



Neural Relation Extraction from Unstructured Texts

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Outline

✓ What is Relation Extraction

✓ Distant Supervision for RE

✓ Multi-Level Structured Attention

✓ Application



An Example: What is Relation Extraction

Company report: "International Business Machines Corporation (IBM or the company) was incorporated in the State of New York on June 16, 1911, as the Computing-Tabulating-Recording Co. (C-T-R)..."

Standard Information Extraction Task:

Company IBM

Location New York

Date June 16, 1911

Original-Name Computing-Tabulating-Recording Co.

Relation Extraction Task:

Founding-year (IBM, 1911)

Founding-location (IBM, New York)



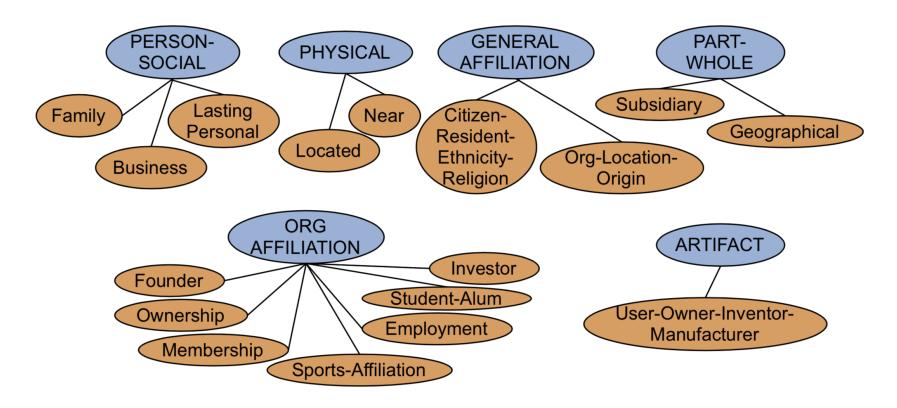
➤ What is it?

- A fundamental task in Information Extraction
- Definition: Given a sentence S with the annotated pairs of nominals e_1 and e_2 , the goal is to identify the relation r from a predefined relation set R for the entity pair (e_1, e_2) , written in the form of a triple (e_1, r, e_2) or (e_2, r, e_1)



➤ Automated Content Extraction (ACE): NIST

• 17 relations from 2008 "Relation Extraction Task"





Relation Types (closed domain)

> SemEval 2010 Task 8

- 9 relations without directionality (plus 'other')
- 19 relations with directionality (including 'other')

Labels	Train	Dev	Test
Entity-Origin (e_1,e_2)	454	114	211
Entity-Origin (e_2,e_1)	118	30	47
Entity-Destination (e_1, e_2)	675	169	291
Entity-Destination (e_2, e_1)	0	1	1
Component-Whole (e_1, e_2)	376	94	162
Component-Whole (e_2, e_1)	376	95	150
Product-Producer (e_1, e_2)	258	65	108
Product-Producer (e_2, e_1)	315	79	123
Instrument-Agency (e_1, e_2)	77	20	22
Instrument-Agency (e_2, e_1)	325	82	134
Content-Container (e_1, e_2)	299	75	153
Content-Container (e_2, e_1)	132	34	39
Cause-Effect (e_1, e_2)	275	69	134
Cause-Effect (e_2, e_1)	527	132	194
Message-Topic (e_1, e_2)	392	98	210
Message-Topic (e_2, e_1)	115	29	51
Member-Collection (e_1, e_2)	62	16	32
Member-Collection (e_2, e_1)	489	123	201
other	1,128	282	454



