BL			27.67	-	-	-	30.48	-	-	-	22.17	-	-	-
			TAG-BL			38.43	-	-	-	40.10	-	-	-	35.17	-	-	-

- info about context of the anaphor lowers results,
- but the **embedding of the head of the anaphor** is important
 - and: more useful for **nominals** compared to pronouns

Exp2: Unrestricted abstract anaphora resolution

CTX	AA	TAG	CUT	FFL1	FFL2	all				nominal				pronominal			
						s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	24.17	43.67	54.50	63.00	29.47	50.63	62.47	72.04	13.79	30.05	38.92	45.32
✗						29.67	52.50	66.00	75.00	33.50	58.19	72.04	80.86	22.17	41.38	54.19	63.55
	✗					22.83	39.00	52.00	61.33	22.42	41.31	54.66	64.48	23.65	34.48	46.80	55.17
		✗	✗			38.33	54.83	63.17	69.33	46.60	64.48	72.54	79.09	22.17	35.96	44.83	50.25
					PS-BL	27.67	-	-	-	30.48	-	-	-	22.17	-	-	-
					TAG-BL	38.43	-	-	-	40.10	-	-	-	35.17	-	-	-

- **omitting syntactic info** helps and **raises MR-LSTM results for nominals above both BLs!**

Exp2: Unrestricted abstract anaphora resolution

						all				nominal				pronominal			
CTX	AA	TAG	CUT	FFL1	FFL2	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	24.17	43.67	54.50	63.00	29.47	50.63	62.47	72.04	13.79	30.05	38.92	45.32
✗						29.67	52.50	66.00	75.00	33.50	58.19	72.04	80.86	22.17	41.38	54.19	63.55
	✗					22.83	39.00	52.00	61.33	22.42	41.31	54.66	64.48	23.65	34.48	46.80	55.17
		✗	✗			38.33	54.83	63.17	69.33	46.60	64.48	72.54	79.09	22.17	35.96	44.83	50.25
shuffling +		✗	✗			43.83	56.33	66.33	73.00	51.89	64.48	73.55	79.85	28.08	40.39	52.22	59.61
		TAG-BL				38.43	-	-	-	40.10	-	-	-	35.17	-	-	-

- additional shuffling of training data boosts results significantly
- we found model variants that **surpass the baselines** for the entire and the nominal part of ARRAU-AA
- results of resolution of shell nouns were in the range 76.09 - 93.14 s@1

Exp2: Unrestricted abstract anaphora resolution

						all				nominal				pronominal			
CTX	AA	TAG	CUT	FFL1	FFL2	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	24.17	43.67	54.50	63.00	29.47	50.63	62.47	72.04	13.79	30.05	38.92	45.32
✗						29.67	52.50	66.00	75.00	33.50	58.19	72.04	80.86	22.17	41.38	54.19	63.55
	✗					22.83	39.00	52.00	61.33	22.42	41.31	54.66	64.48	23.65	34.48	46.80	55.17
		✗	✗			38.33	54.83	63.17	69.33	46.60	64.48	72.54	79.09	22.17	35.96	44.83	50.25
shuffling +		✗	✗			43.83	56.33	66.33	73.00	51.89	64.48	73.55	79.85	28.08	40.39	52.22	59.61
TAG-BL						38.43	-	-	-	40.10	-	-	-	35.17	-	-	-

- our model selects syntactically plausible candidates and – if disregarding syntax – discriminates candidates using deeper features

Exp2: Unrestricted abstract anaphora resolution

						all				nominal				pronominal			
CTX	AA	TAG	CUT	FFL1	FFL2	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	24.17	43.67	54.50	63.00	29.47	50.63	62.47	72.04	13.79	30.05	38.92	45.32
✗						29.67	52.50	66.00	75.00	33.50	58.19	72.04	80.86	22.17	41.38	54.19	63.55
	✗					22.83	39.00	52.00	61.33	22.42	41.31	54.66	64.48	23.65	34.48	46.80	55.17
		✗	✗			38.33	54.83	63.17	69.33	46.60	64.48	72.54	79.09	22.17	35.96	44.83	50.25
shuffling +		✗	✗			43.83	56.33	66.33	73.00	51.89	64.48	73.55	79.85	28.08	40.39	52.22	59.61
w/ the best HPs for pronominal		✗	✗		➔	38.17	52.50	61.33	68.67	43.07	57.43	65.49	72.04	28.57	42.86	53.20	62.07
		PS-BL				27.67	-	-	-	30.48	-	-	-	22.17	-	-	-
		TAG-BL				38.43	-	-	-	40.10	-	-	-	35.17	-	-	-

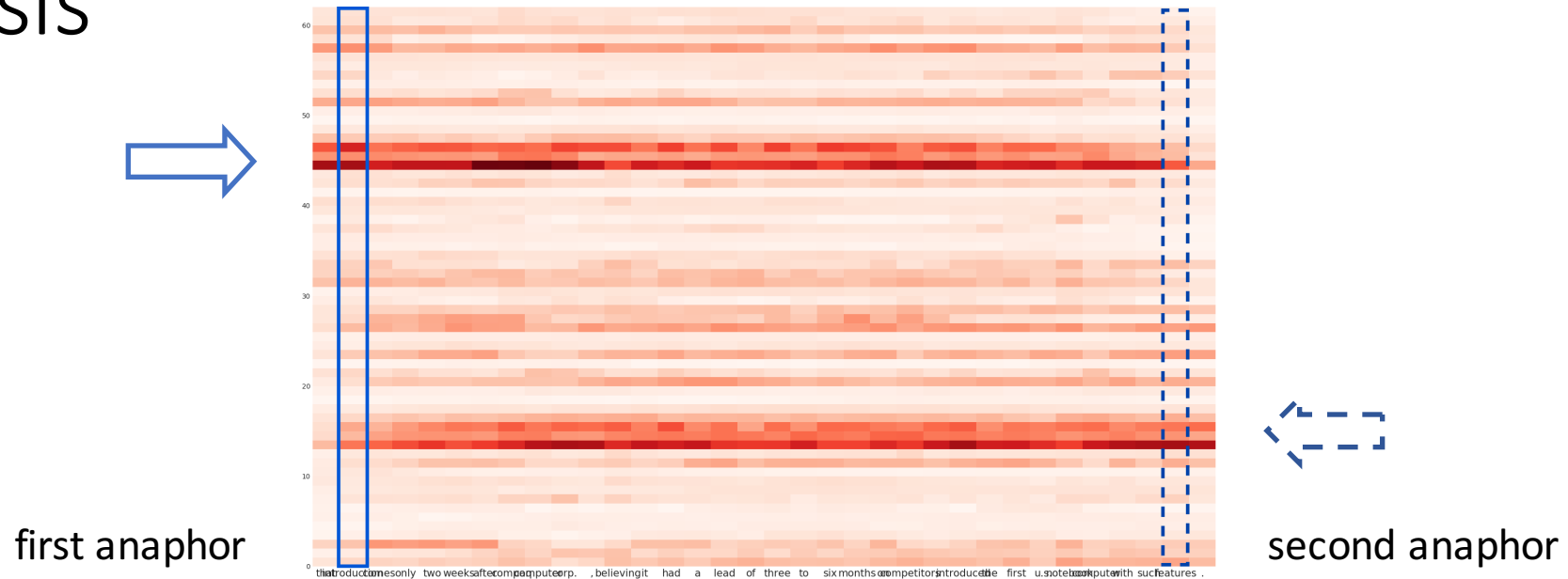
- HPs that yield good performance for nominal anaphors are not good for pronominal ones and vice versa

