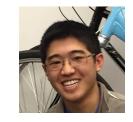
Multi-Sentence Argument Linking





Seth Ebner*, Patrick Xia*, Ryan Culkin, Kyle Rawlins, Benjamin Van Durme









Motivation



More than 50 protesters were *gunned down* in the Maidan, the center of the popular uprising.

Firearm-Attack

Attacker: Ø

Target: More than 50 protesters

Instrument: (

Place: Maidan

Traditional SRL: in-sentence



More than 50 protesters were **gunned down** in the Maidan, the center of the popular uprising.

attacker

Until now the identity of the killers has been a mystery.

Firearm-Attack

Attacker: the killers

Target: More than 50 protesters

Instrument: (

Place: Maidan

Argument Linking: cross-sentence

Beyond NomBank (Gerber and Chai, 2012)

71% relative increase in role coverage on NomBank

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DARPA AIDA Phase 1

38% of events have an argument outside the same sentence as the trigger

Beyond NomBank (Gerber and Chai, 2012)

71% relative increase in role coverage on NomBank

DARPA AIDA Phase 1

38% of events have an argument outside the same sentence as the trigger

90% of arguments can be found within 2 sentences of the trigger

Motivation

Data: Roles Across Multiple Sentences



Model

Results



Based on DARPA AIDA event ontology



Based on DARPA AIDA event ontology



9K+ examples from 4K news articles

Based on DARPA AIDA event ontology



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Annotators mark spans in 5-sentence context window

Based on DARPA AIDA event ontology



9K+ examples from 4K news articles

Annotators mark spans in 5-sentence context window

Protocol and analysis in the paper!

RAMS Example

When Russian <u>aircraft</u> bombed a remote garrison in southeastern <u>Syria</u> last month, alarm bells sounded at the Pentagon and the Ministry of Defense in London.

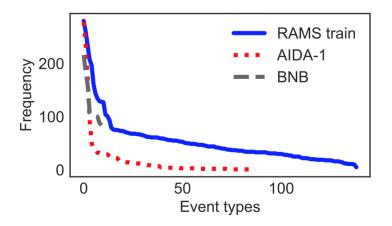


The <u>Russians</u> weren't <u>bombarding</u> a run-of-the-mill <u>rebel outpost</u>, according to U.S. officials.

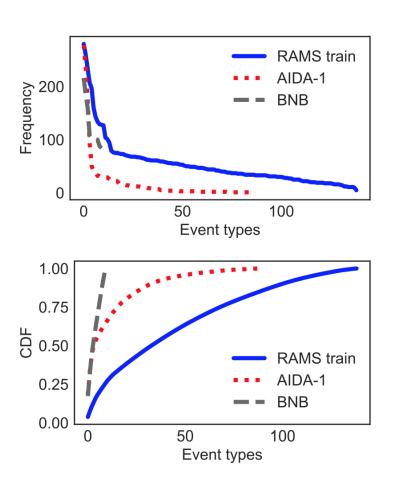
target

Broad + Diverse Coverage of Ontology

Broad + Diverse Coverage of Ontology



Broad + Diverse Coverage of Ontology



Motivation

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Model

Results

Roles are evoked by event triggers, forming *implicit* arguments (implicit discourse referents)

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the <u>place</u> of a *particular* attack event

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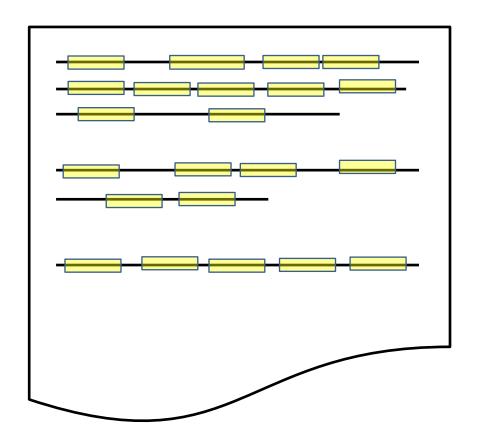
the <u>place</u> of a particular attack event