> Freebase: thousand relations/million entities

Relation name	Size	Example	
/people/person/nationality	281,107	John Dugard, South Africa	
/location/location/contains	253,223	Belgium, Nijlen	
/people/person/profession	208,888	Dusa McDuff, Mathematician	
/people/person/place_of_birth	105,799	Edwin Hubble, Marshfield	
/dining/restaurant/cuisine	86,213	MacAyo's Mexican Kitchen, Mexican	
/business/business_chain/location	66,529	Apple Inc., Apple Inc., South Park, NC	
/biology/organism_classification_rank	42,806	Scorpaeniformes, Order	
/film/film/genre	40,658	Where the Sidewalk Ends, Film noir	
/film/film/language	31,103	Enter the Phoenix, Cantonese	
/biology/organism_higher_classification	30,052	Calopteryx, Calopterygidae	
/film/film/country	27,217	Turtle Diary, United States	
/film/writer/film	23,856	Irving Shulman, Rebel Without a Cause	
/film/director/film	23,539	Michael Mann, Collateral	
/film/producer/film	22,079	Diane Eskenazi, Aladdin	
/people/deceased_person/place_of_death	18,814	John W. Kern, Asheville	
/music/artist/origin	18,619	The Octopus Project, Austin	
/people/person/religion	17,582	Joseph Chartrand, Catholicism	
/book/author/works_written	17,278	Paul Auster, Travels in the Scriptorium	
/soccer/football_position/players	17,244	Midfielder, Chen Tao	
/people/deceased_person/cause_of_death	16,709	Richard Daintree, Tuberculosis	
/book/book/genre	16,431	Pony Soldiers, Science fiction	
/film/film/music	14,070	Stavisky, Stephen Sondheim	
/business/company/industry	13,805	ATS Medical, Health care	



> Entities recognition

- Name entities: Person, Organization, Location, Times, Dates, etc.
- Domain-specific nouns: genes, proteins, diseases, financial terms, etc.

> Relation extraction

Located in, employed by, married to, etc.



Pipeline Modelling

Text



Entity Recognition



Relation Extraction

Mark Elliot Zuckerberg is an American computer programmer and Internet entrepreneur. He is a co-founder of Facebook, and currently operates as its chairman and chief executive officer.



PERSON: Mark Elliot Zuckerberg

LOCATION: American

ORGANISATION: Facebook



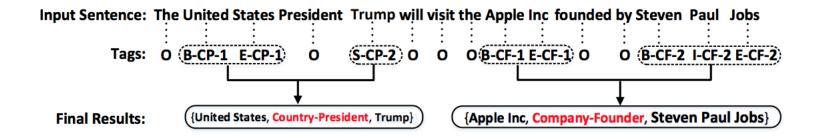
Mark Elliot Zuckerberg is founder of Facebook



Two Categories of Modelling

Joint Modelling







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Distant Supervision for Relation Extraction

> Problems

Human Annotated Data

- SemEval 2007
- SemEval 2010
- BioNLP Shared Task
- ADE-V2
- Data is always important!
- Labeled data is not enough to train a good RE system with a good generalization capability



Distant Supervision for Relation Extraction

> DS-RE:

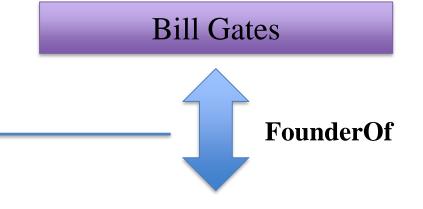
- Automatic labeling via knowledge bases, such as Freebase, DBpedia
- It assumes that if one entity pair appearing in some sentences can be observed in a KB with a certain relationship, then these sentences will be labeled as the context of this entity pair and this relationship.

➤ Advantage

 Effective and efficient method for automatically labeling largescale training data

➤ Disadvantage

 It introduces a severe mislabelling problem due to the fact that a sentence that mentions two entities does not necessarily express their relation in a KB



Microsoft

Relation	Instance		
FounderOf	Microsoft was founded on April 4, 1975, by Bill Gates and Paul Allen in Albuquerque, New Mexico.		
ChairmanOf	In February 2014 Gates stepped down as chairman from Microsoft but continued to serve as a board member.		
Other/NA	Largely on the strength of Microsoft's success, Gates amassed a huge paper fortune as the company's largest individual shareholder.		