Exp2: Unrestricted abstract anaphora resolution

CTX	AA	TAG	CUT	FFL1	FFL2	all				nominal				pronominal			
						s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4	s@1	s@2	s@3	s@4
✓	✓	✓	✓	✓	✓	24.17	43.67	54.50	63.00	29.47	50.63	62.47	72.04	13.79	30.05	38.92	45.32
✗						29.67	52.50	66.00	75.00	33.50	58.19	72.04	80.86	22.17	41.38	54.19	63.55
	✗					22.83	39.00	52.00	61.33	22.42	41.31	54.66	64.48	23.65	34.48	46.80	55.17
		✗	✗			38.33	54.83	63.17	69.33	46.60	64.48	72.54	79.09	22.17	35.96	44.83	50.25
		✗	✗			43.83	56.33	66.33	73.00	51.89	64.48	73.55	79.85	28.08	40.39	52.22	59.61
		✗	✗			38.17	52.50	61.33	68.67	43.07	57.43	65.49	72.04	28.57	42.86	53.20	62.07
			✗			30.17	48.00	57.83	67.33	30.73	50.88	61.21	71.54	29.06	42.36	51.23	59.11
✗	✗	✗	✗			26.33	40.50	50.67	58.67	28.46	41.81	52.14	59.70	22.17	37.93	47.78	56.65
				✗		21.33	41.17	53.17	60.33	23.43	47.36	60.45	69.52	17.24	29.06	38.92	42.36
					✗	12.00	24.67	33.50	41.50	13.35	27.20	37.28	45.84	9.36	19.70	26.11	33.00

- only the head of the anaphor, the first and the second feed-forward layer contribute

Exp2: Unrestricted abstract anaphora resolution – analysis



Does a learned representation between the anaphoric sentence and an antecedent establish a relation between a **specific anaphor we want to resolve and the **antecedent**?**

The heat-maps illustrates the difference in output of the bi-LSTM for the same anaphoric sentence with two anaphors when **the first vs. second anaphor** is considered.

Clearly, the representations differ and consequently, their joint representations with the candidate as well.

What have we learned about AA resolution?

CONTRIBUTIONS

1. first **neural** mention-ranking model for resolving **unrestricted** abstract anaphora – trained on **artificially created training data**
2. **evaluation on more realistic and more challenging evaluation data set** (compared to KZH13)
3. **We outperform the BLs for the nominals in ARRAU-AA without training models for individual anaphors**

LESSONS LEARNED

1. **nominal and pronominal anaphors should be learned independently**
2. the full model **selects syntactically plausible candidates, but** the model w/o syntax info discriminates candidates using **deeper features, with better performance**
3. embedding of the anaphor ensures that **the learned relation between antecedent and anaphoric sentence is dependent on the anaphor under consideration**

Future directions

LESSONS LEARNED

- **nominal** and **pronominal** anaphors should be learned **independently**
- the full model **selects syntactically plausible candidates**, but the model w/o syntax info discriminates candidates using **deeper features, with better performance**
- embedding of the anaphor ensures that **the learned relation between anaphor and antecedent sentence is dependent on the anaphor under consideration**

1. DO THIS

2. LEARN A MODEL
THAT DOES BOTH

3. investigate mixtures of data from different sources (artificial + natural)

4. offer candidates from the larger context

Thank you for your attention!

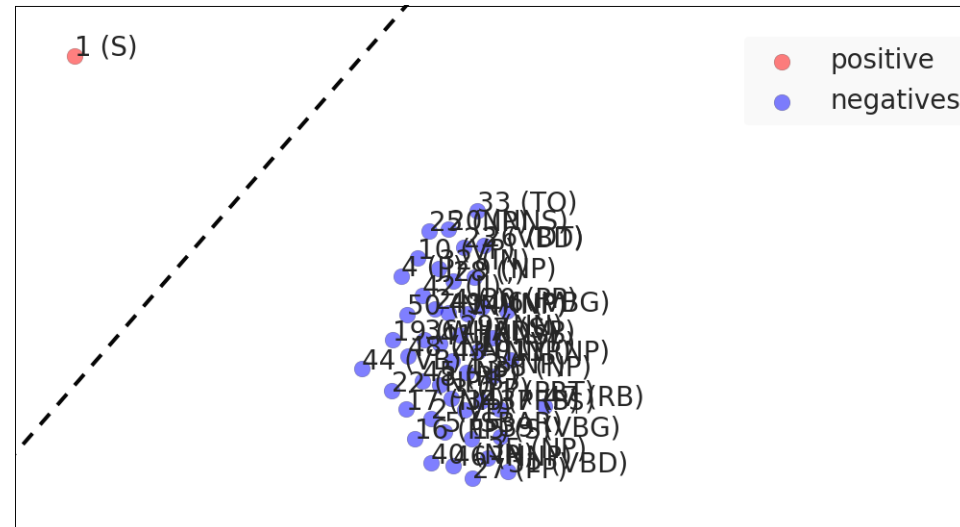
github repo with code:

<https://github.com/amarasovic/neural-abstract-anaphora>

References

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EXP2: unrestricted abstract anaphora resolution – analysis



What does the max-margin objective achieve in the MR-LSTM?

