Automated knowledge base construction

3. Entity Typing

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Scrapping: How to deal with **new websites**?

- Pattern/statement duality / iterative seed-based pattern and statement discovery (Section 6.2.2.1 in FnT 2001, in detail in lecture 5)
  - Spot known statements in new websites to learn extraction patterns
  - Use known extraction patterns to extract new relations
  - Iterate
- Zero-shot structure learning (last part of Section 9.5.2.3 in FnT 2021)
  - Learn fundamental patterns of semi-structured statement expression in websites
  - Allows domain transfer (e.g., education to movies)

Entity typing: Motivation

- Einstein: Scientist, Physicist, Nobel prize winner
- Dudweiler: Village, location, municipality
- RCH₂OH: chemical formula, psychoactive substance

- Entities are the basic block of KBs
- Types often most salient info about entities
- Types help to
  - Organize entities
  - Power search applications
  - Direct and constrain fact extraction
Types and fact extraction

In 1905, Einstein discovered special relativity.

\[
\text{In Zürich, Einstein discovered special relativity.}
\]

dateOfDiscovery(special\_relativity, 1905)
placeOfDiscovery(special\_relativity, Zürich)

After three years in Westmore College, Mary moved to Eastless Academy.
After three years in Software Corp., Mary moved to Hardware Inc.
After three years in Corporate Finance, Mary moved to Controlling.

\[
\text{studiedAt? workedFor? fieldOfWork?}
\]
Outline

1. Named-entity recognition and classification
   1. Problem
   2. Interpretable rule-based NERC
   3. Neural NERC

2. Extractive typing

3. Use cases
   - spaCy
   - WebIsALOD
   - Entyfi
Def: NE Recognition & Classification

Named Entity Recognition and Classification (NERC) is the task of (1) finding entity names in a corpus and (2) annotating each name with a class out of a set of given classes.

(This is often called simply "Named Entity Recognition". We use "Named Entity Recognition and Classification" here to distinguish it from bare NER.)

\[
\text{classes} = \{ \text{Person, Location, Organization} \}
\]

Arthur Dent eats at Milliways.

Person \hspace{2cm} Organization
Classes/Types

NERC usually focuses the classes person, location, and organization. But some also extract money, percent, phone number, job title, artefact, brand, product, protein, drug, etc.

**ENAMEX [1996]**

Person
- Individual
  - Family name
  - Title
- Group
- Organization
  - Government
  - Public/private company
  - Religious
  - Non-government
    - Political Party
    - Para military
    - Charitable
    - Association
- GPE (Geo-political Social Entity)
- Media

Location
- Place
  - District
  - City
  - State
  - Nation
  - Continent
- Address
  - Water-bodies
  - Landscapes
  - Celestial Bodies

- Manmade
  - Religious Places
  - Roads/Highways
  - Museum
  - Theme parks/Parks/Garden
  - Monuments

- Facilities
  - Hospitals
- Institutes
- Library
  - Hotel
  - Restaurants/Lodges
  - Plants/factories
  - Police Station
  - Fire Services
  - Public Comfort Stations
  - Airports
  - Ports
  - Bus-Stations

- Locomotives
- Artifacts
  - Implements
  - Ammunition
  - Paintings
  - Sculptures
  - Cloths
  - Gems & Stones

- Entertainment
  - Dance
  - Music
  - Drama/Cinema
  - Sports
  - Events/Exhibitions/Conferences

- Cuisine’s
- Animals
- Plants
**NERC examples**

Arthur Dent visits Milliways, a restaurant located at End of the Universe Street 42.

**In XML**

<per>Arthur Dent</per> visits <org>Milliways</org>, a restaurant located at <loc>End of the Universe Street 42</loc>.

**In TSV**

- 41 towel OTHER
- 41 . OTHER
- 42 Arthur PER
- 42 Dent PER
- 42 visits OTHER
- 42 Milliways ORG

**TSV file of**

- sentence number
- token
- class
Now do it here:

We have determined the crystal structure of a triacylglycerol lipase from Pseudomonas cepacia (Pet) in the absence of a bound inhibitor using X-ray crystallography. The structure shows the lipase to contain an alpha/beta-hydrolase fold and a catalytic triad comprising of residues Ser87, His286 and Asp264. The enzyme shares ...
NERC is not easy

• Organization vs. Location
  England won the World Cup.
The World Cup took place in England.