Implicit arguments linked to explicit mentions in text

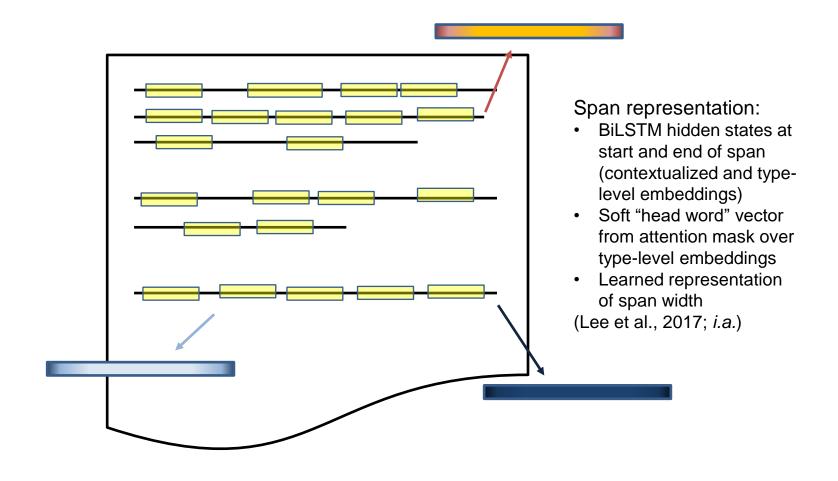
1) Learn span representations for each trigger span and candidate argument span

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- 2) For each trigger, prune to top-*k* candidate arguments

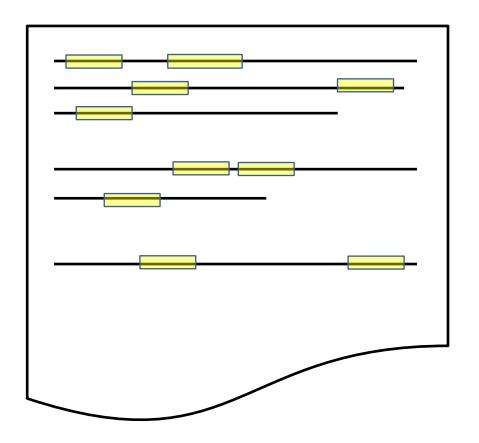
- 1) Learn span representations for each trigger span and candidate argument span
- 2) For each trigger, prune to top-*k* candidate arguments
- 3) Score reps of implicit arguments with reps of explicit arguments using a decomposable scoring function



Enumerate candidate argument spans up to a fixed width



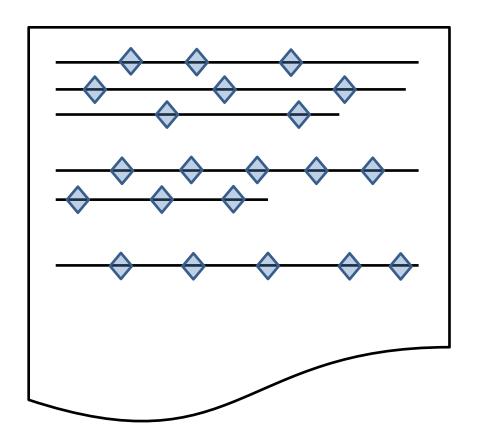
Create argument representations for every span



Score each representation, and keep the top $\lambda_A n$

n: document length λ_A : hyperparameter

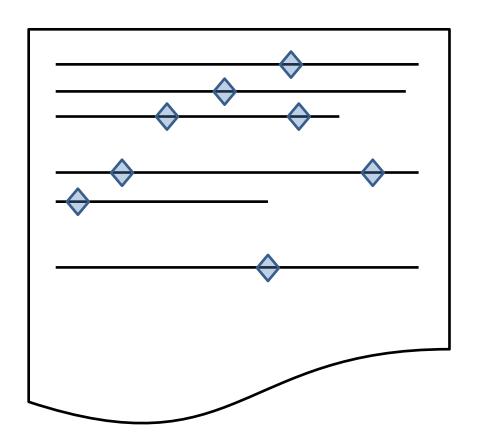
Prune to find good spans



Span representation:

- BiLSTM hidden states at start and end of span (contextualized and typelevel embeddings)
- Soft "head word" vector from attention mask over type-level embeddings
- Learned representation of span width
 (Lee et al., 2017; *i.a.*)

