CS918: LECTURE 11

Information Extraction and Named Entity Recognition

Arkaitz Zubiaga, 7th November, 2018

LECTURE 11: CONTENTS

- What is Information Extraction?
- Named Entity Recognition (NER).
- Relation Extraction (RE).
- Other Information Extraction tasks.

INFORMATION EXTRACTION (IE)

- **Information extraction (IE):** automatically extracting structured information from unstructured texts.

Subject: **meeting**

Date: 8^{th} January, 2018

To: Arkaitz Zubiaga

Hi Arkaitz, we have finally scheduled the meeting.

It will be in the Ada Lovelace room, next Monday 10am-11am.

-Mike

Create new Calendar entry

Event: Meeting w/ Mike
Date: 15 Jan, 2018
Start: 10:00am
End: 11:00am
Where: A. Lovelace

ON WIKIPEDIA… THERE ARE INFOBOXES…

- Structured information:

Royal Leamington Spa	
Population	49,491 (2011 census)
OS grid reference	SP316660
Civil parish	Royal Leamington Spa
District	Warwick
Shire county	Warwickshire
Region	West Midlands
Country	England
Sovereign state	United Kingdom
Post town	LEAMINGTON SPA
Postcode district	CV31, CV32, CV33
Dialling code	01926
Police	Warwickshire
Fire	Warwickshire
Ambulance	West Midlands
EU Parliament	West Midlands
UK Parliament	Warwick and Leamington

List of places: UK · England · Warwickshire
52.292°N 1.537°W

…AND SENTENCES

- Unstructured text:

Leamington Spa

From Wikipedia, the free encyclopedia

"Royal Leamington Spa" redirects here. For other uses, see Leamington (disambiguation).

Royal Leamington Spa, commonly known as **Leamington Spa** or **Leamington** /ˈlɛmɪŋtən/ (listen), is a spa town in Warwickshire, England. Following the popularisation of the medicinal qualities of its water in the 18th century,[1] in the 19th century the town experienced one of the most rapid expansions in England.[2] It is named after the River Leam, which flows through the town; the town's name is often abbreviated to *Leam* by locals.

The town contains especially fine ensembles of Regency architecture,[3] particularly in parts of the Parade, Clarendon Square and Lansdowne Circus.

The town comprises six electoral wards: Brunswick, Milverton, Manor, Crown, Clarendon and Willes. The total population for those wards in 2011 was 49,491.[4]

USING IE TO POPULATE WIKIPEDIA INFOBOXES

WARWICK

- We can use information extraction to populate the infobox automatically.

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INFORMATION EXTRACTION

WARWICK

- IE is the process of **extracting some limited amount of semantic content from text**.
- We can view it as the task of automatically **filling a questionnaire or template** (e.g. database table).
- An important NLP application since the 1990s.

INFORMATION EXTRACTION: SUBTASKS

WARWICK

- Broad area, includes the following **subtasks**:
  - Named Entity Recognition.
  - Relation Extraction.
  - Temporal expression extraction.
  - Coreference resolution.
  - Event extraction.
  - Slot filling.
  - Entity linking.

NAMED ENTITY RECOGNITION

NAMED ENTITY RECOGNITION

- **Named Entity (NE):** anything that can be referred to with a **proper name**.
- Usually **3 categories: person, location and organisation**.
  - Can be extended to **numeric expressions** (price, date, time).

Citing high fuel prices, [ORG United Airlines] said [TIME Friday] it has increased fares by [MONEY $6] per round trip on flights to some cities also served by lower-cost carriers. [ORG American Airlines], a unit of [ORG AMR Corp.], immediately matched the move, spokesman [PER Tim Wagner] said. [ORG United], a unit of [ORG UAL Corp.], said the increase took effect [TIME Thursday] and applies to most routes where it competes against discount carriers, such as [LOC Chicago] to [LOC Dallas] and [LOC Denver] to [LOC San Francisco].

NAMED ENTITIES

WARWICK

- Example of extended set of named entities.

