Information Extraction

Extracting limited forms of information from text

- Named entity recognition (NER) seeks to
  - Identify where each named entity is mentioned
  - Identify its type: person, place, organization, ...
  - Unify distinct names for the same entity
    - United = United Airlines
- Foundational step for virtually any kind of advanced reasoning
  - Extracting relations as to build knowledge graphs
  - Extracting events
  - Answering questions

Suggest a few uses of NER

Named Entity Recognition

- Entities that can be named
  - For news: Person, location, organization
  - For medicine: drugs, ...
- Even entities that aren't named, e.g., dates and numbers
- The sentence:

  This Friday United is selling $100 fares to The Big Apple on their new Dreamliner

- Yields this markup:

  This [$_{\text{TIME}}$Friday] [$_{\text{ORG}}$United] is selling [$_{\text{MONEY}}$\$100] fares to [$_{\text{LOC}}$The Big Apple] on their new [$_{\text{VEH}}$Dreamliner]

- Challenges
  - Segmentation: what are the boundaries of an entity
  - Ambiguity: JFK can be a person, an airport, ...
  - Exacerbated by metonymy: Washington (city, government, sports teams)

Named Entity Types

Type	Tag	Sample Categories
People	PER	People, characters
Organization	ORG	Companies, teams
Location	LOC	Regions, mountains, seas
Geopolitical Entity	GPE	Countries, provinces
Facility	FAC	Bridges, buildings, airports
Vehicle	VEH	Planes, trains, automobiles

IOB Tagging for Named Entity Recognition

Similar to IOB for chunking

- Introduce $2n+1$ tags (given n types—earlier chunk, here NER)
  - B_k: Beginning of type k
  - I_k: Inside of type k
  - O: Outside of all types
- Example of IOB chunking for NER:

Woodson	,	Chancellor	of	NC	State	University
[B$_{\text{PER}}$]	O	[B$_{\text{PER}}$]	O	[B$_{\text{ORG}}$]	[I$_{\text{ORG}}$]	[I$_{\text{ORG}}$]
	,	is	a	professor		
	O	O	O	O		

IO Tagging for Named Entity Recognition

Simpler variant of IOB: Omit the Begin tags

- Requires only $n+1$ tags for n types
- Confuses contiguous names *of the same type* as one name
- Such contiguous names are rare in English, though

Woodson	,	Chancellor	of	NC	State	University
[I_{PER}]	O	[I_{PER}]	O	[I_{ORG}]	[I_{ORG}]	[I_{ORG}]
	,	is	a	professor		
	O	O	O	O		

Feature-Based Named Entity Recognition

- Word-based features

This word	Neighboring Words
Identity	Identity
Embedding	Embedding
POS	POS
Base-phrase label (IOB tag)	Base-phrase label (IOB tag)
Presence in a gazetteer (list of place names)	

- Character-based features, geared toward unknown words

This word	Neighboring Words
Specific prefix up to length 4	
Specific suffix up to length 4	
All upper case	
Hyphenated	
Word shape	Word shape
Short word shape	Short word shape

Word Shape and Short Word Shape

- Word shape: a pattern based on the symbols in a word
  - Map upper case letter to X
  - Map lower case letter to x
  - Digit to d
  - Retain hyphens, apostrophes, periods
  - L'Occitane ⇒ X'Xxxxxxxx (X'Xx^7)
  - DC10-30 ⇒ XXdd-dd (X^2d^2-d^2)
  - I.M.F. ⇒ X.X.X.
- Short word shape: reduce consecutive character types to one
  - L'Occitane ⇒ X'Xx
  - DC10-30 ⇒ Xd-d
  - I.M.F. ⇒ X.X.X.