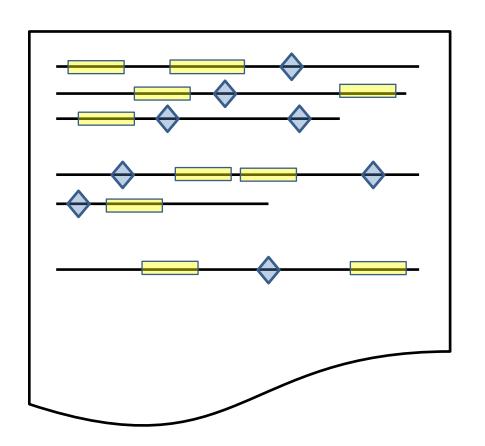
Create event trigger representations for every span

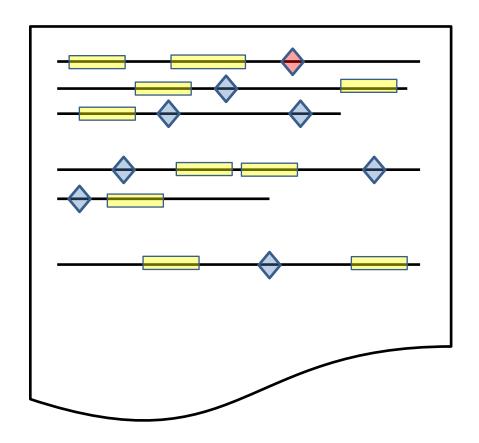


Score each representation, and keep the top $\lambda_{E}n$

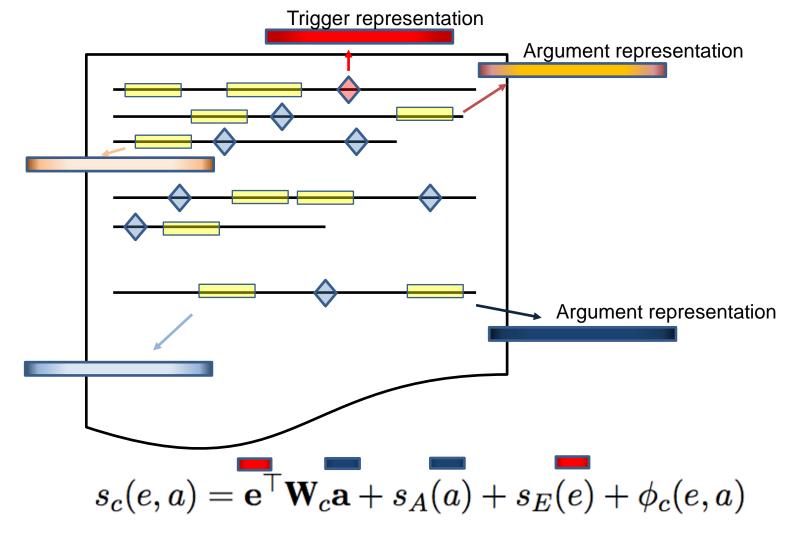
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Prune to find good spans

