

Integrating Relation Constraints with Neural Relation Extractors

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Relation Extraction



Relation Extraction (RE) aims to extract <u>predefined relations</u> between two <u>marked entities</u> in plain texts.

Barack Obama married Michelle Obama on October 3, 1992.

Entity₁

Entity₂

Spouse

Motivation



<usa, new="" york="">, LargestCity</usa,>

<usa, d.c.="" washington="">, Capital</usa,>

<richard fuld,="" usa="">, <i>Nationality</i></richard>	

Motivation



<USA, New York>, *LargestCity*

Capital: 0.5

LargestCity: 0.4

LocationCity: 0.05

<USA, Washington D.C.>, *Capital*

Capital: 0.95

LocationCity: 0.03

<Richard Fuld, USA>, *Nationality*

Nationality: 0.7

BirthPlace: 0.2

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Relation Constraints



Set	Sampled Positive Rules
C^{ts}	(almaMater, knowFor), (city, region), (spouse, child)
$oldsymbol{C^{to}}$	(almaMater, owner), (city, hometown), (capital, city)
C^{tso}	(birthPlace, capital), (child, spouse), (city, country)
C^{cs}	almaMater, country, city, hometown
C^{co}	foundationPerson, child, knownFor, product

Table 1: Example rules for each constraint set C^{ϕ} .

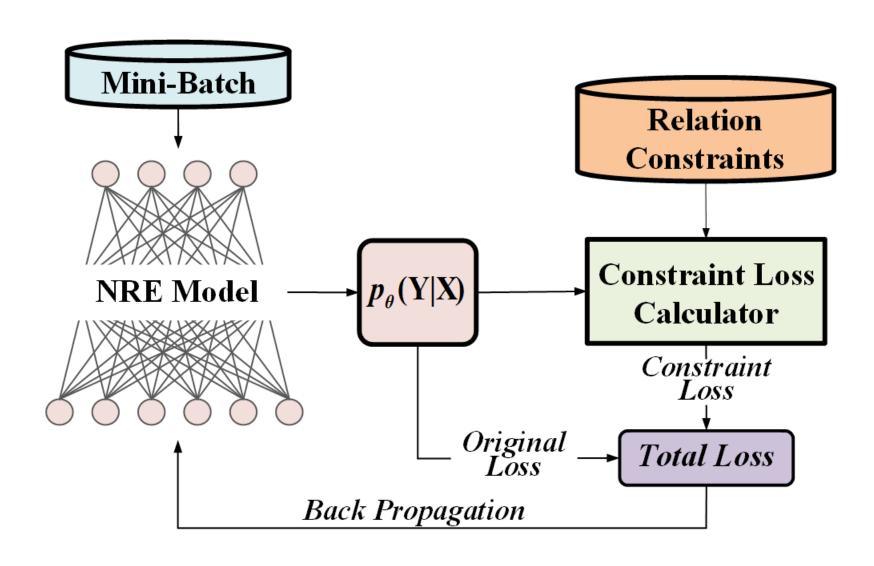
Relation Constraints



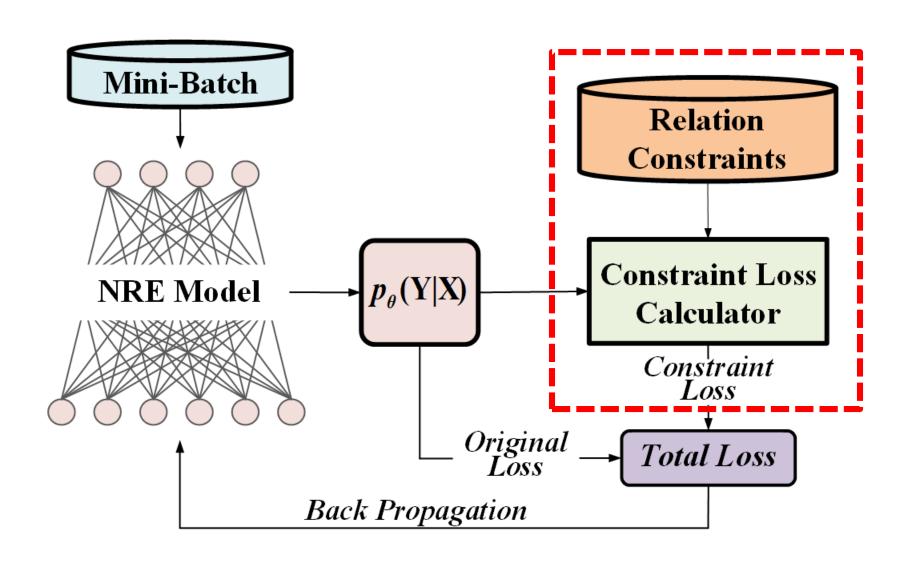
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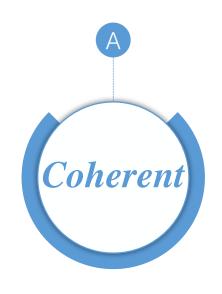