Distant Supervision for Relation Extraction

DS-RE is different from the traditional RE

- It is a multi-instance learning problem
- It is a multi-label classification problem
- It contains a lot of noise

Distant Supervision Data

- New York Times
- Google's RE Corpus
- NIST KBP
- Portuguese DBpedia



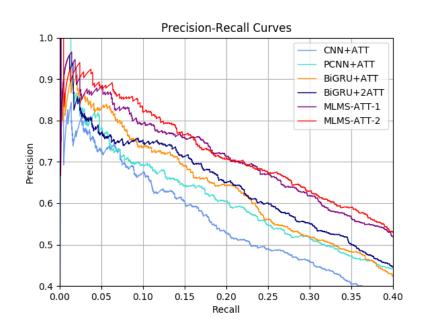
Compute P/R/F1

$$P = \frac{\text{# of correctly extracted relations}}{\text{Total # of extracted relations}}$$

$$F_1 = \frac{2PR}{P+R}$$

$$R = \frac{\text{\# of correctly extracted relations}}{\text{Total \# of gold relations}}$$

- > PR Curve
- > AUC





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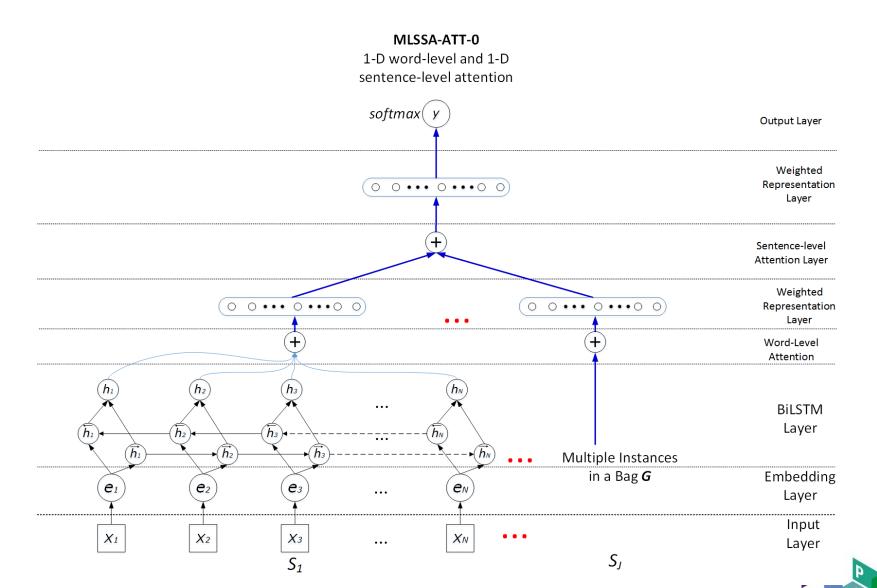
✓ Application



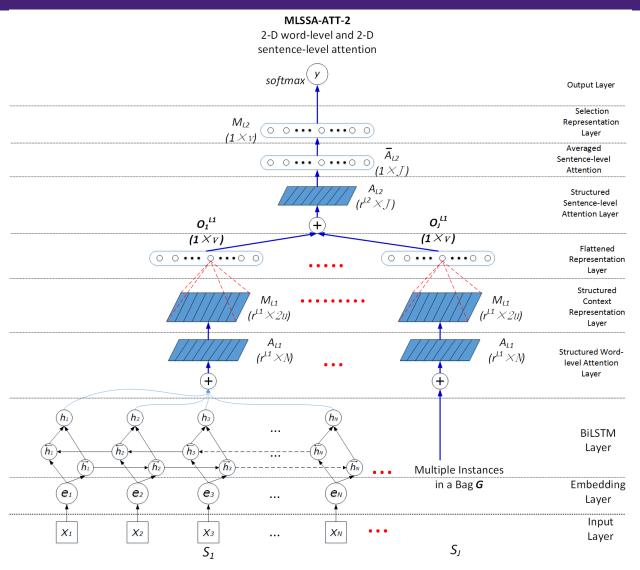
Deep Learning for Supervised RE

- Neural Networks for RE
 - Convolutional NN
 - Recurrent NN (LSTM, GRU, Bidirectional RNN)
 - Attention mechanism
- ➤ Like other NLP tasks, neural relation extraction has become the state-of-the-art.