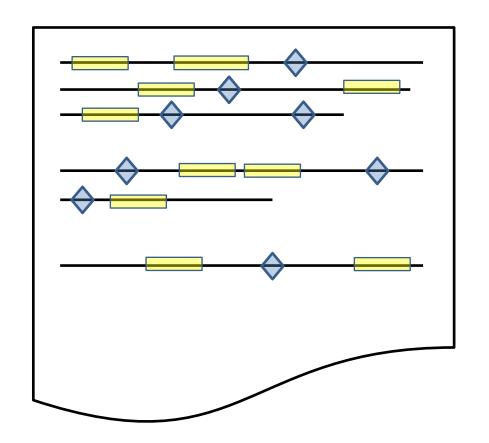


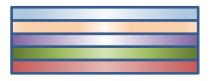


Further prune to find good arguments for a particular event

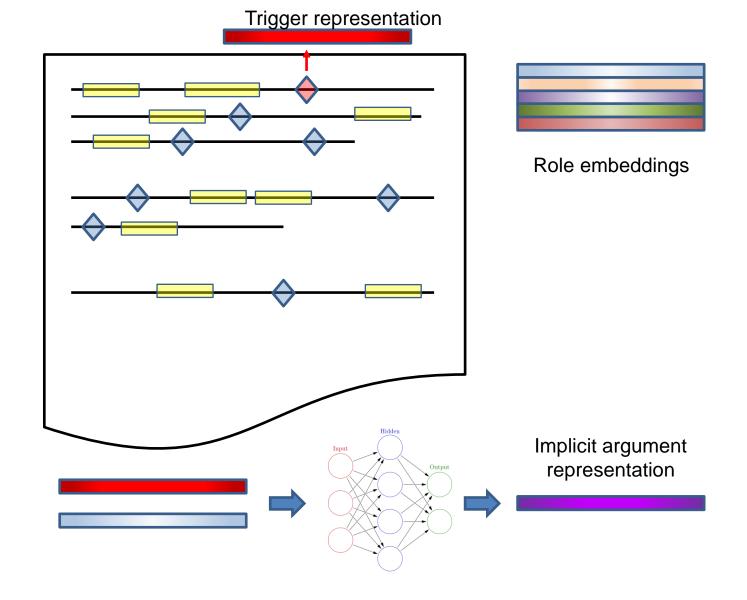


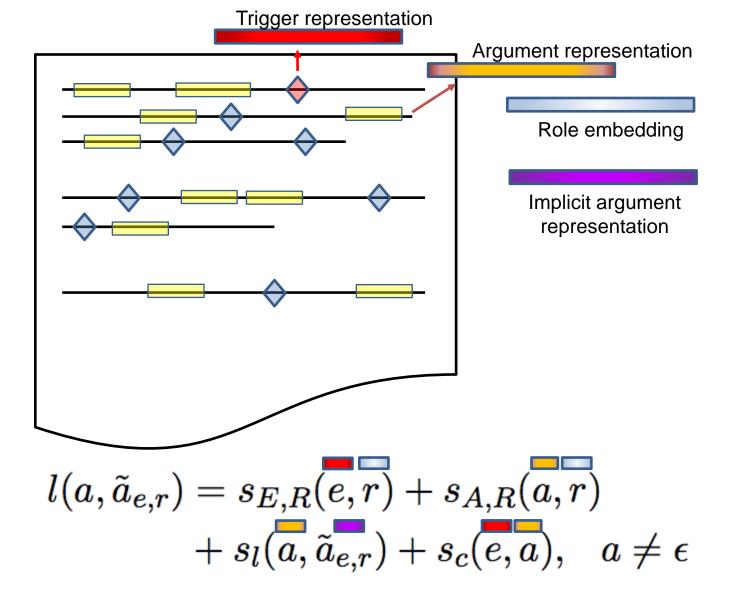
Further prune to find good arguments for a particular event