It separates the best scoring antecedent from the best scoring negative candidate by separating their respective joint representations with the anaphoric sentence.

dropout

emb(token)

emb(issue)

average(this,
issue, .)

emb(S-tag)

an audience of hundreds of people, including children, were
present for most of these hangings

candidate

dropout

emb(token)

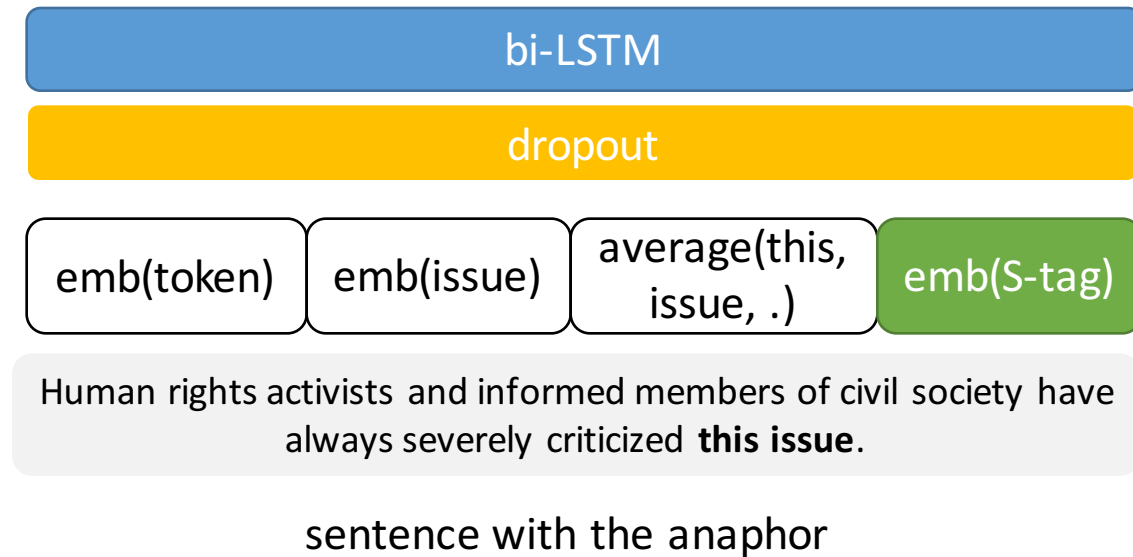
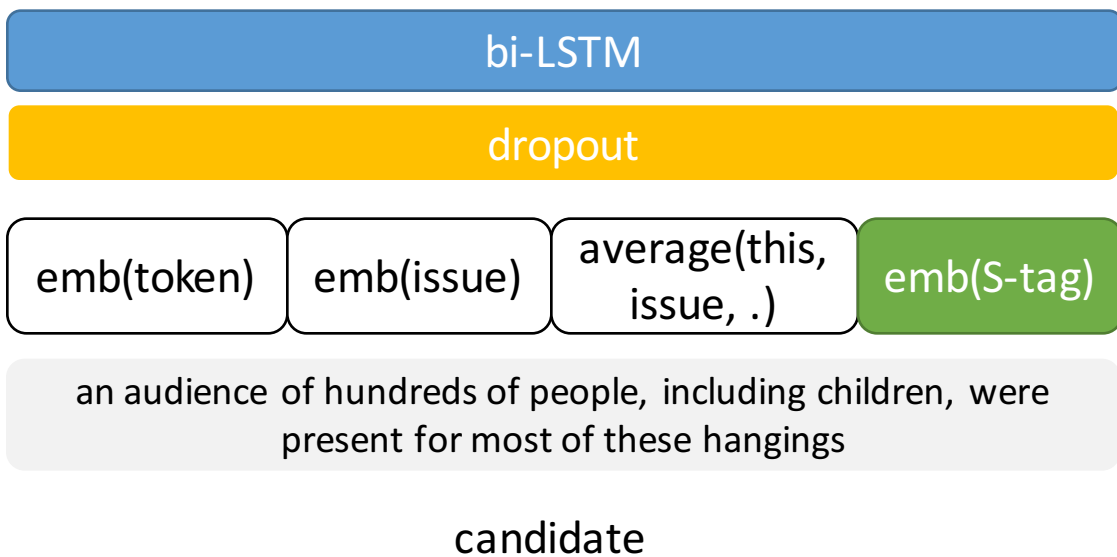
emb(issue)

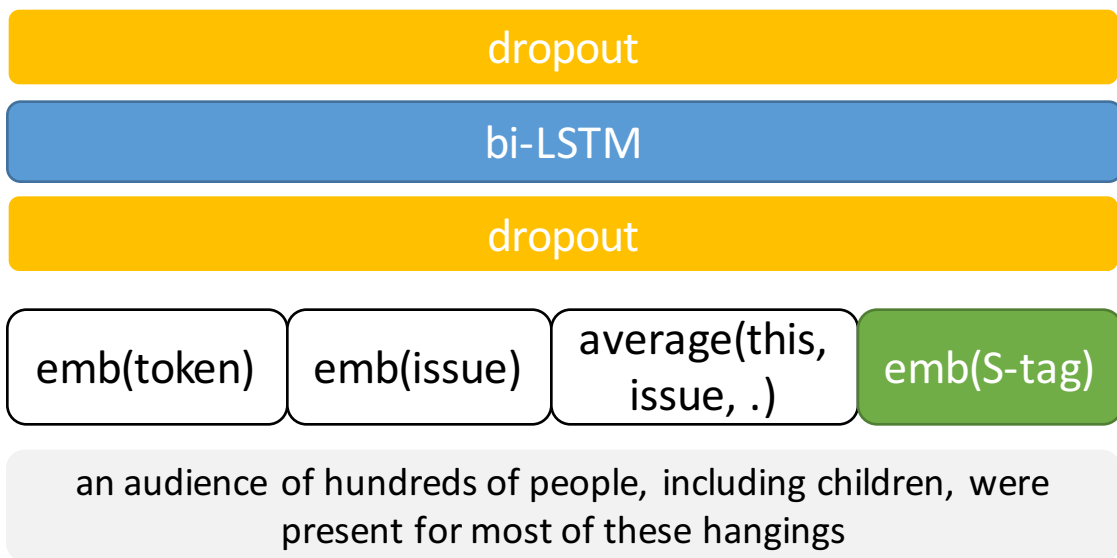
average(this,
issue, .)

emb(S-tag)

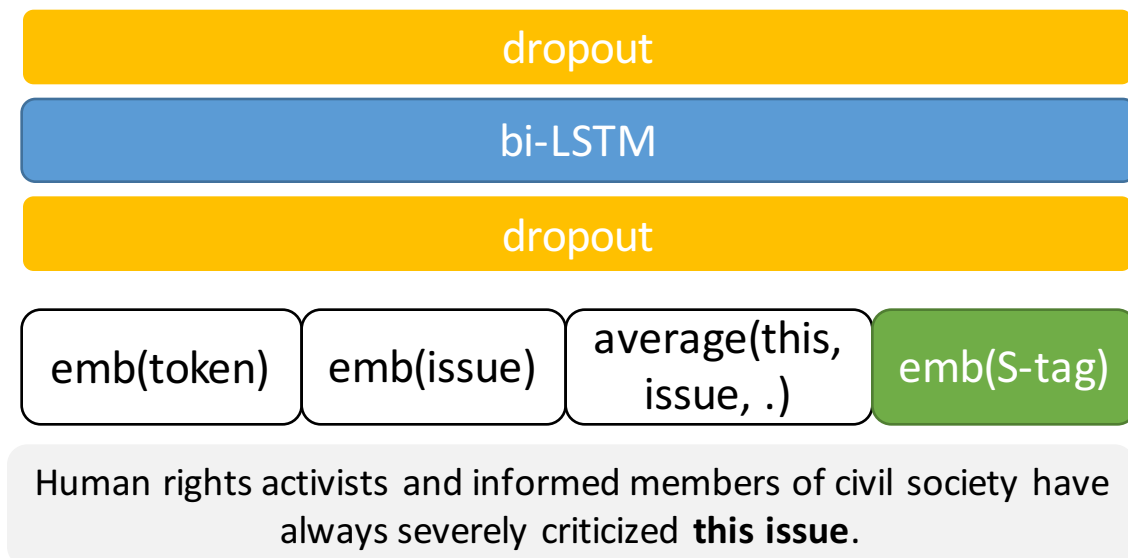
Human rights activists and informed members of civil society have
always severely criticized **this issue**.