Computing NER

- Sequence labeling via
  - Neural models
  - Maximum Entropy Markov Models (logistic regression plus Viterbi)
  - Both rely of inputs such as
    - Features of current, preceding, and following words
    - Labels of preceding words
- Rules: multiple passes each seeking to improve recall
  - High-precision rules for unambiguous names
  - Substrings of identified names
  - Domain-specific name lists
  - Sequence labeling (probabilistic, as above) to complete the list

Relation Extraction

Identify and classify semantic relations between entities found in the text

- General purpose
  - Child-of: taxonomy
  - Part-whole: meronomy
  - Geospatial
- Domain specific
  - Employee of (domain of human resources)
  - Additive for (domain of chemistry)

Generic Relations

Read each relation label as a path in a hierarchy

Relation	**Type Pair**	**Example**
Physical:Located	PER-GPE	IBM, head-quartered in Armonk NY,
Part:Whole:Subsidiary	ORG-ORG	XYZ, the parent of ABC,
Person:Social:Family	PER-PER	Clinton's daughter, Chelsea
Org-Affiliation:Founder	PER-ORG	Microsoft founder, Bill Gates,

Relations in Medical Language

Using National Library of Medicine (NLM)'s UMLS, the Unified Medical Language System
https://www.nlm.nih.gov/research/umls/pdf/AMIA_T12_2006_UMLS.pdf

- 135 subject categories (entity types)
- 54 relations between categories

Relation	**Type Pair**	**Example**
isa	Entity-Entity	Lab Result isa Finding Enzyme isa Biologically Active Substance
	Relationship-Relationship	prevents isa affects
treats	Pharmacologic Substance – Pathologic Function	Calcium channel blockers treat hypertension
diagnoses	Finding – Pathologic Function	Echocardiogram diagnoses stenosis

- Domain-independent: isa, part of, causes
- Domain-specific (for medicine): treats, diagnoses

Structured Information on the Web

Usable for NL
Potentially extractable from NL

- Wikipedia Infoboxes
  - Provide structure for facts suited to a given entry
  - Structured facts are relations
- Resource Description Framework (RDF), a W3C recommendation (standard)
  - Expresses statements as triples in the form of
  - Subject, Predicate, Object
- Crowdsourced ontologies such as DBpedia
- WordNet: to be discussed later
- Infoboxes in web search results: provided by a webmaster

How Can we Extract Instances of a Known Relation?

Assume a large corpus of text

- Given isa, discover
  - Aspirin is a Medication
  - Cardiologist is a Medical Practitioner

Lexico-Syntactic Patterns

Manually constructed

- (Hearst patterns) Hyponym relations are often apparent in the syntax
  - Seeing "A, such as B, ..."
  - We can conclude that B is a hyponym of A
- Coordination applies naturally by forcing type agreement
  - Seeing "A, such as B and C, ..."
  - We can conclude that B is a hyponym of A
  - We can conclude that C is a hyponym of A
- Key idea: identify lexical markers of hyponym-hypernym relations
  - Including
  - Especially: Z, especially X, ...
  - And other: X, Y, and other Zs,

Regular Expressions as Generalized Patterns

Can tackle broader relations

- per, position of org
  - Relates the instance of person as holder of the specified position in the referenced organization instance
  - [$_{\text{PER}}$George Marshall], [$_{\text{POSITION}}$Secretary of State] of the [$_{\text{ORG}}$United States]
- per (named| appointed| . . .) per (Prep?) position
  - [$_{\text{PER}}$Truman] appointed [$_{\text{PER}}$Marshall] [$_{\text{POSITION}}$Secretary of State]
- (Xibin Gao) "In case of xxx, the contract is null and . . ."
  - Not about named entities
  - Helps identify exceptions highlighted in a contract—such exceptions are common within a business domain

Features for Supervised Relation Extraction

- Identify *mentions* M_1 and M_2
- Important features as word embeddings
  - Headwords of M_1 and M_2
  - Concatenation of headwords of M_1 and M_2
  - Adjacent words to M_1 and M_2
  - N-grams between M_1 and M_2
- NER features
  - Types of M_1 and M_2 and their concatenation
  - Entity (constituent) level from Name, Nominal, Pronoun
  - Number of intervening entities between M_1 and M_2
- Syntactic structure, expressed via *syntactic paths* from M_1 and M_2 of
  - Base chunks: NP, NP, PP, VP, NP, NP
  - Constituents: NP $\uparrow$ NP $\uparrow$ S $\uparrow$ S $\downarrow$ NP
  - Dependencies: Airlines $\leftarrow_{\text{subj}}$ matched $\leftarrow_{\text{comp}}$ said $\rightarrow_{\text{subj}}$ Wagner