Role embeddings





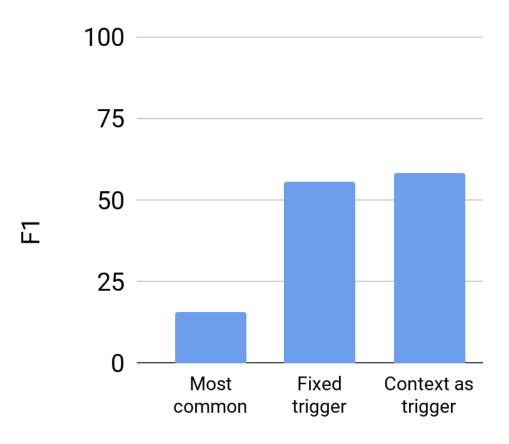
Motivation

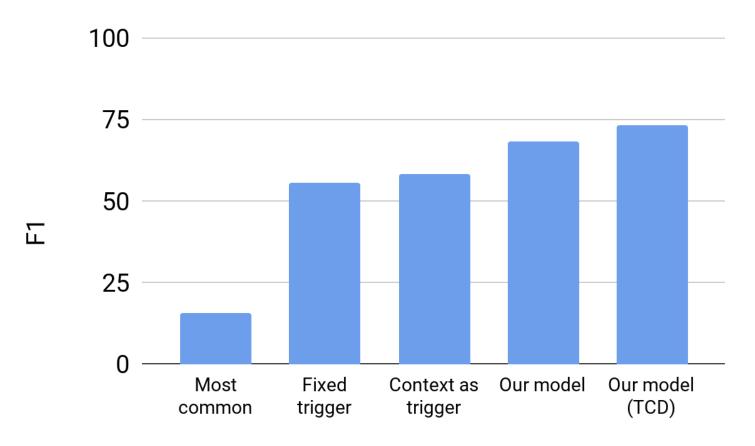
Data: Roles Across Multiple Sentences



Model

Results

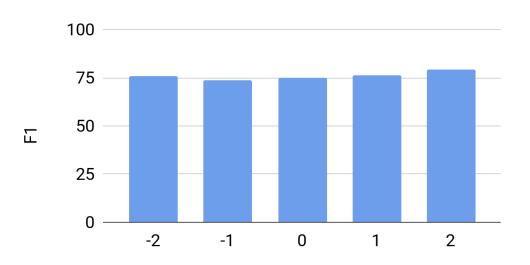




RAMS Results vs. Distance

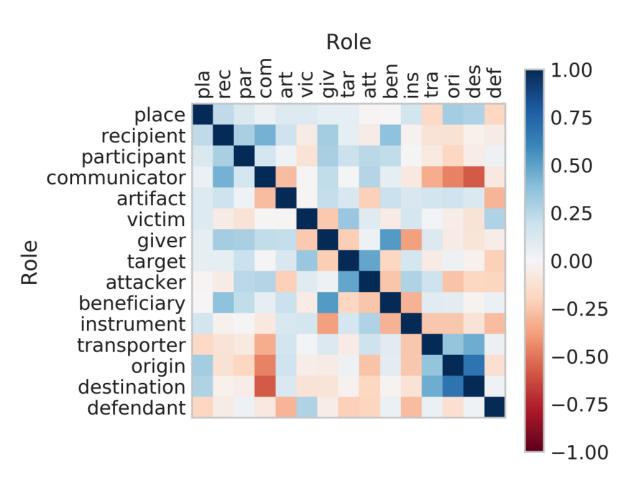
RAMS Results vs. Distance

Performance does not degrade over distance

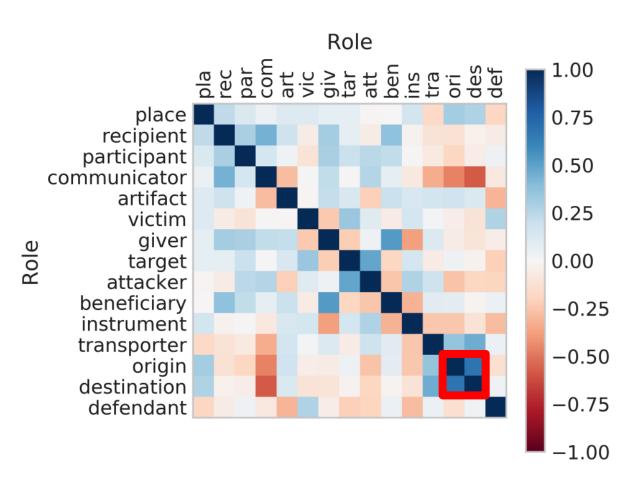


sentences between trigger and argument

Role Embedding Similarity



Role Embedding Similarity



Role Embedding Similarity



Koum grew up in the Ukraine under Soviet rule before immigrating to the US as a teenager...



Gun Violence Database

Pavlick et al., 2016

ST. LOUIS (KTVI) – The St. Circuit Attorney's Office charged a 50-year-old Friday for allegedly gunning another man down in a north city neighborhood back in December. According to Schron Jackson, a spokeswoman for the St. Louis Metropolitan Police Department, the shooting happened at 12:10 p.m. on December 2, 2015 in the 3000 block of N. 20th Street in the St. Louis Place neighborhood. The victim, identified as 32-year-old Leonard Arnold, was found lying unconscious outside. Arnold had been shot multiple times and was pronounced dead at the scene, Jackson said. The suspect, Maurice Alexander, was charged with first-degree murder, first-degree assault, and two counts of armed criminal action. ...