• Company vs Artefact
  shares in MTV
  watching MTV

• Location vs. Organization
  She took the bus from Saarland University
  Saarland University has 25 Bachelor programs

• Ambiguity
  May (month, person, or verb?), Washington, etc.
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NERC Feature

An NERC feature is a property of a token that could indicate a certain NERC class for the main token of a window.

<table>
<thead>
<tr>
<th></th>
<th>know, ”, said, Arthur, “, I, really</th>
</tr>
</thead>
<tbody>
<tr>
<td>is stopword</td>
<td>0      0      0      0      1  1</td>
</tr>
<tr>
<td>matches [A-Z][a-z]+</td>
<td>0      0      0      1  0  0  0</td>
</tr>
</tbody>
</table>
| is punctuation   | 0      1      0      0  1  0  0  }
Syntactic Features

- capitalized word
- all upper case word
- smallcase word
- mixed letters/numbers
- number
- special symbol
- punctuation
- Regular expression

Fenchurch
WSOGMM
planet
HG2G
42
$
.,;:?!
[A-Z][a-z]+
Dictionary Features

• cities
• countries
• titles
• common names
• airport codes
• words that identify a company
• common nouns
• hard-coded words

Vassilian
UK
Dr.
Arthur
CDG
Inc, Corp, ...
car, president, ...
M2

... if you have a dictionary.

The dictionary can be implemented, e.g., as a trie.

Michael Loster, Zhe Zuo, Felix Naumann, Oliver Maspufuhl, Dirk Thomas:
“Improving Company Recognition from Unstructured Text by using Dictionaries”
EDBT 2017
Def: POS

A Part-of-Speech (also: POS, POS-tag, word class, lexical class, lexical category) is a set of words with the same grammatical role.

Alizée wrote a really great song by herself
POS Tag Features for NERC

DT    Determiner
IN    Preposition or subordinating conjunction
JJ    Adjective
NN    Noun, singular or mass
NNP   Proper noun, singular
PRP   Personal pronoun
RB    Adverb
SYM   Symbol
VBZ   Verb, 3rd person singular present
...

[Penn Treebank symbols]
Morphological features

- word endings
- word contains an n-gram

- ish, -ist, ...
  Par, ari, ris

Intuition: quite often, the morphology of the word gives a hint about its type. Examples:
Dudweiler, Landsweiler, Wellesweiler $\rightarrow$ LOC
Cotramoxazole $\rightarrow$ DRUG
Def: NERC by rules

NERC by rules uses rules of the form

$$f_1^d, \ldots, f_k^d \ [ f_1^o, \ldots, f_l^o ] \ f_1^o, \ldots, f_m^o \Rightarrow c$$

...where $f_1^d, \ldots, f_m^d$ are features and $c$ is a class.
$f_1^o, \ldots, f_l^o$ are the designated features.

If a window of tokens matches $f_1^d \ldots f_m^d$, we annotate the tokens of the designated features with $c$.

"in" [ ([A-Z][a-z]+) ] "City" => Location

She works in **London City** each day.
Examples for NERC rules

Dictionary: Title "." [CapWord{2}] => Person

[CapWord (Street|Av|Road)] => Location

"a pub in" [CapWord] => Location

"based in" [CapWord] => Location

"to the" Compass "of" [CapWord] => Location
NERC examples from GATE [1995]

Rule: TheGazOrganization
Priority: 50
// Matches “The <in list of company names>”
({Part of speech = DT | Part of speech = RB} {DictionaryLookup = organization})
→ Organization

Rule: LocOrganization
Priority: 50
// Matches “London Police”
({DictionaryLookup = location | DictionaryLookup = country} {DictionaryLookup = organization} {DictionaryLookup = organization}? ) → Organization