Type	Tag	Sample Categories
People	PER	Individuals, fictional characters, small groups
Organization	ORG	Companies, agencies, political parties, religious groups, sports teams
Location	LOC	Physical extents, mountains, lakes, seas
Geo-Political Entity	GPE	Countries, states, provinces, counties
Facility	FAC	Bridges, buildings, airports
Vehicles	VEH	Planes, trains, and automobiles

NAMED ENTITY RECOGNITION

WARWICK

- **Named Entity Recognition (NER) task:** (1) **identify** spans of text that constitute **proper names**, (2) **categorise** by entity type.

- First step in IE, also useful for:
  - Reduce sparseness in text classification.
  - Identify target in sentiment analysis.
  - Question answering.

CHALLENGES IN NAMED ENTITY RECOGNITION

- Challenges in NER:
  - Ambiguity of segmentation (is it an entity? boundaries?):

    I’m on the **Birmingham New Street**-**London Euston** train.

    $\underbrace{\text{Birmingham New Street}}_{\text{location}}$ - $\underbrace{\text{London Euston}}_{\text{location}}$

  - Ambiguity of entity type:

    Downing St.: location (street) or organisation (govt)?

    Warwick: location (town) or organisation (uni)?

    Georgia: person (name) or location (country)?

NER AS A SEQUENCE LABELLING TASK

WARWICK

- Standard NER algorithm is a **word-by-word sequence labelling** task, where labels capture both boundaries and entity type, e.g.:

[$_{\text{ORG}}$ American Airlines], a unit of [$_{\text{ORG}}$ AMR Corp.], immediately matched the move, spokesman [$_{\text{PER}}$ Tim Wagner] said.

NER AS A SEQUENCE LABELLING TASK

WARWICK

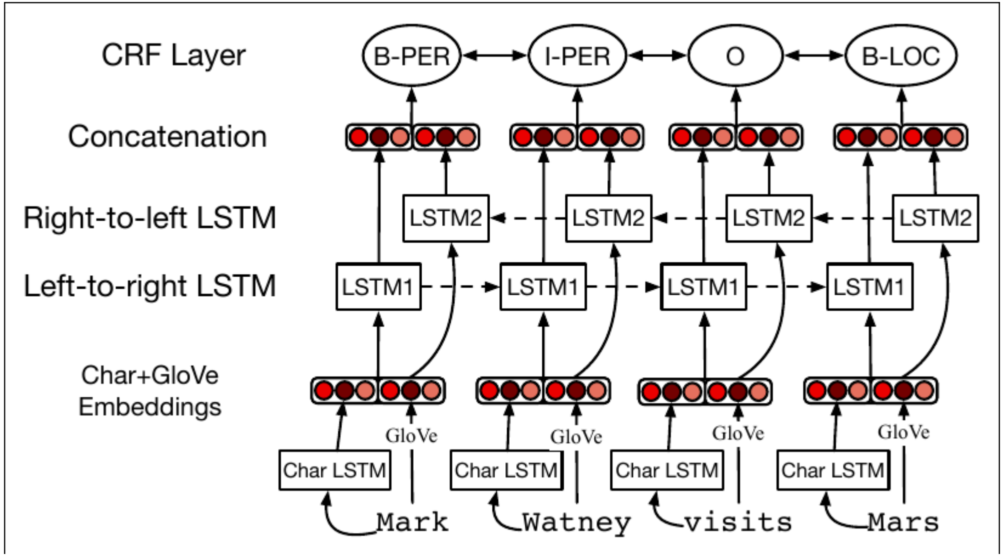
[ORG American Airlines], a unit of [ORG AMR Corp.], immediately matched the move, spokesman [PER Tim Wagner] said.

- Convert it to **BIO format:** **(B): beginning, (I): in, (O): out.**

Words	BIO Label	IO Label
American	B-ORG	I-ORG
Airlines	I-ORG	I-ORG
,	O	O
a	O	O
unit	O	O
of	O	O
AMR	B-ORG	I-ORG
Corp.	I-ORG	I-ORG
,	O	O
immediately	O	O
matched	O	O
the	O	O
move	O	O
,	O	O
spokesman	O	O
Tim	B-PER	I-PER
Wagner	I-PER	I-PER
said	O	O
.	O	O

NEURAL ALGORITHM FOR NER

- Bi-LSTM combining left-to-right and right-to-left LSTMs.