sentence with the anaphor

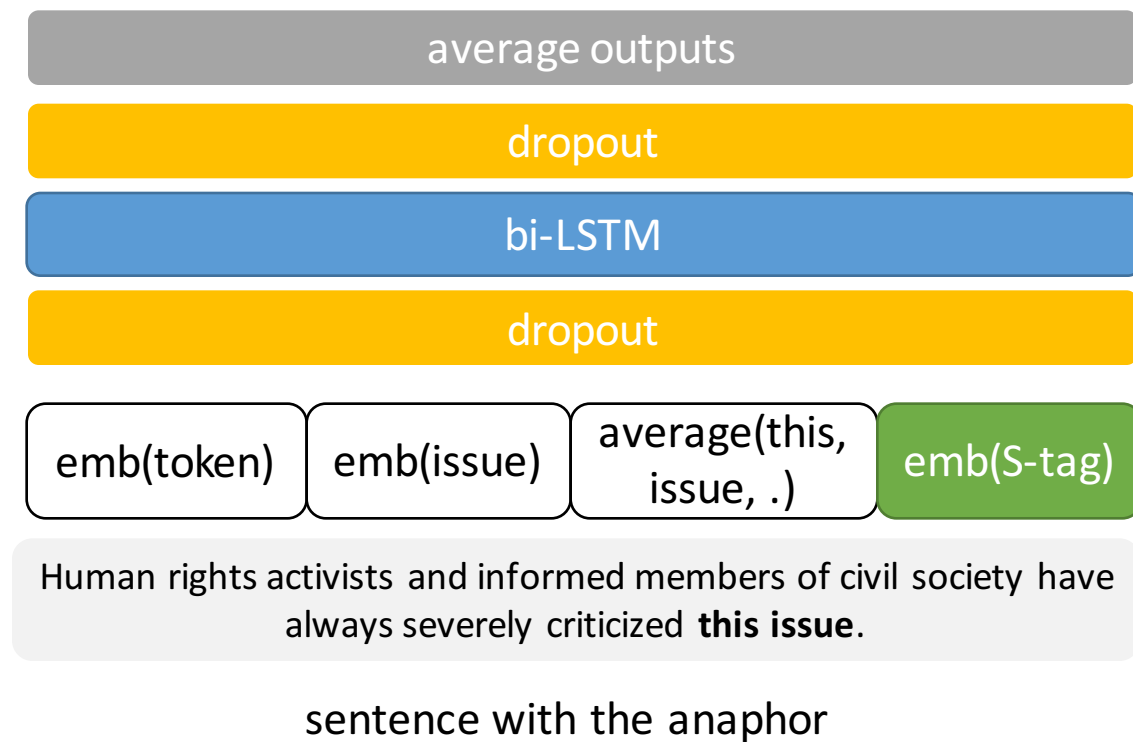
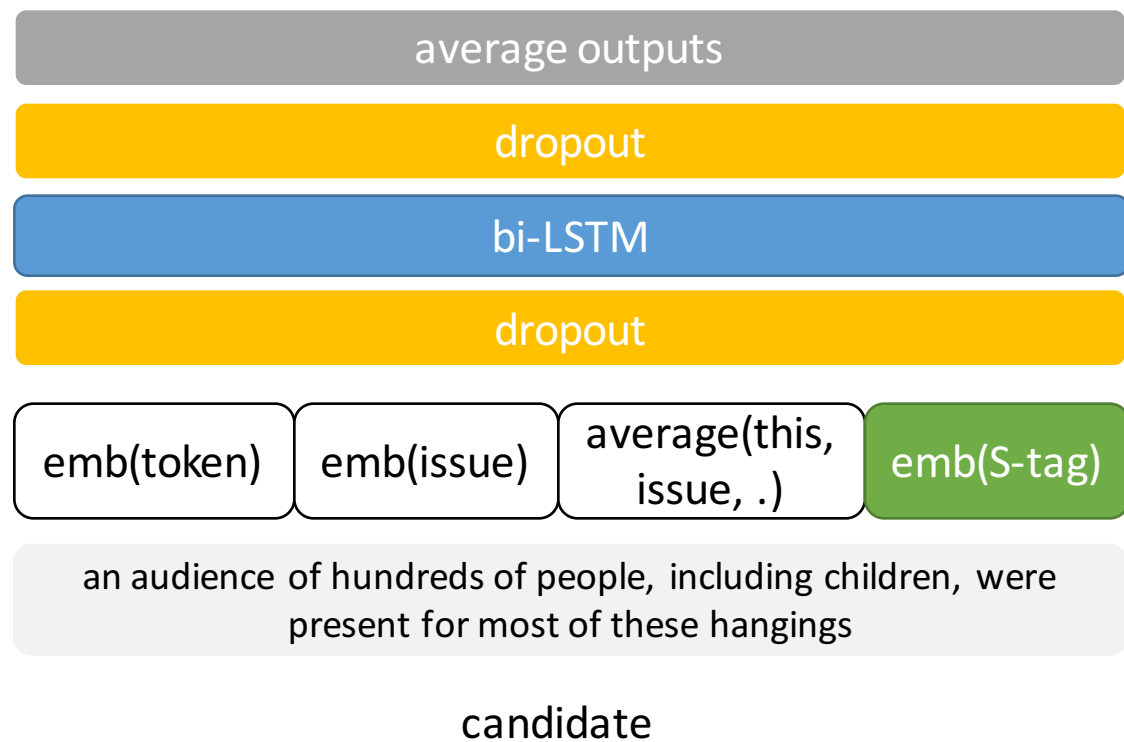