Rule: INOrgXandY
Priority: 200
// Matches “in Bradford & Bingley”, or “in Bradford & Bingley Ltd”
([{Token string = “in”}] )
({Part of speech = NNP}+ {Token string = “&”} {Orthography type = upperInitial}+ {DictionaryLookup = organization end}? )\:orgName → Organization\:orgName

Rule: OrgDept
Priority: 25
// Matches “Department of Pure Mathematics and Physics”
({Token.string = “Department”} {Token.string = “of”} {Orthography type = upperInitial}+ ({Token.string = “and”} {Orthography type = upperInitial}+)? ) → Organization

Sunita Sarawagi: Information Ext
https://gate.ac.uk/
Task: NERC patterns

Design NERC patterns that can find planets in the following text. Describe each feature.

(Patterns should generalize beyond the names in this text.)

Lamuella is the nice planet where Arthur Dent lives.
Santraginus V is a planet with marble-sanded beaches.
Magrathea is an ancient planet in Nebula.
The fifty-armed Jatravartids live on Viltvodle VI.

Example:

[CapWord] “is a planet”

(this pattern does not work, it’s here for inspiration)
Possible Solution: NERC patterns

[CapWord] "is" (thelalan) Adj "planet"

• CapWord: A word that starts with a capital letter.
• “is”, “planet”: plain strings
• (thelalan): the words “the”, “a”, or “an”
• Adj: an adjective (dictionary lookup)

[CapWord RomanNumeral]

• CapWord: as above
• RomanNumeral: A roman numeral (I, II, V, X, ...
Conflicting NERC rules

If two NERC rules match overlapping strings, we have to decide which one to apply. Possible strategies:

• annotate only with the rule that has a longer match
• manually define order of precedence
Def: Cascaded NERC

Cascaded NERC applies NERC to the corpus annotated by a previous NERC run.

Main Street 42, West City

First NERC run

<street>Main Street 42</street>, <city>West City</city>

Second NERC run

<adr><street>Main Street 42</street>, <city>West City</city></adr>

Cascaded NERC rule:

[Street City] => Adr

- Street: a previously annotated street
- City: a previously annotated city
Task: Cascaded NERC

Write NERC rules for the first run and the second, cascaded run of a NERC to recognize person names as in

Dr. Bob Miller
Monsieur François Hollande
Mademoiselle Alizée Jacozey
Ms Gary Day-Ellison
Possible Solution: Cascaded NERC

First run:
  Dictionary: AcademicTitle => Title
  Dictionary: FrenchTitle => Title
  Dictionary: EnglishTitle => Title
  CapWord-CapWord => Name
  CapWord => Name

Second run:
  Title Name Name => Person
Learning NERC Rules

NERC rules are often designed manually (as in the GATE system). However, they can also be learned automatically (as in the Rapier, LP2, FOIL, and WHISK systems).

We will now see a blueprint for a bottom-up rule learning algorithm.
Example: Rule learning

0. Start with annotated training corpus

1. Find a NERC rule for each annotation

2. Merge two rules by replacing a feature by a more general feature

3. Merge two rules by dropping a feature

4. Remove redundant rules

5. Repeat

---

\[
\text{\langle pers\rangle Arthur\langle/\text{pers}\rangle says "Hello"}
\]

\[
\text{[Arthur] "says "Hello"" } \Rightarrow \text{ pers}
\]

\[
\text{[Ford] "says "Hello"" } \Rightarrow \text{ pers}
\]

\[
\text{Generalize}
\]

\[
\text{[CapWord] "says "Hello"" } \Rightarrow \text{ pers}
\]

\[
\text{[CapWord] "says "Bye"" } \Rightarrow \text{ pers}
\]

\[
\text{Drop}
\]

\[
\text{[CapWord] "says" } \Rightarrow \text{ pers}
\]

\[
\text{[CapWord] (sayslyells|screams) } \Rightarrow \text{ pers}
\]
NERC rule learning is not easy

Then [Ford] "says “Hello”" => pers
And [Arthur] "yells “Bye”" => pers
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Neural NERC