NER AS A SEQUENCE LABELLING TASK

- NER generally tackled as a sequential task:
  - MEMM or CRF is trained, to label each token in a text as being **part of a named entity or not**.
  - Use **gazetteers to assign labels** to those tokens.
  - **Gazetteers:** lists of place names, first names, surnames, organisations, products, etc.
    - GeoNames.
    - National Street Gazetteer (UK).
    - More gazetteers.

EVALUATION OF NER

WARWICK

- Standard measures: **Precision, Recall, F-measure**.
- The entity rather than the word is the unit of response, i.e:

$$\text{Precision:} = \frac{\text{number of correctly recognised entities}}{\text{number of entities returned}}$$

$$\text{Recall:} = \frac{\text{number of correctly recognised entities}}{\text{number of entities in the gold standard}}$$

- Segmentation component makes evaluation more challenging:
  - Using words for training but entities as units of response means → if we have **Leamington Spa** in the corpus, and our system identifies **Leamington** only, that's a mistake.

COMMERCIAL NER SYSTEMS

- **Statistical sequence models** are the norm in **academic research**.

- **Commercial NER** are often hybrids of **rules & machine learning**:
    1. Use **high precision rules** to tag unambiguous entities.
    2. Search for **substring matches** of those unambiguous entities.
    3. Use **application-specific name list** to identify other entities.
    4. Use **probabilistic sequence labelling** to complete that.

RELATION EXTRACTION

RELATION EXTRACTION

WARWICK

- **Relation extraction:** process of identifying relations between named entities.

  The spokesman of the **UK**'s **Downing Street**, **James Slack**,…

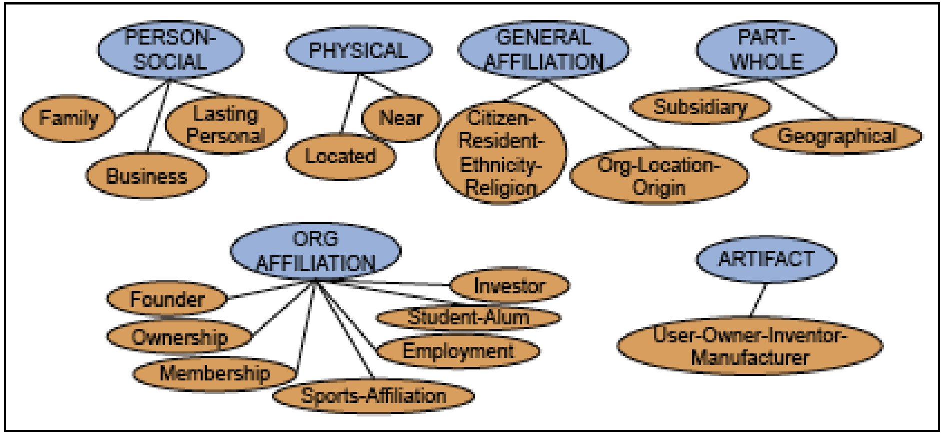
  location organisation person

- Relations:
  - **Downing Street** is in the **UK** (ORG-LOC).
  - **James Slack** is spokesperson of **Downing Street** (PER-ORG).
  - **James Slack** works in the **UK** (PER-LOC).

RELATION TYPES

WARWICK

- Examples of types of relations:



- There are databases that define these relation types.

RELATION TYPES

- For example, there is the UMLS (Unified Medical Language System), a network that describes 134 broad subject categories, entity types and 54 relations between entities. e.g.

Entity	Relation	Entity
Injury	disrupts	Physiological Function
Bodily Location	location-of	Biologic Function
Anatomical Structure	part-of	Organism
Pharmacologic Substance	causes	Pathological Function
Pharmacologic Substance	treats	Pathologic Function

- Relations usually describe properties of the entities.

RELATION EXTRACTION

- Wikipedia infoboxes can be used to create a corpus.

- Convert it into relations as RDF triples:
  Univ. of Warwick – located_in – Coventry
  Univ. of Warwick – established_in – 1954
  …

Motto	*Mens agitat molem* (Latin)
Motto in English	Mind moves matter
Type	Public research university
Established	1965
Endowment	£8.9 million (as of 31 July 2015)[1]
Chancellor	Sir Richard Lambert
Vice-Chancellor	Stuart Croft
Administrative staff	5,678 incl. 1,842 academics/researchers[2]
Students	23,570[2]
Undergraduates	13,049[2]
Postgraduates	9,317[2]
Location	Coventry, England

RELATION EXTRACTION USING PATTERNS

- First approach used in the 90s using lexical/syntactic patterns.
  - combined with regular expressions.