Victim Name: Leonard Arnold Shooter Name: Maurice Alexander

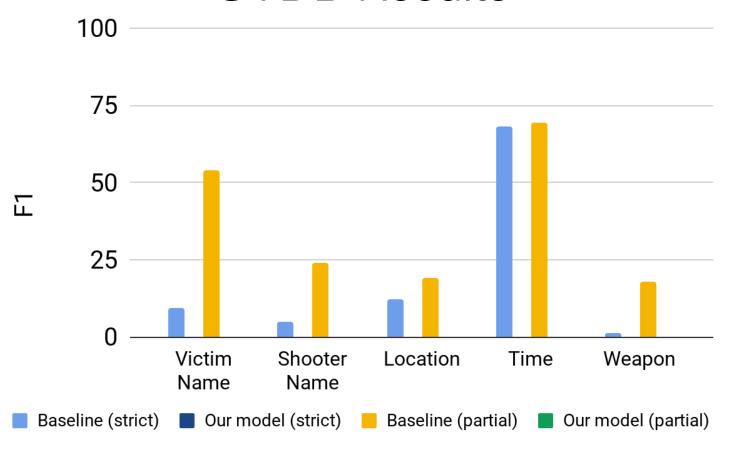
Location: 3000 block of ...

Weapon: Ø

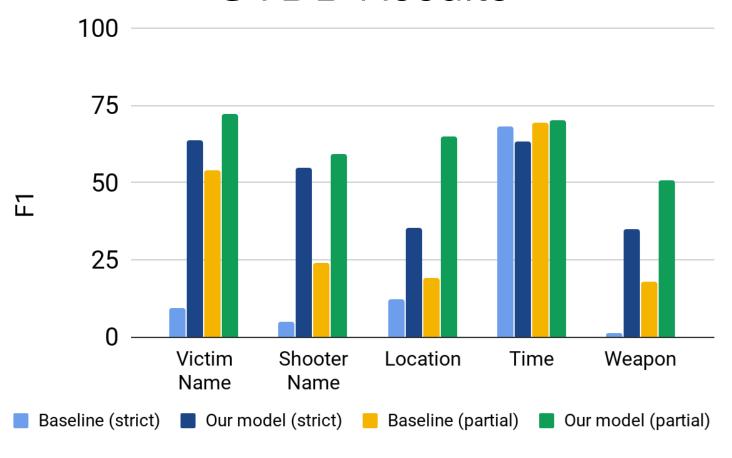
Shots: shot multiple times

. . .

GVDB Results



GVDB Results



Model finds argument spans anywhere in a document that fill roles for events

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RAMS dataset has broader coverage than prior datasets

Model finds argument spans anywhere in a document that fill roles for events

RAMS dataset has broader coverage than prior datasets

Model works well on other tasks too (more results in the paper!)

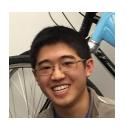


Thanks!