- Problem well suited for **machine learning**
  - Few to moderately many output labels
  - Well-scoped problem (typically small context sufficient)
  - Realistic to acquire sufficient training data
Not-yet neural ML for NERC

- Rule mining is actually a machine learning paradigm
- Instead of rule mining, can plug any favourite ML technique
  - Nearest neighbor
  - Regression
  - (Pre-trained) neural nets
Excursus: Neural language models (LMs)

Huge multi-layer neural networks self-trained on large corpora, later fine-tuned to a variety of tasks

- **Huge**: Only recently became trainable (e.g., GPT-3: 175B parameters)
- **Self-training**: Require no further human labels - predict randomly masked words, or sentence order on existing texts
- **Fine-tuning to applications**: Can be transferred to a range of text-related tasks with relatively few labelled samples
- **Popular instances**: ELMo, BERT, GPT, T5

The lion chased the zebra.

[?] = zebra
Pre-trained neural LMs for NERC
Pre-trained neural LMs for NERC

Kevin Durant plays basketball for the Brooklyn Nets

B-per  I-per  O  O  O  O  B-org  I-org

B = beginning  
I = inside  
O = outside

https://towardsdatascience.com/named-entity-recognition-with-bert-in-pytorch-a454405e0b6a
Examples

• https://demo.allennlp.org/named-entity-recognition/named-entity-recognition
• https://huggingface.co/dslim/bert-base-NER?text=My+name+is+Wolfgang+and+I+live+in+Berlin
Automated training data creation

• Manual training data possible, but we love automation

• Wiki markup provides disambiguation from surface forms to Wiki entities
  • “The [Max Planck Society | MPG] was founded in 1911 as the Kaiser Wilhelm Society for basic research.”
  • “[Monopotassium glutamate | MPG] is used to enhance the taste of ...”

• Wiki categories provide type-like information about entities
  • Max Planck Society → Scientific organization, Research units, ...
  • Monopotassium glutamate → Flavor enhancers, Potassium compounds, E-number additives, ...

• Idea: Train a supervised classifier that predicts categories from mention context
  • “The MPG was founded in 1911 as the Kaiser Wilhelm Society for basic research.” → Scientific organization, Research units
  • “MPG is used to enhance the taste of...” → Flavor enhancers, Potassium compounds, E-number additives

~> Weak labels/distant supervision
Summary: NERC

NERC (named entity recognition and classification) finds entity names and annotates them with predefined classes.

<pers>Arthur</pers> eats at <org>Milliways</org>

- Rule-based NERC
  
  [CapWord] eats => pers

- Pre-trained neural nets
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Limitations of NERC

• Classification limited by target set
  • Traditionally 5-20
  • Lately up to 10k types
  • Still inherently limited by target set

• Single mentions often provide limited context
  • Extraction may consider larger text corpus
Examples — Types beyond typical inventories

In the Simpson episode "HOMR", Doctor Monson discovers a crayon in Homer's brain and removes it. His IQ goes up from 55 to 105, but he feels uncomfortable and wants it back. Moe, who is not only a bartender but also an unlicensed physician, puts the crayon back, returning Homer to the idiot.
Def: IsA

Observation: The relations “subclass” and “type” are expressed very similarly in natural language:

Elvis is a singer.  
A dog is an animal.  

type(Elvis, singer)  
subclassof(dog, animal)

For now, let us ignore the distinction between the two.

IsA is the relation that holds between $x$ and $y$ if $x$ is an instance of $y$, or $x$ is a subclass of $y$.

is-a(Elvis, singer)  
is-a(dog, animal)
Def: Hearst Patterns

A Hearst pattern is a simple textual pattern that indicates an IsA fact that is mentioned implicitly.

"Y such as X"

...idiots such as Homer... \( \rightarrow \) is-a(Homer, idiot)
Def: Hearst Patterns

A Hearst pattern is a simple textual pattern that indicates an IsA fact that is mentioned implicitly.