PER, POSITION of ORG:
George Marshall, Secretary of State of the United States

PER (named|appointed|chose|etc.) PER Prep? POSITION
Truman appointed Marshall Secretary of State

PER [be]? (named|appointed|etc.) Prep? ORG POSITION
George Marshall was named US Secretary of State

- -: Such patterns are high precision but typically low recall.
- -: Difficult to generalise to new domain and new IE tasks.

RELATION EXTRACTION USING PATTERNS

WARWICK

NP {, NP}* {,} (and|or) other NP_H	temples, treasuries, and other important civic buildings
NP_H such as {NP,}* {(or|and)} NP	red algae such as Gelidium
such NP_H as {NP,}* {(or|and)} NP	such authors as Herrick, Goldsmith, and Shakespeare
NP_H {,} including {NP,}* {(or|and)} NP	common-law countries, including Canada and England
NP_H {,} especially {NP}* {(or|and)} NP	European countries, especially France, England, and Spain

RE USING SUPERVISED MACHINE LEARNING

WARWICK

- Supervised machine learning approaches typically do:
  1. A fixed set of relations and entities is chosen.
  2. A corpus is manually annotated with the entities and relations to create training data.
  3. A classifier is trained on the corpus and tested on an unseen text to classify potential relations between entity pairs, e.g. SVM, Logistic Regression, Naive Bayes, Perceptron.

RE USING SUPERVISED MACHINE LEARNING

WARWICK

- Important to choose good features, e.g. dependencies, POS tags.
- Example: **American Airlines**, a unit of **AMR**, immediately matched the move, spokesman **Tim Wagner** said.

M1 headword	*airlines*
M2 headword	*Wagner*
Word(s) before M1	NONE
Word(s) after M2	*said*
Bag of words between	{*a, unit, of, AMR, Inc., immediately, matched, the, move, spokesman* }
M1 type	ORG
M2 type	PERS
Concatenated types	ORG-PERS
Constituent path	$NP \uparrow NP \uparrow S \uparrow S \downarrow NP$
Base phrase path	$NP \rightarrow NP \rightarrow PP \rightarrow NP \rightarrow VP \rightarrow NP \rightarrow NP$
Typed-dependency path	$Airlines \leftarrow_{subj} matched \leftarrow_{comp} said \rightarrow_{subj} Wagner$

RE USING SEMI-SUPERVISED LEARNING

WARWICK

- Bootstrapping can be used to expand our training data with instances where our classifier's predictions are very confident.

```
function BOOTSTRAP(Relation R) returns new relation tuples

    tuples ← Gather a set of seed tuples that have relation R
    iterate
        sentences ← find sentences that contain entities in seeds
        patterns ← generalize the context between and around entities in sentences
        newpairs ← use patterns to grep for more tuples
        newpairs ← newpairs with high confidence
        tuples ← tuples + newpairs
    return tuples
```

RE USING DISTANT SUPERVISION

WARWICK

- Distant supervision for relation extraction:
  - Combine best of both worlds:
    - bootstrapping + supervised machine learning.

- Use the Web (e.g. Wikipedia) to build large sets of relations.

- We can now train a more reliable supervised classifier.

EXAMPLE USING DISTANT SUPERVISION

- Suppose we're **looking for alternative names** of people.

- We can use knowledge bases to get limited cases of names:

Michael Jackson is also known as:

MJ, The King of Pop, Michael Joe Jackson, Michael Joseph Jackson
Roi de la Pop, MJJ
Jacko, King of Pop

Jennifer Aniston is also known as:

Jennifer Joana Aniston, Jennifer Anastassakis, Rachel Green

etc.

EXAMPLE USING DISTANT SUPERVISION

- Look for matches of those names in e.g. Wikipedia:

  Michael Jackson, **aka** King of Pop
  Michael Joseph Jackson, **commonly known as** Michael Jackson
  Jennifer Aniston, **née** Jennifer Anastassakis
  Jennifer Aniston, **born** Jennifer Anastassakis
  …

- This gives us a lot more training data.