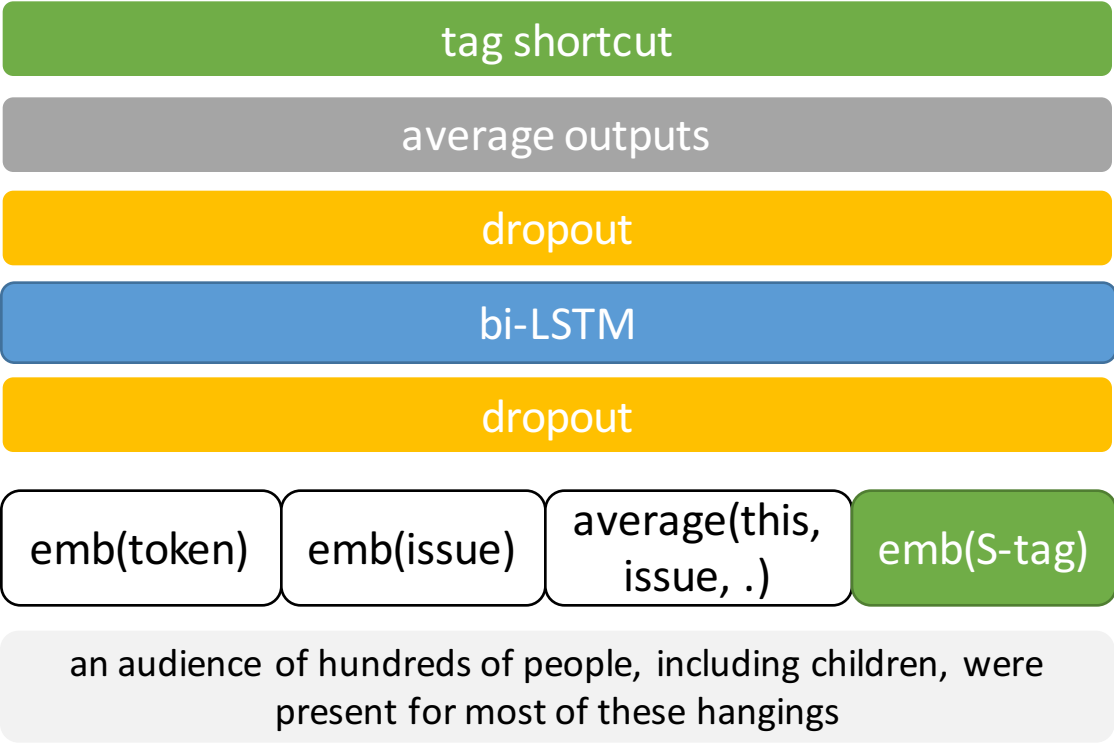
candidate



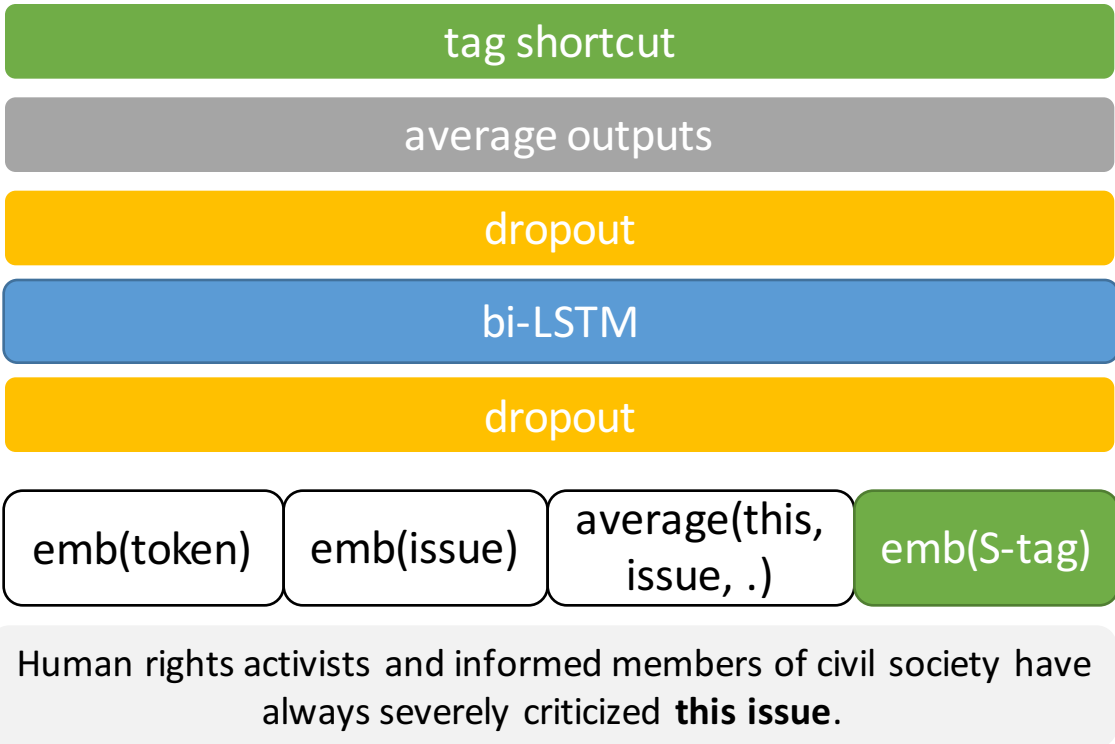
sentence with the anaphor



info about the constituent tag may be lost \Rightarrow add embedding of the constituent tag to the representation produced by bi-LSTM (**tag shortcut**)



candidate



sentence with the anaphor

feed-forward layer for more expressivity

feed-forward layer

tag shortcut

average outputs

dropout

bi-LSTM

dropout

emb(token)

emb(issue)

average(this,
issue, .)

emb(S-tag)

an audience of hundreds of people, including children, were
present for most of these hangings

candidate

feed-forward layer

tag shortcut

average outputs

dropout

bi-LSTM

dropout

emb(token)

emb(issue)

average(this,
issue, .)

emb(S-tag)

Human rights activists and informed members of civil society have
always severely criticized **this issue**.

sentence with the anaphor

$$h_{cand,AnaphS} = \text{concat}(|h_{cand} - h_{joint}|; h_{cand} \odot h_{AnaphS})$$

joint representation

feed-forward layer

tag shortcut

average outputs

dropout

bi-LSTM

dropout

emb(token) emb(issue) average(this, issue, .) emb(S-tag)

an audience of hundreds of people, including children, were present for most of these hangings

candidate

feed-forward layer

tag shortcut

average outputs

dropout

bi-LSTM

dropout

emb(token) emb(issue) average(this, issue, .) emb(S-tag)