"Y such as X"

...idiots such as Homer... → is-a(Homer, idiot)

...many activists, such as Lisa...
  is-a(Lisa, activist)
...some animals, such as dogs...
  is-a(dog, animal)
...some scientists, such as computer scientists...
  is-a(computer, scientist) ?
...some plants, such as nuclear power plants....
  is-a(nuc.Pow.Plants, plants) ?

Hearst patterns need
  • NER
  • disambiguation
  • plural removal
Def: Classical Hearst Patterns

The classical Hearst Patterns are

Y such as X+
such Y as X+
X+ and other Y
Y including X+
Y, especially X+

...where X+ is a list of
names of the form
“\(X_1, \ldots, X_{n-1} \text{ (and/or)}? X_n\)”.
(In the original paper, the \(X_i\) are noun phrases)

These imply is-\(\alpha(X_i, Y)\).
(assuming that the words are noun phrases and disambiguated)
Task: Classical Hearst Patterns

Apply

1. Y such as X+
2. such Y as X+
3. X+ and other Y
4. Y including X+
5. Y, especially X+

I lived in such countries as Germany, France, and Bavaria.

Trump is a candidate for the Nobel Peace Prize, together with Kim-Jon-Un and other world-class-leaders.

I love people that are not genies, especially Homer.
Example: Hearst on the Web

"cities such as"

https://www.google.com/search?client=firefox-b-d&q=%22cities+such+as%22

https://en.wikipedia.org/w/index.php?search=%22cities+such+as%22&title=Special%3ASearch&go=Go&ns0=1
Example: Hearst in the NELL project

NELL: "Robin"

categories

- **bird (98.4%)**
  - CPL @722 (87.1%) on 06–apr–2013 [ "_ sized birds" "_ was singing from" "small birds, such as _" "carolling of _" "Birds such as _" "_ singing outside" "_ twittered from" "_ flew away as" "plumage of _" "nesting habits of _" "_ 's feathers" "owl, black _" "_ vert between _" "_ various birds including _" "_ 's feather" "_ 's nests" "_ is a small bird" "_ bird called _" "_ builds a nest" "_ was the first bird" "_ breeding habitat" "_ is the state bird" "_ interesting birds like _" "_ swoop out of" "_ common birds like _" "_ nesting success" "_ 's eye view" "_ smaller birds such as _" "_ flew right in" "_ DNS round _" "_ red breasted _" "_ is the only bird" "_ returned yesterday" "_ 's beak" "_ birds including _" "_ birds, like _" "_ tail feathers of _" "_ favorite bird is _" "_ building a nest" "_ foraging amongst _" "_ Birds, including _" "_ does not make a spring" "_ birds, including _" "_ had made a nest" "_ 's nest high" "_ 's egg" "_ has a brown back" "_ 's egg blue" "_ birds include _" "_ migratory birds such as _" "_ had built a nest" "_ birds, except _" "_ birds, such as _" "_ songbirds like _" "_ flock of American _" "_ bird, whether _" "_ bird known as _" "_ carrying twigs" "_ nest sites for _" "_ 's plumage" "_ 's nest" "_ unusual sighting of _" "_ 's egg blue color" "_ birds like _" "_ colony of little _" "_ Island subspecies of _" "_ birds such as _" "_ is a thrush" "_ has built a nest" "_ 's nest bed" "_ has nested at _" "_ is a denizen" "_ larger birds such as _" "_ 's wings" "_ kept diving" "_ ground birds such as _" "_ garden birds such as _" "_ 's nest" "_ many birds such as _" "_ larger birds like _" "_ is also the state bird" "_ bird such as _" "_ arrival was heralded by _" "_ State bird is _" "_ Red breasted _" "_ was banded in _" "_ first bird was _" "_ 's chirp" "_ wing feathers of _" "_ flying overhead on _" "_ has made a nest" "_ has a yellow beak" "_ other birds, such as _" "_ wild birds, such as _" "_ is a songbird _" "_ eats insects "_ small birds such as _" "_ such birds as _" "_ built a nest" "_ cackle of _" "_ songbirds include _" "_ is the national bird" "_ state bird is _" "_ Common birds include _" "_ winter birds such as _" "_ is a migratory species _" ] using robin
Problems with Hearst Patterns

Hearst Patterns won’t extract the right is–a facts from

• domestic animals other than dogs such as cats ...
• companies such as IBM, Nokia, Proctor and Gamble ...
• classic movies such as Gone with the Wind ...
• people in Europe, Russia, Brazil, China, and other countries ...