OPEN IE: UNSUPERVISED RE

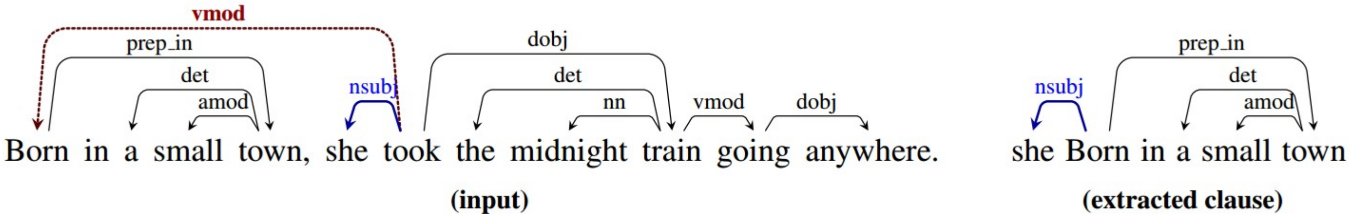
- The main difference is that the **schema** for these relations **does not need to be specified in advance**.

- The relation name is just the text linking two arguments, e.g.:
  "Barack Obama was born in Hawaii" would create
  Barack Obama; was born in; Hawaii

- The challenge lies in identifying that two entities connected with a verb do constitute an actual relation, not a false positive.

STANFORD OPENIE

- Stanford's state-of-the-art OpenIE system:
    1. Using dependencies, splits sentence into clauses.
    2. Each clause is maximally shortened into sentence fragments.
    3. These fragments are output as OpenIE triples.



EVALUATION OF RELATION EXTRACTION

WARWICK

- **Precision, Recall, F-measure** for **supervised methods**.
- For unsupervised methods evaluation is much harder.
  Can estimate Precision using a small labelled sample:

$$\hat{P} = \frac{\text{\# of correctly extracted relation tuples in the sample}}{\text{total \# of extracted relation tuples in the sample.}}$$

- Precision at different levels of recall, e.g. 1000 new relations, 10,000 new relations etc.

TEMPORAL EXPRESSION EXTRACTION

TEMPORAL EXPRESSION EXTRACTION

WARWICK

- Finding temporal references in text.

- Three types of temporal expressions:
  - **Absolute:** 20^{th} March 2020, afternoon, 5^{th} January,...
  - **Relative:** yesterday, next week,...
  - **Duration:** 3 hours, 5 minutes, 1 week,...

TEMPORAL EXPRESSION EXTRACTION

WARWICK

- We need to identify temporal lexical triggers:
  - Can be nouns, proper nouns, adjective, adverb.

Category	Examples
Noun	*morning, noon, night, winter, dusk, dawn*
Proper Noun	*January, Monday, Ides, Easter, Rosh Hashana, Ramadan, Tet*
Adjective	*recent, past, annual, former*
Adverb	*hourly, daily, monthly, yearly*

TEMPORAL EXPRESSION EXTRACTION

- BIO tags are used, as for NER:

A	*fare*	*increase*	*initiated*	*last*	*week*	*by*	*UAL*	*Corp's...*
O	O	O	O	B	I	O	O	O

TEMPORAL EXPRESSION EXTRACTION

- Usually sequential classifiers are used, with features including:

  - **Token:** The target token to be labelled.
  - **Tokens in window:** Bag of tokens in a window around a target.
  - **POS tags:** Parts of speech of target and window words.
  - **Lexical triggers:** Presence in a list of temporal terms.

TEMPORAL NORMALISATION

WARWICK

- Sometimes we need to normalise temporal expressions, e.g.:

  ”last week”
  → what week is that specifically?

  ”it lasted 5 months”
  → can we determine when it started and ended specifically?

TEMPORAL NORMALISATION

WARWICK

- After normalisation, we want something like this:

```
<TIMEX3 id=''t1'' type="DATE" value="2007−07−02" functionInDocument="CREATION_TIME"
    > July 2, 2007 </TIMEX3> A fare increase initiated <TIMEX3 id="t2" type="DATE"
    value="2007−W26" anchorTimeID="t1">last week</TIMEX3> by United Airlines was
    matched by competitors over <TIMEX3 id="t3" type="DURATION" value="P1WE"
    anchorTimeID="t1"> the weekend </TIMEX3>, marking the second successful fare
    increase in <TIMEX3 id="t4" type="DURATION" value="P2W" anchorTimeID="t1"> two
    weeks </TIMEX3>.
```

TEMPORAL ANCHOR

- Knowing the creation date/time of a document or a quotation can help.
  - We call this the **temporal anchor**.