Data, code, and models nlp.jhu.edu/rams







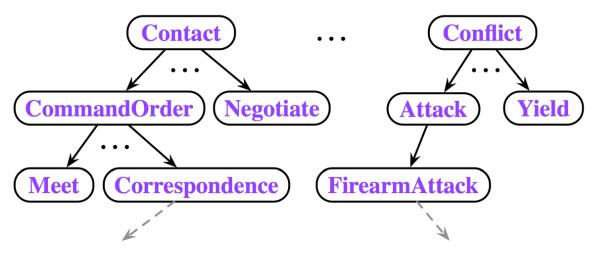




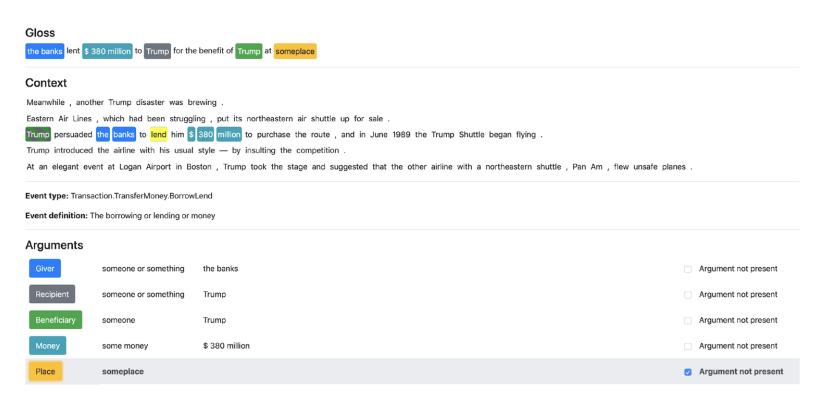
Additional Slides

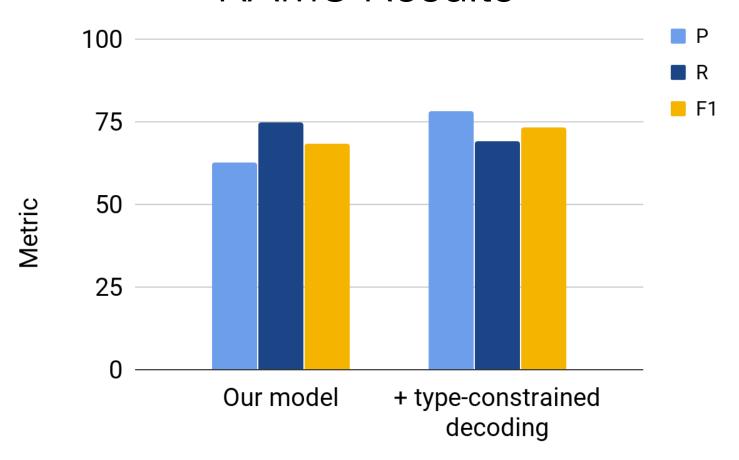
Note: these slides may be either outdated or even incorrect (based on much earlier versions of the model or buggy graphing code). Use at your own risk.

Motivation

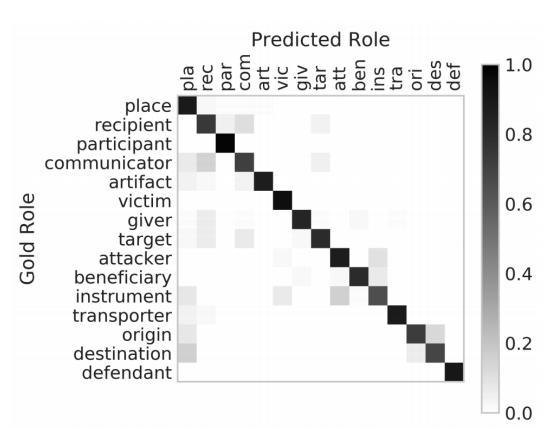


{ Communicator, Recipient, Place } { Attacker, Target, Instrument, Place }





Error Analysis

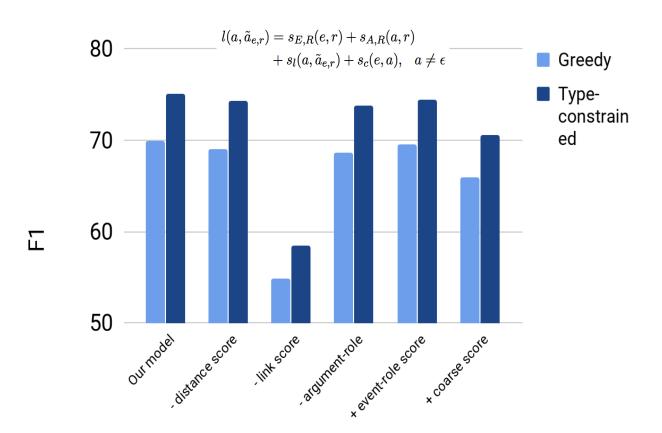


Ablations

Model	Greedy	TCD
Our model	69.9	75.1
- distance score	69.0	74.3
- $s_l(a, ilde{a}_{e,r})$	54.9	58.4
- $s_{A,R}(a,r)$	68.6	73.8
$+ s_{E,R}(e,r)$	69.5	74.4
$+ s_c(e,a)$	65.9	70.6
w/ argmax decoding	69.9	75.1
BERT 6–9	69.6	75.3
ELMo	68.5	75.2

Table 3: F_1 on RAMS dev data when link score components are separately included/excluded (Equation 2) or other contextualized encoders are used in the best performing model. TCD = type-constrained decoding.