Wentao Wu, Hongsong Li, Haixun Wang, Kenny Q. Zhu:
Determining the right super-concept

- Domestic animals other than dogs such as cats...

1. Extract all possible super-concepts and all possible sub-concepts
   - is-a(cat, dog)?
   - is-a(cat, domestic animal)?

2. Choose the most likely one, given what we have seen before
   - We have seen is-a(cat, animal) more often than is-a(cat, dog)
   - => is-a(cat, domestic animal)
Determining the right sub-concept

- ...people in **Europe**, **Russia**, **Brazil**, **China**, and other **countries** ...

1. The words that are close to the pattern words are most likely correct

   is-a(China, country)

2. If a word has been seen before, then all words between it and the pattern are most likely correct.

   Assume we have seen is-a(Russia, country) before
   => is-a(Brazil, country)
Distinguishing word senses

plants such as trees, grass, and herbs
plants such as trees, grass, and flowers

is-a

plant

tree grass herb

plant

tree grass flower

plants such as nuclear power plants

plant

nuclear power plant
Distinguishing word senses

- plants such as trees, grass, and herbs
- plants such as trees, grass, and flowers
- plants such as nuclear power plants
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Use case 1: Classification: spaCy

- [https://spacy.io/api/annotation#named-entities](https://spacy.io/api/annotation#named-entities)

- Trained on OntoNotes 5 dataset
  - 18 types
  - Few frequent ones (person, location, geopolitical entity, ..)


```python
import spacy
nlp = spacy.load("en_core_web_sm")

text = """Mary likes icecream. John gives Mary a book. They pay 50 Euro for a ticket. They visit the MoMa to watch an exhibition on Aliens. On Tuesday Washington negotiates a trade agreement with the Vatican."""
doc = nlp(text)

print([(X.text, X.label_) for X in doc.ents])

from spacy import displacy
displacy.render(doc, style="ent")
```
Use case 2: Extraction: WebIsALOD

- Huge dataset (400m) of noisy isA-edges extracted from general web crawl (CommonCrawl) via 58 Hearst-style patterns

[http://webisa.webdatacommons.org]
WebIsALOD - Noise

- Pure application of 58 patterns
  → 75% of results are considered wrong by human annotators
  → Thresholding by source and pattern frequency helps little
WebIsALOD — supervised scoring

- RandomForest trained on 400 instances
- Features:
  - Frequency of matches
  - #distinct patterns
  - #distinct domains
  - Binary feature per pattern
  - Hypernym/hyponym length, modifier existence
  - Min/max/avg token distance in source
  - ROC AUC 0.72–0.83
Data access

http://webisa.webdatacommons.org/sparql

PREFIX isa: <http://webisa.webdatacommons.org/concept/>
PREFIX isaont: <http://webisa.webdatacommons.org/ontology#>
SELECT ?hyponymLabel ?confidence
WHERE{
  GRAPH ?g {
    isa:_frankfurt_ skos:broader ?hyponym.
  }

  ?g isaont:hasConfidence ?confidence.
}
ORDER BY DESC(?confidence)
Use case 3: Joint system: Entyfi

- Existing approaches overfit to Wikipedia, or assume huge corpora

- Fiction and fantasy as archetypes of long-tail universes where Wikipedia has insufficient coverage

“After Melkor’s defeat in the First Age, Sauron became the second Dark Lord and strove to conquer Arda by creating the Rings”

Melkor: Ainur, Villain
Sauron: Maiar, Villain
Rings: Jewelry, Magic Things

First Age: Eras, Time
Dark Lord: Ainur, Title
Arda: Location

[Chu et al., WSDM 2020]
Entify - Overview

[1] Type System Construction
- Taxonomy Induction
  \[ \text{wikia} \rightarrow u_1, u_2, \ldots, u_n \]