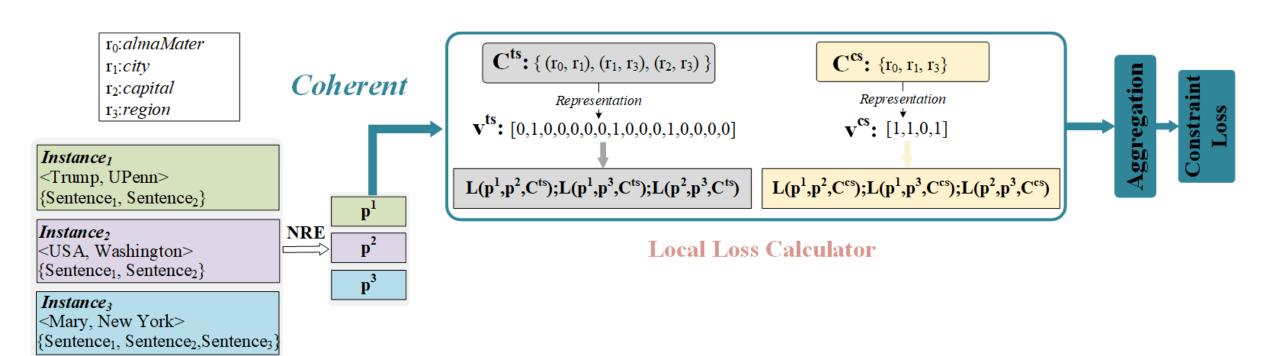




Coherent treats one constraint set as a whole.

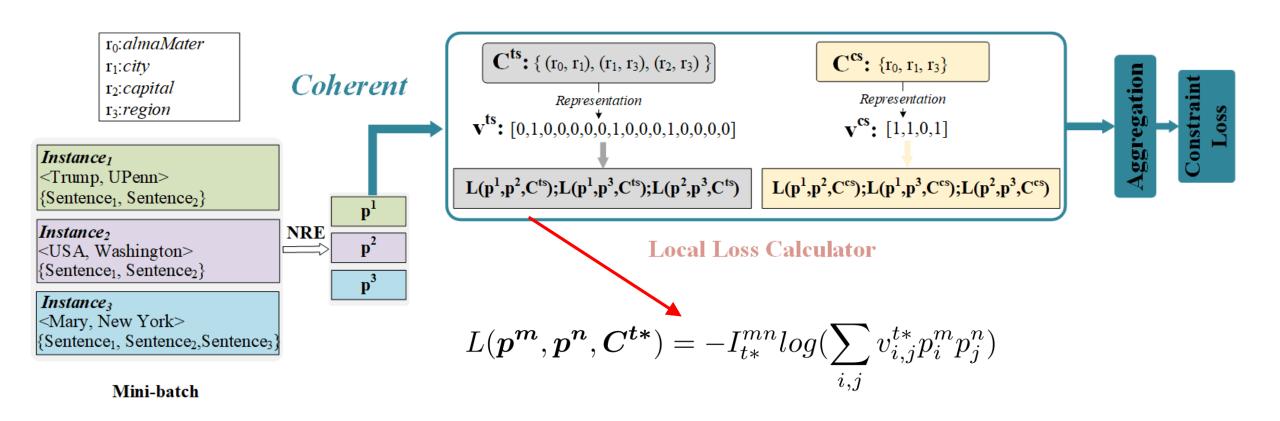
Semantic pays more attention to which specific rules in the constraint sets the pairwise local predictions should satisfy.