- Then having that as a starting point,
  - We know what’s yesterday.
  - We know what’s 10 minutes later.

FULLY QUALIFIED TEMPORAL EXPRESSIONS

FQTE →

5th November, 2019
November 5, 2019
17.03 on 3rd January, 2019

- But we rarely use them. **We don't say**:

I went to the dentist on 3rd July, 2018, then on 4th July, 2018 I had to stay home recovering.

I watched a movie from 5.04pm to 6.53pm on 3rd September, 2018.

REALITY

- While sequential classifiers work very well for temporal expression extraction.

- For **temporal normalisation**, most current approaches are still **rule-based**.
  - A long way to go…

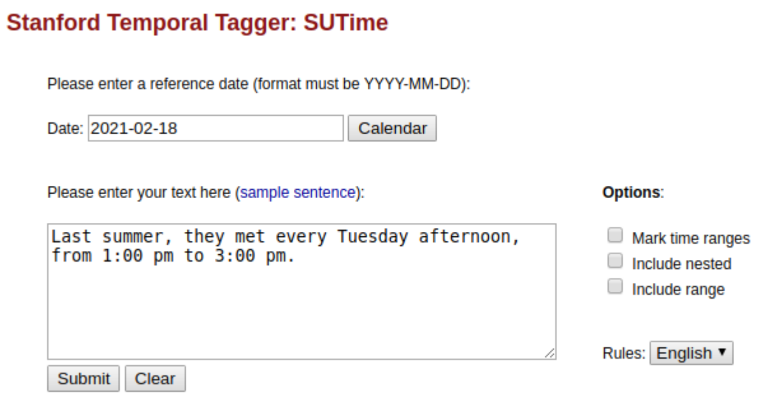
STANFORD TEMPORAL TAGGER

WARWICK

- You can try Stanford Temporal Tagger: http://nlp.stanford.edu:8080/sutime/process

STANFORD TEMPORAL TAGGER

- You need to enter the temporal anchor.



STANFORD TEMPORAL TAGGER

WARWICK

Annotated Text
(tagged using sutime)

Last summer, they met every Tuesday afternoon, from 1:00 pm to 3:00 pm.

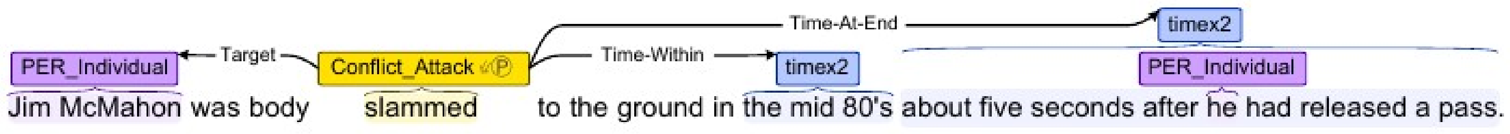
Temporal Expressions

Text	Value	Timex3 Tag
Last summer	2020-SU	<TIMEX3 tid="t1" type="DATE" value="2020-SU">Last summer</TIMEX3>
every Tuesday afternoon	XXXX-WXX-2TAF	<TIMEX3 periodicity="P1W" quant="every" tid="t2" type="SET" value="XXXX-WXX-2TAF">every Tuesday afternoon</TIMEX3>
1:00 pm	2021-02-18T13:00	<TIMEX3 tid="t3" type="TIME" value="2021-02-18T13:00">1:00 pm</TIMEX3>
3:00 pm	2021-02-18T15:00	<TIMEX3 tid="t4" type="TIME" value="2021-02-18T15:00">3:00 pm</TIMEX3>

MULTIPLE EVENTS

WARWICK

- It becomes more difficult when we have multiple events occurring at different points in time.