[2] Reference Universe Ranking
- \[ \text{Input: } \{ U_1: r_1 \}, U_2: r_2, \ldots \]
- \[ \text{Output: } \{ \{ T_1, KB_1 \}, \{ T_2, KB_2 \}, \ldots \} \]

- LSTM
- Decoding
- Mention: e, Context: c_l, c_r

- [4.1] Supervised
  - e, c_l, c_r
  - [4.1.1] Fictional Typing
    - [4.1.1.1] Patterns
    - [4.1.1.2] Dependency
  - [4.1.2] Real-world Typing
- [4.2] Unsupervised
  - e, c_l, c_r
  - [4.2.1] Patterns
  - [4.2.2] Dependency
- [4.3] KB Lookup
  - e \rightarrow \{ KB_1, KB_2, \ldots \}

[5] Type Consolidation
- e: t_1, t_2, t_3, \ldots, t_n \rightarrow \text{ILP Model}
Entify – 1. Type system construction

- Scrape categories and subcategory relations from 200 diverse Wikia universes

- Clean extracted data to derive coherent taxonomies
  - Remove meta-categories
  - Remove unsuited relations
  - Forward reference: more details next lecture
Entify – 2. Type system ranking

• Demo:
  • First example LoTR+GoT
  • The Maya god of rain, one of the most important deities in the Mayan pantheon Panon. Chaac was often described as having four divine aspects or incarnations, connected to the four cardinal directions and colored green, red, white, and black respectively. In some Maya traditions there were also many demigods, also known as Chaacob, who served the great god Chaac and often appeared to humans as dwarves or giants, like Ebxywz.

• https://d5demos.mpi-inf.mpg.de/entyfi/
  • (runtime → run 1, 4, 5)
Entify — 4.1 — supervised typing

- Existing Wikipedia models: 112 or 10331 types
  - [Sonse Shimaoka, Pontus Stenetorp, Kentaro Inui, and Sebastian Riedel. Neural architectures for fine-grained entity type classification. In EACL, 2017]

- Attentive neural architectures on 16-words span around mention

- Trained via disambiguated links and categories in Wikia reference universes
Entify – 4.2/4.3 – Unsupervised+lookup

• Unsupervised typing:
  • 36 Hearst patterns
  • Dependency parses
    • King Robert was the ruler of Dragonstone Castle

• Lookups:
  • Fiction frequently creates mashups and reuses previous ideas
    • Freya not only in “Edda”, but also in “Nibelungen”
    • Lookups as practical way to obtain candidates
Entify – 5. Consolidation

• Most typing modules are noisy

• Top-level hard constraints
  • Location and living_thing exclude each other

• Soft correlations
  • Dwarves are frequently axe-wielders, rarely archers
  • Secret agents are usually middle-aged singles

• Consolidation across multiple mentions
  • Gondor decided to join the war.
  • Frodo joined the ranks of Gondor.

• ILP encodes hard constraints and rewards for respecting correlations
Lab 3

• Input: First sentence from Wikipedia
• Task: Extract/predict the Wikidata types

• Automated evaluation on unseen evaluation data
  • Precision/recall/F1
  • Macro (per row), micro (per prediction/ground truth type instance)
  • Full match or headword only (British writer/English writer)
  • How good is a method? Random baseline

• Hints:
  • Consider data distribution — max bang per buck?
  • Target labels do not always match text
References

Sunita Sarawagi: Information Extraction
Diana Maynard: Named Entity Recognition
Sven Hertling and Heiko Paulheim. WebIsALOD: Providing
Hyponymy Relations extracted from the Web as Linked Open Data,
ISWC 2017
Chu et al., ENTYFI: Entity Typing in Fictional Texts, WSDM 2020
Slides adapted from Fabian Suchanek
Take home

1. **NERC major AKBC task**
   1. Entity types a core piece of knowledge
   2. Types help in relation extraction

2. **Classification vs. extraction**
   • Rules for classification
   • Pre-trained neural architectures
   • Hearst patterns for extraction

Next week: Organizing types in taxonomies, entity coreference and disambiguation