

Automatic Extraction of Archaeological Events from Text

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Outline

Overview

- project setting and data used

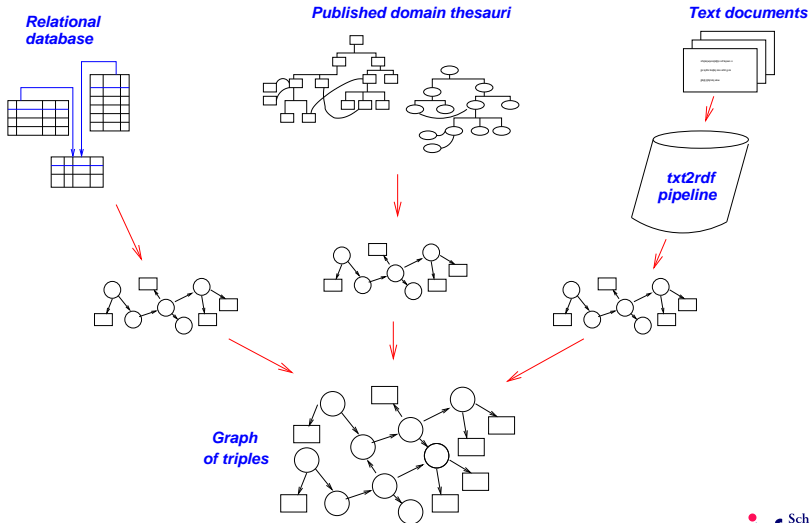
Event Extraction

- finding relations between textual entity mentions

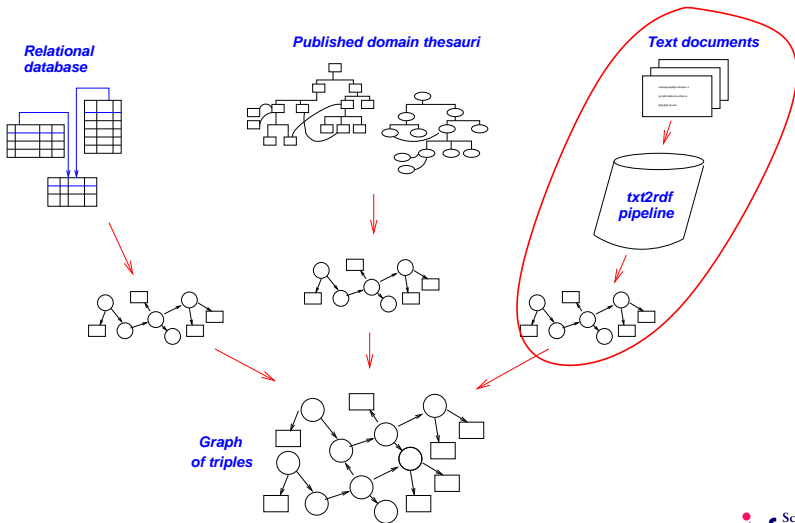
Results

- for NER, RE and the combination

Overview of *Tether*



Overview of *Tether*



Data from RCAHMS

- The “memory keeper” for Scotland
- <http://www.rcahms.gov.uk/>
- One of Scotland’s 6 National Collections



- Recording **Scotland's places**, from the Neolithic to Now:
 - Skara Brae
 - Informatics Forum
- Extracting events is a requirement

Finding Binary Relations in Text

- Named Entity Recognition as first step
- Special attention paid to NE nesting
- Then look for relations between pairs of NEs:
 - generate all possible pairings per document
 - add features –
NE classes, word separation, POS tags, nesting, in sentence...
- Sequential tagger labels each pairing

Supervised Learning for Relation Extraction

The following **were found** in **Unst** by Mr **A T Cluness** : a **steatite dish** , ...

Supervised Learning for Relation Extraction

FIND EVENT *PLACE* *PERSNAME* *ARTEFACT*
↓ ↓ ↓ ↓
The following **were found** in **Unst** by Mr **A T Cluness** : a **steatite dish** , ...

were_found unst
were_found a_t_cluness
were_found steatite_dish
unst a_t_cluness
unst steatite_dish
a_t_cluness steatite_dish

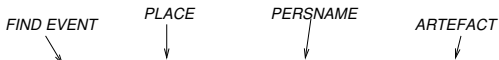
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FIND EVENT *PLACE* *PERSNAME* *ARTEFACT*

The following **were found** in **Unst** by Mr **A T Cluness** : a **steatite dish** , ...

<i>eventLocation</i>	were_found	unst
<i>eventAgent</i>	were_found	a_t_cluness
<i>eventPatient</i>	were_found	steatite_dish
O	unst	a_t_cluness
O	unst	steatite_dish
O	a_t_cluness	steatite_dish

Supervised Learning for Relation Extraction



The following **were found** in **Unst** by Mr **A T Cluness** : a **steatite dish** , ...