Bootstrapping

- Given instances of a relation as M_1–R–M_2 (Aspirin–treats-headache)
  - Identify occurrences of M_1 and M_2 in the corpus
  - Identify patterns that fit those occurrences
  - Apply resulting patterns to identify additional instances
- Semantic drift: Risk of bootstrapping
  - Errors in the initial pattern (e.g., confusing ferry hub for airport hub) propagate
- Pattern confidence, as measure of quality, possibly normalized to [0,1]
- Estimated based on a given set T of relation tuples (instance)

$$\mathrm{conf}(p) = \frac{\mathrm{hits}_p}{\mathrm{finds}_p} \log(\mathrm{finds})_p$$

- Confidence of a tuple t based on at least one pattern that finds t

$$\mathrm{confidence}(t) = 1 - \prod_{p \text{ is a pattern for } t} (1 - \mathrm{conf}(p))$$

- Confidence threshold for acceptance

Extracting Temporal Expressions

- Main varieties
  - Absolute
  - Relative
  - Durational
  - How can we classify holidays, e.g., Memorial Day, Easter, Diwali?
- Often associated with lexical triggers
  - Nouns: Dusk, dawn,
  - Proper Nouns: January, Monday, Ides of March, Rosh Hashana, Ramadan
  - Adjectives: Recent, annual, former
  - Adverbs: hourly, usually
- False hits: temporal expressions used atemporally
  - 1984 (the book or movie)
  - Sunday Bloody Sunday (song by the Irish group U2)

Temporal Ambiguity

- Where to anchor an expression?
  - Reichenbach's theory, later
- Which polarity to adopt given an anchor (before or after)?
  - Next
  - This

Event Extraction

How events link to various entities

- Event coreference
  - Which mentions of an event refer to the same event
- Temporal expressions
  - Days, dates, times
  - Relative expressions, such as “next month”
- Normalization with respect to
  - Calendar
  - Discourse, e.g., time of utterance or reference

Event Extraction

Identify events or states from text

- Classically, events are occurrences, not states, which are indicated by verbs such as
  - Be, is, are
  - Know, feel, believe
- In the extraction literature, events include states
  - Verbs: increased
  - Nouns: the increase
  - Gerunds: increasing
- Nonevents
  - Verbs indicating transition into an event: took effect
  - Weak or light verbs (make, take, have) that rely on a direct object to bring out an event

Event Details

- Tense: past, future, present
- Aspect: more complex
  - Progressive: leaving
  - Perfective: left
  - Perfect: has left
- Famous example:

  Einstein has left Princeton
  vs.
  Einstein left Princeton
- Subtypes of events
  - States
  - Actions
  - Reporting events (geared toward news)
  - Perception events

Temporal Relations and Ordering

James Allen's thirteen relations between two temporal intervals

Each relation has an inverse

- Before and after
- Overlaps
- Meets
- Equals
- Starts
- Finishes
- During

Draw these relations out

Template Filling

How to flesh out set patterns or stereotypical situations

- For an application on business intelligence in the airline industry, we might have an event such as

Fare-raising	Leader airline	United Airlines
	Amount	$66
	Effective date	2018-10-07
	Follower	American Airlines

- As a template, the attributes below are fixed but the values are found in the text

Event type	Attribute 1	Value 1
	Attribute 2	Value 2
	Attribute 3	Value 3
	Attribute 4	Value 4

Suggest a short example for the personal fitness industry

Prototypical Event Structures

Schank ∼1960s: Scripts and Stories

- Postulated as central representation in cognition
- Relate to Lakoff's conceptual schemas, which additionally signify how events are *framed*
- Scripts highlight a typical structure
  - For having dinner at a restaurant
  - For attending a cocktail party
  - For experiences as a college student
- Facts retrieved from a narrative flesh out a relevant script
  - Provides slots to be filled
  - The slots are interrelated: filler of one constrains another
- A script helps fill in the gaps
  - Between entering a restaurant and receiving food would be the ordering event
  - A waiter would be a normal character in a restaurant script

Machine Learning for Template Filling

1 Component: Template Recognizer, a text classifier
   - Whether a template occurs in a sentence
   - Learns a template from instances of sentences that fill any slot in the template
   - Collective across all slots in a template

2 Component: Slot Filler (Role Filler), a text classifier
   - One for each slot, e.g., Lead Airline, in a template
   - Needs coreference resolution to reconcile alternatives for the same concept