Mini-batch

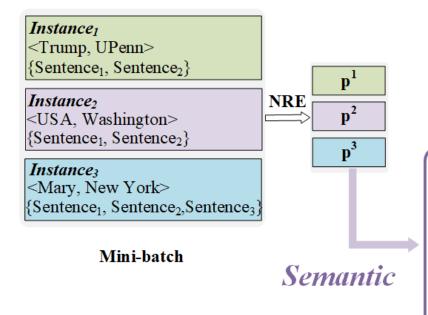




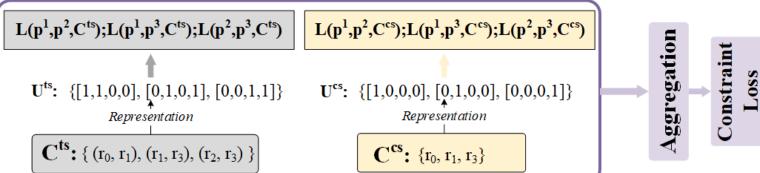


r₀:almaMater r₁:city r₂:capital

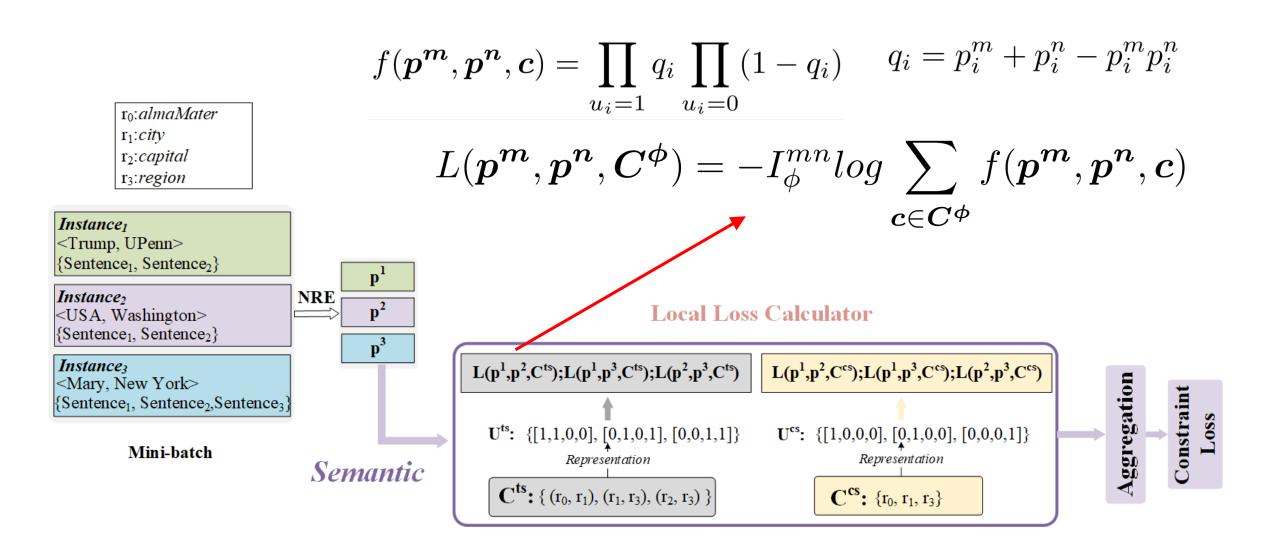
r₃:region



Local Loss Calculator









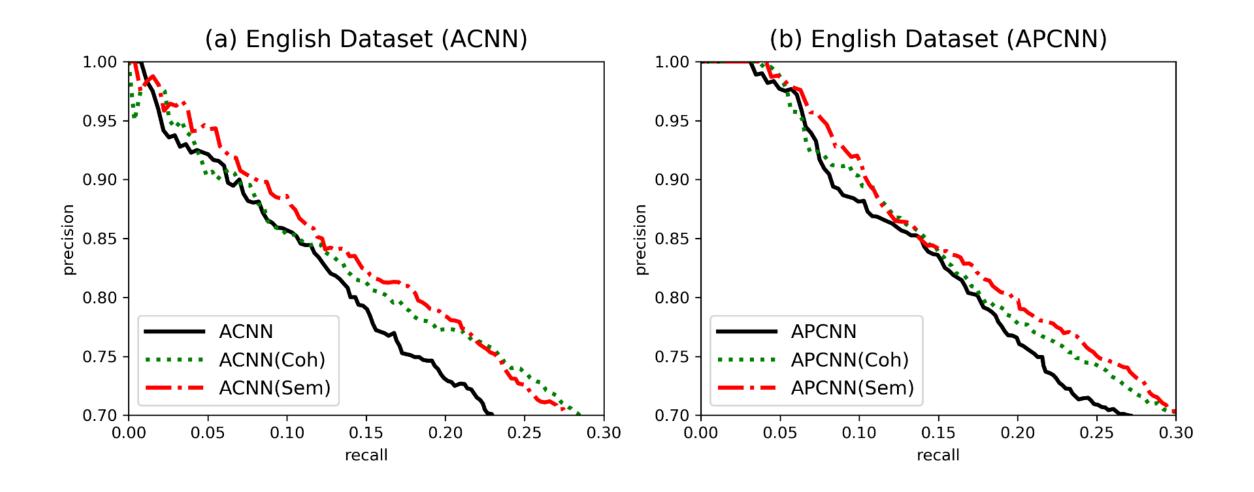
Datasets

- ◆ English Dataset: constructed by mapping triples in *Dbpedia* to sentences in the *New York Times* corpus
- ◆ Chinese Dataset: built by mapping the triples of *HudongBaiKe*, a large Chinese encyclopedia, with four Chinese economic newspapers

	Dolotiona	Train Set		Test	Set	Constraints	
	Relations	# Triples	# Sent	# Triples	# Sent	Constraints	
English Dataset	51	50k	134k	30k	53k	541	
Chinese Dataset	28	60k	120k	40k	83k	110	



Main Results





Main Results

	English Dataset					
Model Name	P@100	P@200	P@300	Mean	Δ_{Base}	
ACNN	96.70	92.61	91.72	93.68	_	
ACNN(Coh)	97.39	93.78	90.69	93.96	+0.3	
ACNN(Sem)	97.62	95.87	94.12	95.87	+2.2	
ACNN+ILP	97.87	94.36	93.16	95.13	+1.5	
ACNN(Coh)+ILP	97.73	94.51	91.29	94.51	+0.8	
ACNN(Sem)+ILP	98.17	96.6	95.48	96.75	+3.1	
APCNN	100	98.97	97.41	98.79	_	
APCNN(Coh)	100	99.57	97.33	98.97	+0.2	
APCNN(Sem)	100	100	97.95	99.32	+0.5	
APCNN+ILP	100	99.13	97.55	98.89	+0.1	
APCNN(Coh)+ILP	100	100	98.03	99.34	+0.6	
APCNN(Sem)+ILP	100	100	98.39	99.46	+0.7	



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After equipped with our *CLC* modules, i.e., *Coherent* and *Semantic*, both *ACNN* and *APCNN* obtain improvement on the English dataset.



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Applying ILP to our approach can obtain further improvement.



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r	- ACNN	96.70	92.61	91.72	93.68	_		
1.5	ACNN(Coh)	97.39	93.78	90.69	93.96	+0.3		
0.5	ACNN(Sem)	97.62	95.87	94.12	95.87	+2.2		
	− ACNN+ILP	97.87	94.36	93.16	95.13	+1.5		
0.9	ACNN(Coh)+ILP	97.73	94.51	91.29	94.51	+0.8		
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Conclusions



- ➤ A unified framework to integrate relation constraints with neural networks for RE
 - Coherent (general perspectives), Semantic (precise perspectives)
 - Validating our approach on English and Chinese datasets
- ➤ Our study reveals that learning with the constraints can better utilize the constraints from a different perspective compared to the ILP post-processing method



Thank you! Q&A

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