<i>eventLocation</i>	were_found	unst	cls1=event	cls2=place	wdsep=+2...
<i>eventAgent</i>	were_found	a_t_cluness	cls1=event	cls2=persname	wdsep=+5...
<i>eventPatient</i>	were_found	steatite_dish	cls1=event	cls2=artefact	wdsep=+9...
O	unst	a_t_cluness	cls1=place	cls2=persname	wdsep=+9...
O	unst	steatite_dish	cls1=place	cls2=artefact	wdsep=+9...
O	a_t_cluness	steatite_dish	cls1=persname	cls2=artefact	wdsep=+9...

Named Entity Recognition

- 11 categories:
ORG, PERSNAME, ROLE, SITETYPE, ARTEFACT, PLACE, SITENAME, ADDRESS, PERIOD, DATE, EVENT
- Unorthodox ones:
 - EVENT - verb phrases not noun phrases: *visited, was found*
 - SITETYPE, ARTEFACT, ROLE, EVENT – class terms
- Nesting:
[[[Edinburgh]^{PLACE} University]^{ORG} Library]^{ORG}

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Relation Extraction

- Basic predicate categories:
eventRel, hasLocation, hasPeriod, instanceOf, partOf, sameAs, seeAlso
- *n*-ary eventRel predicate:
eventAgent, eventAgentRole, eventDate, eventPatient, eventPlace
- event types: SURVEY, EXCAVATION, FIND, VISIT, DESCRIPTION, CREATION, ALTERATION

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Mapping Text Relations to RDF

site456

[SOUTH WALLS] , [MISBISTER] , [THE LOFTS]

[ND38NW 29 centred 3325 8885]

Sites [recorded] during an [archaeological survey] undertaken on the lands of [the Loft] , [Longhope] , as part of the pilot scheme for the [Historic [Scotland]] [Farm] [Ancient] [Monument] Survey Grant Scheme] . [ND 3311 8890] Two [small cairns] . [ND 3336 8889] [Cairn] . [ND 3339 8885] [Cairn] . [ND 3339 8886] [Clearance cairn] . [ND 3342 8884] [Sub-rectangular cairn] . [ND 3339 8883] [Well] Sponsors : [Historic [Scotland]] , [M J Jones] . [N Card] [1998]

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The diagram shows a text snippet with several elements highlighted in different colors. Three arrows point from labels below to specific parts of the text: 'eventPatient' points to the word 'recorded' (highlighted in yellow); 'eventPlace' points to the phrase 'Historic [Scotland]' (highlighted in red); and 'event' points to the phrase 'archaeological survey' (highlighted in blue). A light blue curved line connects the 'recorded' and 'archaeological survey' areas.

eventPatient

eventPlace

site456 – hasEvent – recordingX
recordingX – hasLocation – "ND 3342 8884"
recordingX – hasPatient – "Sub-rectangular cairn"

Results – NER Step

	Precision %	Recall %	F-score %	Count
ADDRESS	82.40	81.61	82.00	3,458
PLACE	95.00	66.80	78.44	2,503
SITENAME	64.55	61.20	62.83	2,712
DATE	95.12	82.08	88.12	3,519
PERIOD	84.02	45.54	59.07	400
EVENT	94.98	63.66	76.22	3,176
ORG	99.39	89.66	94.27	2,730
PERSNAME	96.71	74.82	84.37	2,318
ROLE	98.00	54.44	70.00	90
SITETYPE	85.24	52.39	64.89	5,668
ARTEFACT	75.83	18.06	29.17	879
Average	88.02	67.75	76.57	(27,453)

IAA F-score 78.09%

Results – Extracting Event Relations

Relation	Precision %	Recall %	F-score %	Found
eventAgent	98.42	98.70	98.56	3,794
eventAgentRole	69.23	30.00	41.86	13
eventDate	98.75	98.68	98.71	3,189
eventPatient	87.77	84.61	86.16	1,553
eventPlace	83.58	72.70	77.76	341
Events Average	87.55	76.94	80.61	(8,890)
Overall Average	83.41	69.27	75.68	(21,932)

- IAA F-score 82.51%
- Note deliberate preference of Precision over Recall

Results for Full Pipeline (Event Relations)

Relation	Avg Precision	Avg Recall	Avg F-score
eventAgent	97.46	82.18	88.72
eventAgentRole	0.00	0.00	0.00
eventDate	87.75	71.73	78.64
eventPatient	90.69	42.99	48.46
eventPlace	36.36	17.33	27.62
Overall Average	73.35	48.24	57.51

- Evaluation over only 10% of corpus, so sparse categories lost
- eventAgent and eventDate are largest categories

Summary

- Event modelling is unorthodox in NER terms but results good
 - EVENT NE recognition: 76% F-score (avg: 77%)
- Event relations are **easier** than others:
 - overall 81% F-score for event relations (overall avg: 70%)
- Models deliberately trained to favour Precision over Recall
- Extraction to RDF graph, as shown...
- ...or to populate RDB tables if desired
- Automatic extraction of events from text is feasible

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