Our Work: Multi-Level Structured Self-Attention Mechanism



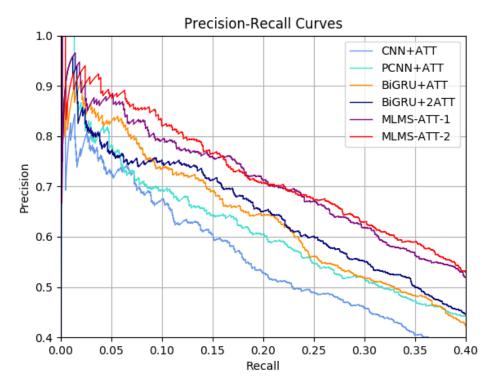
Jinhua Du et al. Multi-Level Structured Self-Attentions for Distantly Supervised Relation Extraction Accepted by EMNLP 2018. **E-Mail: jinhua.du@adaptcentre.ie**

Relation Extraction with Multi-Level and Multi-Scale Self-Attention

Motivation:

- fully use contextual knowledge in the input sentence
- select valid instances, and surpass the noisy instances

• Results:





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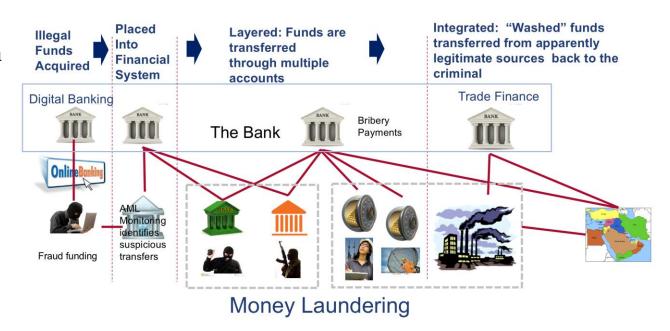
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Applications of Relation Extraction: A Case Study: Anti-money Laundering Monitoring

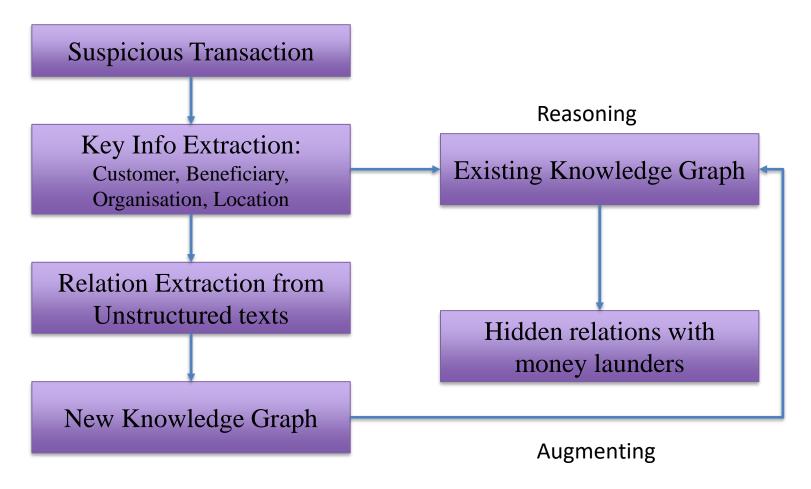
- Money Laundering: three stages
 - Placement
 - Layering
 - Integration



Transaction Monitoring solutions: attempt to detect high risk or out of character funds transfers that may indicate money laundering activity

RE for AML www.adaptcentre.ie

➤ Basic Workflow



Jinhua Du et al. NextGen AML: Distributed Deep Learning based Language Technologies to Augment Anti Money Laundering Investigation. Proceedings of ACL 2018. E-Mail: jinhua.du@adaptcentre.ie







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