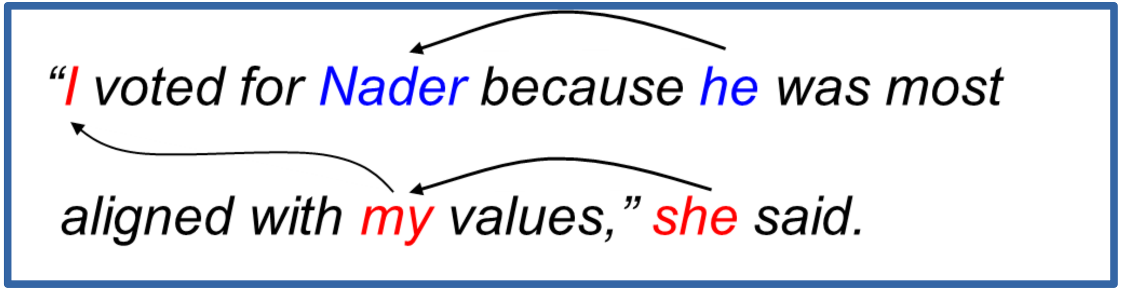


- Event 1: mid 80’s → released a pass.
- Event 2: ~5 seconds later → slammed to the ground.

OTHER INFORMATION EXTRACTION TASKS

COREFERENCE RESOLUTION

- **Coreference resolution:** finding all expressions that refer to the same entity in a text.



- **Neural coref:** python package for co-reference resolution. https://github.com/huggingface/neuralcoref

- And you can **try it online**: https://huggingface.co/coref/

NEURAL COREF: EXAMPLE

EVENT EXTRACTION

WARWICK

- **Event extraction:** Extracting structured information about events from text. Often <entity>-<verb>-<entity>, as in relation extraction. Very useful to analyse news stories.

  Steve Jobs died in 2011 → Steve Jobs;death in;2011

  New Android phone was announced by Google →
  New Android phone;announcement by;Google

TEMPLATE/SLOT FILLING

WARWICK

- **Slot filling (aka Knowledge Base Population):** task of taking an incomplete knowledge base (e.g., Wikidata), and a large corpus of text (e.g., Wikipedia), and completing the incomplete elements of the knowledge base.

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ENTITY LINKING

- **Entity linking:** task of taking ambiguous entity mentions, and "link" them with concrete entries in a knowledge base.

Alex Jones has a new film.

which of them? →

Alex Jones (born 1974) is an American radio host, conspiracy theorist,

Alex Jones may also refer to:

- Alex Jones (Welsh presenter) (born 1977), Welsh television present
- Alex Jones (journalist) (born 1946), American journalist
- Alex Jones (actor), American actor and advocate for the deaf
- Alex Jones (playwright), British actor, playwright and filmmaker
- Alex Jones (preacher) (1941–2017), African-American Roman Cath
- Alex Jones (baseball) (1869–1941), American Major League Baseba
- Alex Jones (footballer, born 1964) (born 1964), English football defe
- Alex Jones (cricketer) (born 1988), Welsh cricketer
- Alex Jones (racing driver) (born 1988), Welsh racing driver
- Alex Jones (rugby league) (born 1993), Welsh rugby league player
- Alex Jones (footballer, born 1994) (born 1994), English football forw

- Can be defined as:
  - Classification task.
  - Similarity task.
  - ...

INFORMATION EXTRACTION: SUMMARY

WARWICK

- Involves a broad range of tasks, with a common goal:
  unstructured text → structured data

- **Sequence classification** is often useful.

- As with many other tasks, **availability of data is crucial**:
  - Labelled corpora.
  - Gazetteers.
  - Thesauri.

RESOURCES

- Stanford CRF NER: https://nlp.stanford.edu/software/CRF-NER.shtml
- Stanford CoreNLP: https://stanfordnlp.github.io/CoreNLP/

- iepy: https://pypi.python.org/pypi/iepy
- Stanford-OpenIE-Python: https://github.com/philipperemy/Stanford-OpenIE-Python

ASSOCIATED READING

- Jurafsky, Daniel, and James H. Martin. 2009. Speech and Language Processing: An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics. 3rd edition. **Chapter 17**.

- Bird Steven, Ewan Klein, and Edward Loper. Natural Language Processing with Python. O’Reilly Media, Inc., 2009. **Chapter 7**.