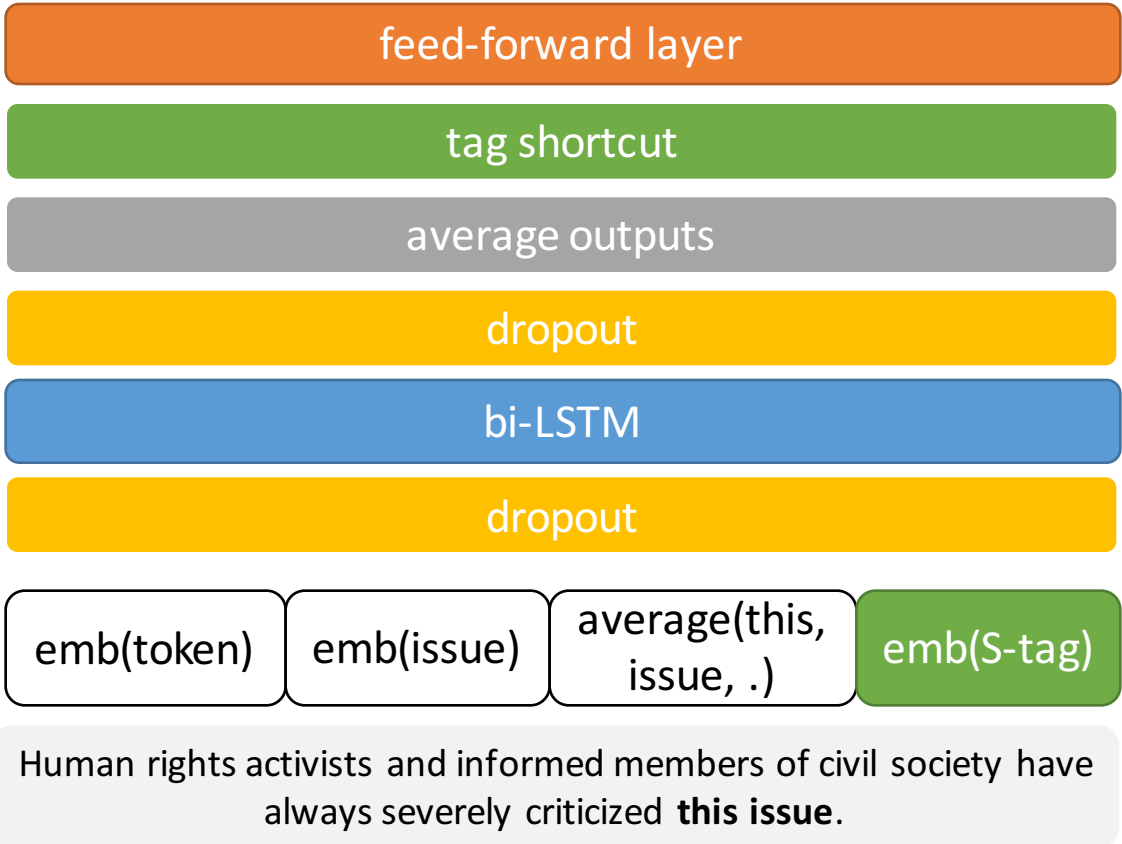
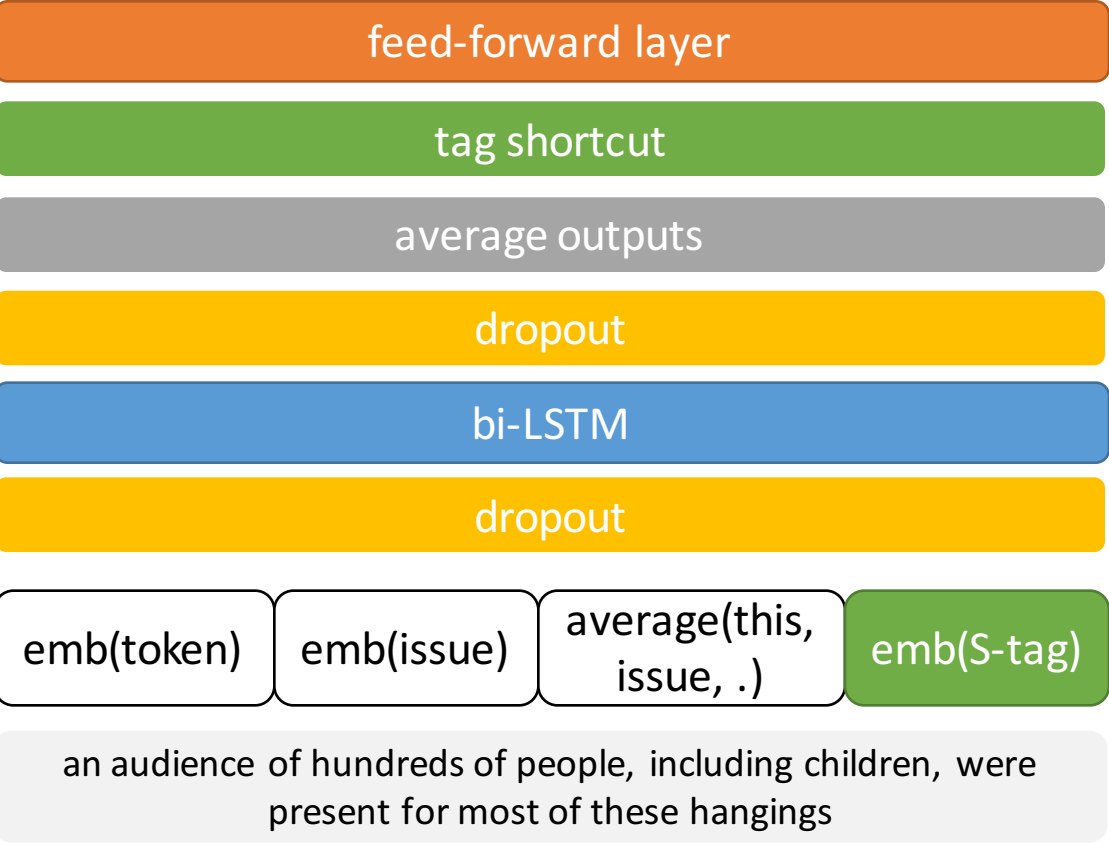
Human rights activists and informed members of civil society have always severely criticized **this issue**.