Ablations



RAMS Results vs. Distance

Dist.	# Gold	# Predict	P	R	F_1
-2	79	69	81.2	70.9	75.7
-1	164	151	76.8	70.7	73.7
0	1,811	1,688	77.7	72.4	75.0
1	87	83	78.3	74.7	76.5
2	47	39	87.2	72.3	79.1
Total	2,189	2,030	78.0	72.3	75.1

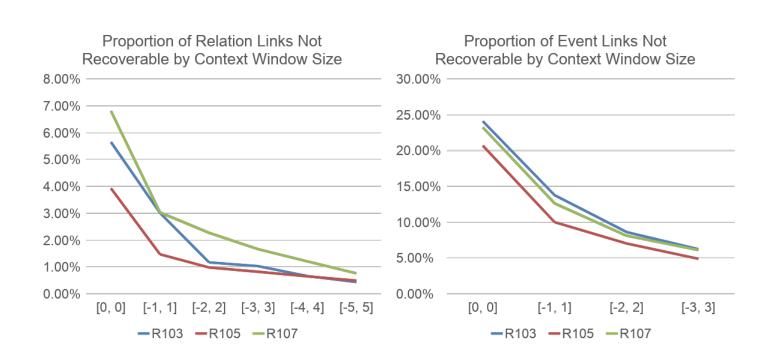
Table 4: Performance breakdown by distance (number of sentences) between argument and event trigger for our model using TCD over the development data.

Performance doesn't degrade over distance

RAMS works as pre-training

Strategy	Dev. F ₁	P	R	F_1
No pre-training	25.0	36.6	12.9	19.1
No pre-training ^T	27.1	53.5	11.0	18.2
RAMS pre-training	34.1	43.9	16.9	24.4
RAMS pre-training ^T	34.2	62.5	15.4	24.8

Table 8: P(recision), R(ecall), and F_1 on AIDA-1 English development and test data. T designates the use of ontology-aware type-constrained decoding.



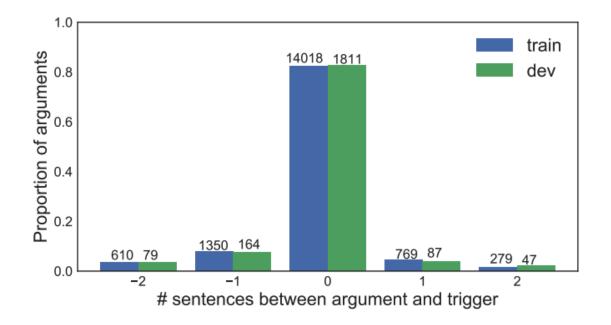


Figure 5: Distances between triggers and arguments in RAMS and proportion of arguments at that distance (counts are shown above each bar). Negative distances indicate that the argument occurs before the trigger.

Threshold	Conjunctive	Disjunctive	Start	End
0	55.3	78.0	59.8	73.5
1	69.9	80.3	74.9	75.3
2	73.9	82.0	78.2	77.8
3	76.4	83.6	80.9	79.1
4	78.8	84.3	82.7	80.4

Table 6: Pairwise span boundary inter-annotator agreement statistics for various span difference thresholds.

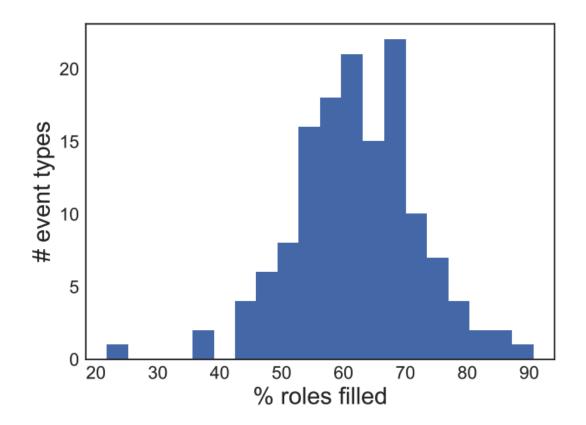


Figure 8: Number of event types for which a given percentage of roles are filled in RAMS train set.

Model	Dev. F ₁	P	R	F_1
Our model	69.9	62.8	74.9	68.3
Our model ^{TCD}	75.1	78.1	69.2	73.3
Most common	17.3	15.7	15.7	15.7
Fixed trigger ^{TCD}	60.2	83.7	41.9	55.8
Context as trigger ^{TCD}	62.1	80.5	45.8	58.4

Table 2: P(recision), R(ecall), and F_1 on RAMS development and test data. TCD designates the use of ontology-aware type-constrained decoding.

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