sentence with the anaphor

$$h_{cand,AnaphS} = concat(|h_{cand} - h_{joint}|; h_{cand} \odot h_{AnaphS})$$

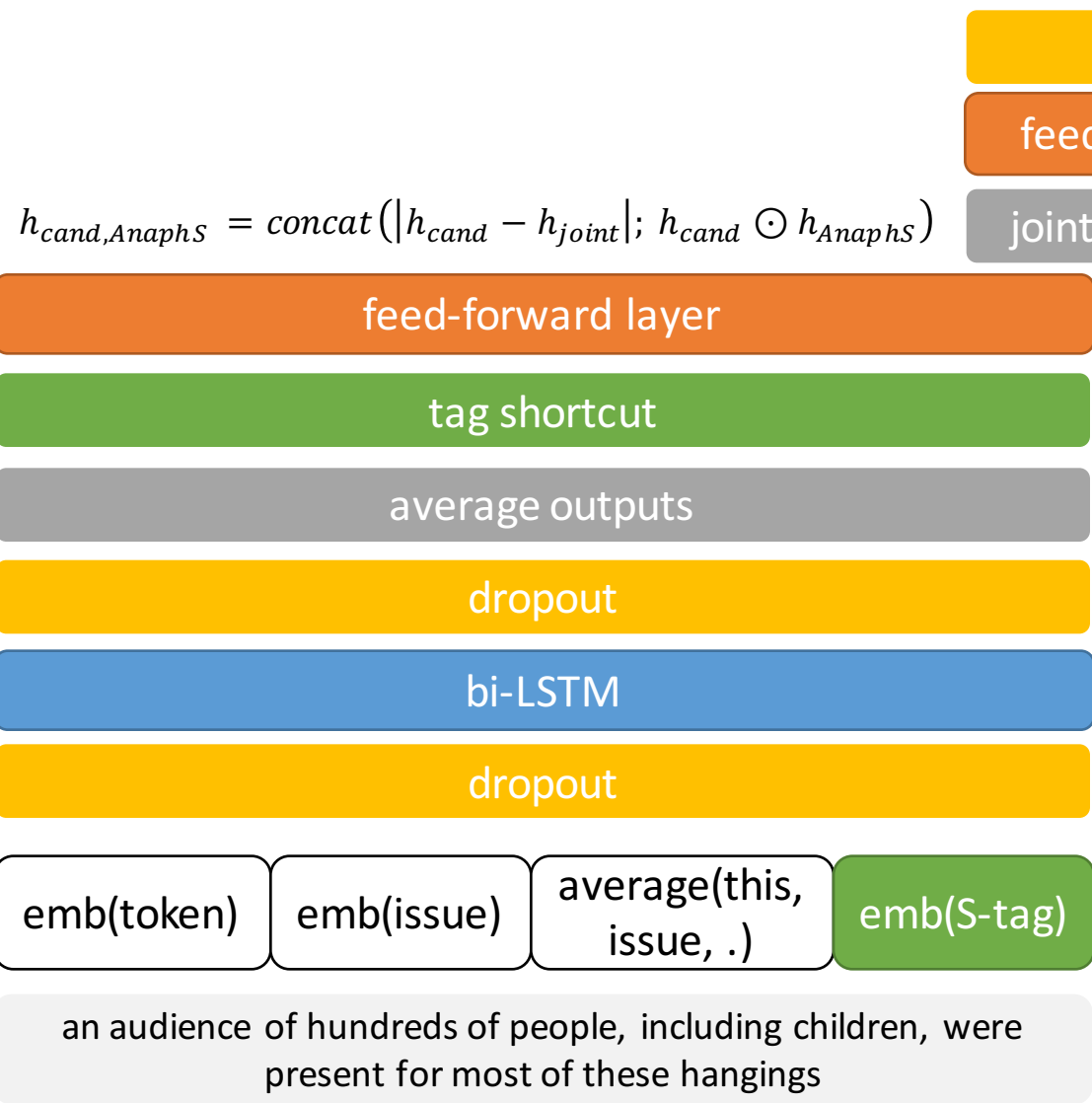
feed-forward layer

joint representation

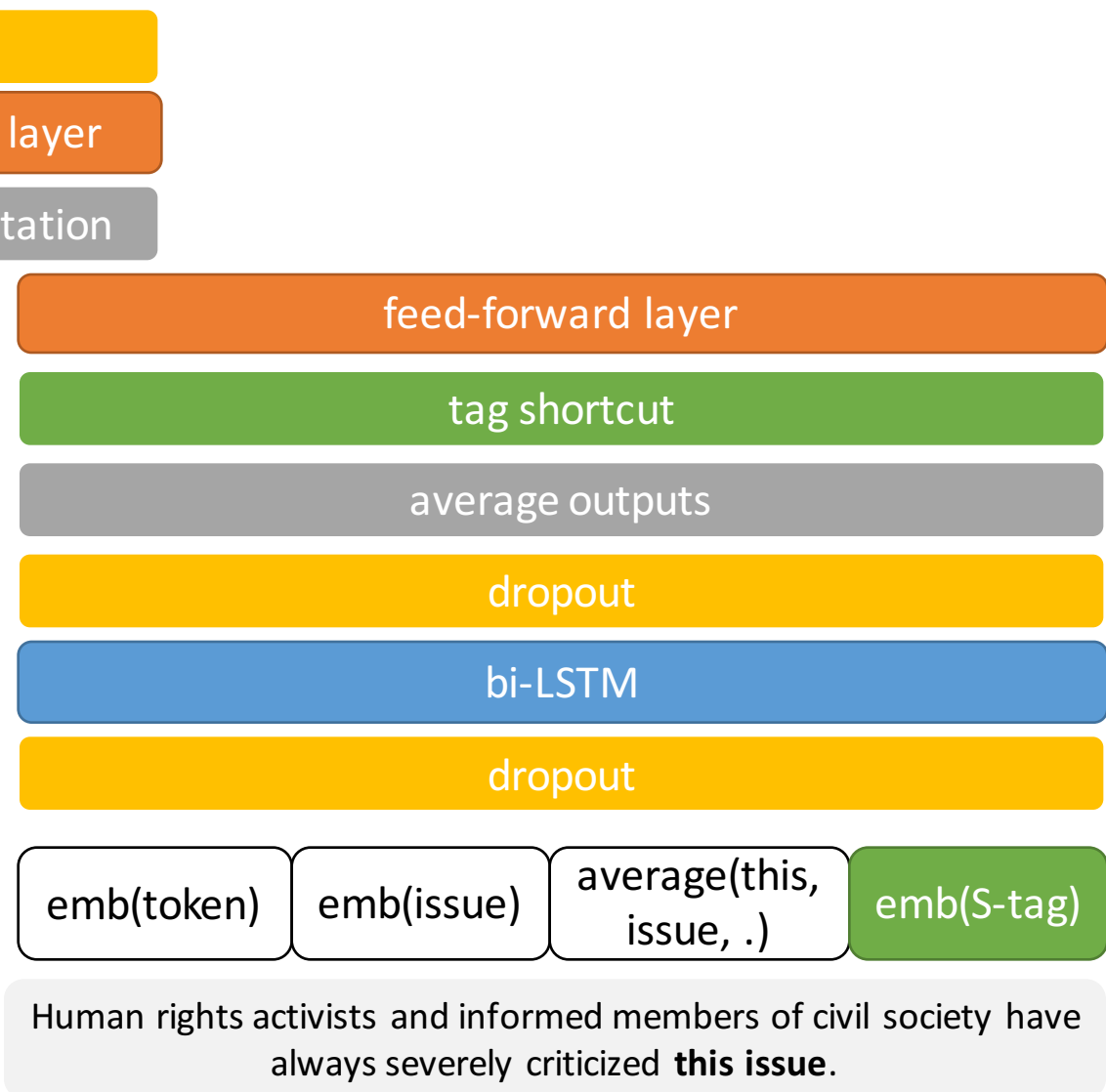


candidate

sentence with the anaphor

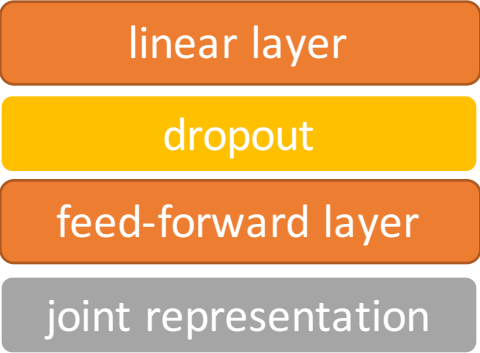


candidate

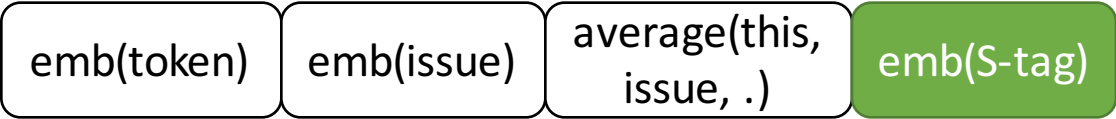
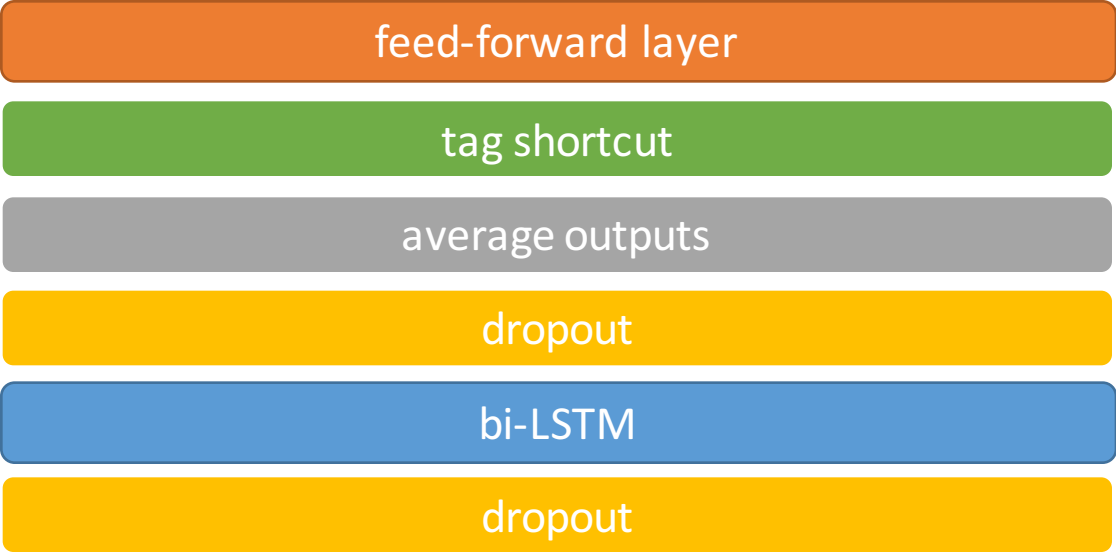


sentence with the anaphor

$$\text{score}(\text{cand}, \text{AnaphS}) = Wh_{\text{cand}, \text{AnaphS}} + b \in \mathbb{R}$$

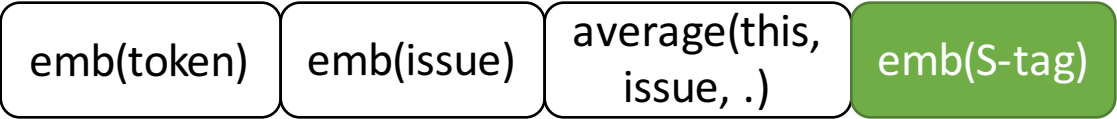
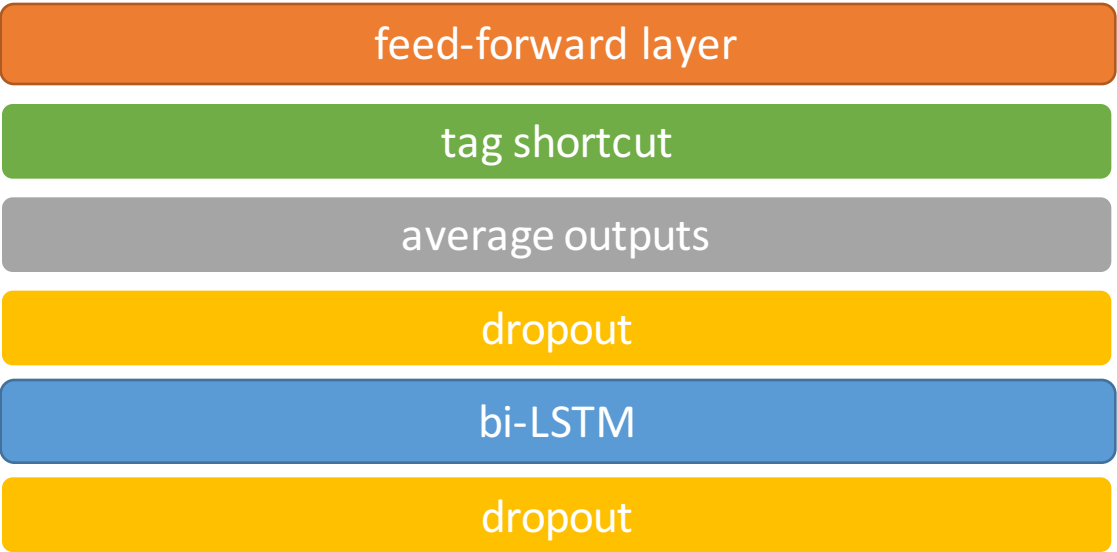


$$h_{\text{cand}, \text{AnaphS}} = \text{concat}(|h_{\text{cand}} - h_{\text{joint}}|; h_{\text{cand}} \odot h_{\text{AnaphS}})$$



an audience of hundreds of people, including children, were present for most of these hangings

candidate



Human rights activists and informed members of civil society have always severely criticized **this issue**.

sentence with the anaphor

train with the max-margin objective

$$\text{score}(\text{cand}, \text{AnaphS}) = Wh_{\text{cand}, \text{AnaphS}} + b \in \mathbb{R}$$

linear layer

dropout

feed-forward layer

$$h_{\text{cand}, \text{AnaphS}} = \text{concat}(|h_{\text{cand}} - h_{\text{joint}}|; h_{\text{cand}} \odot h_{\text{AnaphS}})$$

joint representation

feed-forward layer

tag shortcut

average outputs

dropout

bi-LSTM

dropout

emb(token)

emb(issue)

average(this,
issue, .)

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emb(token)

emb(issue)

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issue, .)

emb(S-tag)

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sentence with the anaphor