

Information Extraction: Beyond Named Entities

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Outline

- What is Information Extraction?
- ACE Entities, Relations and Events
- Timex and TimeML



What is Information Extraction?

- The automatic extraction of (structured) information
 - Extract lists and tables from text
- Input: possibly limited set of documents
- Output: usually a task-defined template to fill in
- Definitions:
 - Typically idiosyncratically defined for task
 - Can include technology (SRL, etc.) that helps IE
- Comparison with Question Answering
 - QA more opened ended – depends on questions
 - QA: paragraph output vs. IE structured output
 - Some IE techniques, e.g., if answer = short phrase
 - Some IR techniques, e.g., if answer = paragraph
 - Rest of lecture sticks with IE (not related QA problems)



Some Sample IE Tasks

- Extract instances of organizations mentioned in a set of documents
- Extract instances of people starting jobs and ending jobs
 - Identify: person, start or stop time, company
- Extract instances of Entity1 attacking Entity2, where entities include people, GPEs (locs), facilities or vehicles
 - Identify: aggressor, victim, weapon, time
- Extract instances of disease outbreak
 - Identify: victims, disease, start time, time span, location
- Extract advertisements for cameras
 - Identify: seller, brand, model, price, date
- Identify family, social and business relations between individuals



Some ACE History

- Entities: English, Chinese, Arabic, Spanish
- Relations: English, Chinese, Arabic
- Events: English, Chinese, Arabic
- Documentation for various versions of tasks:
 - <https://www ldc.upenn.edu/collaborations/past-projects/ace/annotation-tasks-and-specifications>
- Different years (from 2000 to 2008)
 - Different tasks and subtasks
 - Different versions of specifications
 - We discuss latest available versions of English tasks



Named Entity Review

- Tend to be phrases consisting of proper nouns
 - Capitalization, uniquely identify entity in real world, ...
 - Ex: *The Association for Computational Linguistics*
- Internal structure may differ from common NPs
 - Ex: *Adam L. Meyers, Ph.D.*
- Only certain types are marked
 - Task-specific
 - ACE task: GPE, Person, Organization, Location, Facility
 - In some versions: Vehicle and Weapon



ACE Entities

- An Entity = a list of coreferential NPs
 - Each of these NPs is a “mention” of the entity
 - Finding coreference will be part of a different lecture
- Types of mentions: names, common nouns, pronouns
- Names: what we have been calling named entities
- Nominal mentions: phrases headed by common nouns
 - same semantic classes: GPE, ORGANIZATION, ...
 - EX: *that country, the government, the agency, the whimsical pediatrician, the terrorist wearing a hat*
- Pronominal mentions: pronouns
 - Must refer to markable semantic class (e.g., by coreference)
 - *He, she, it, they, themselves, their, her, everyone, ...*



Detecting ACE Entity Mentions

- Detecting ACE name mentions
 - Sequence labeling, typically with BIO tags (Nymbol, HW5, etc.)
- Detecting ACE common noun mentions:
 - Find common nouns from training corpus
 - Generalize
 - Stemming
 - WordNet, clustering, or a list of words
 - statistical methods for semantically similarity
 - Identify non-generic cases
 - **Gardeners are lousy plumbers.** [Generic]
 - **The gardener was a lousy plumber.** [Non-Generic]
 - Baseline: definite determiners plus past tense → non-generic
- Pronoun Mention – dependent on coreference techniques
- Coreference Component – more detail next lecture



ACE Relations and Events

- Predicate + Arguments
- Predicates \approx triggers
 - Event mention triggers: words
 - Specs discuss choice of nouns/verbs: *launch an attack*
 - Relation mention triggers: grammatical constructions
 - ACE specs refer to these constructions as relation classes
 - ML must learn which words trigger which relations
- Arguments of Event and Relation Mentions
 - Usually, NPs belonging to ACE Entity classes:
 - Named Entities, common noun phrases, pronouns
 - Values – times, extents, crimes, ...
 - <https://www.ldc.upenn.edu/sites/www.ldc.upenn.edu/files/english-values-guidelines-v1.2.4.pdf>
 - Relations always take exactly 2 arguments
 - Event arguments vary in number (and a given argument may be absent)



ACE Relations

- <https://www ldc.upenn.edu/sites/www ldc.upenn.edu/files/english-relations-guidelines-v6.2.pdf>
- Relation Entity: set of coreferential relation mentions
 - Same arguments
 - Refer to same predication
- Relation types
 - Physical: Location and Near
 - Part-Whole: Geographical and Subsidiary
 - Per-Social: Business, Family, Lasting-Personal
 - Org-Affiliation: Employee, Owner, Member, ...
 - Agent-Artifact: User-Owner-Inventor-Manufacturer
 - Gen-Affiliation: Citizen-Resident-Religion-Ethnicity, Org-Location-Origin
- Relation Classes: Syntactic environments (sentence internal only)
 - Verbal, Possessive, PreMod, Coordination, Preposition, Formulaic, Participial, Other



ACE Relation Examples

- ***George Bush traveled to France on Thursday for a summit.***
 - Physical.located(***George Bush, France***)
 - Class = Verbal, Modality = Asserted, Tense = Past
- ***Microsoft's chief scientist***
 - Org-Aff.employment(***Microsoft's chief scientist, Microsoft***)
 - Class = Possessive, Modality = Asserted, Tense = Unspecified
- ***New York police***
 - Part-Whole.Subsidiary(***New York police, New York***)
 - Class = PreMod, Modality = Asserted, Tense = Unspecified
- ***Dick Cheney and a hunting partner***
 - Per-Social.Lasting(***Dick Cheney, a hunting partner***)
 - Class = Coordination, Modality = Asserted, Tense = Present
- ***A linguist from New York***
 - Gen-Aff.CRRE(***A linguist from New York, New York***)
 - Class = Preposition, Modality = Asserted, Tense = Unspecified
 - ***CRRE = Citizen, Resident, Religion, Ethnicity***



ACE Relation Detection

- Most Systems use ML and a variety of features
- 2 Possible Testing environments
 - Entity detection system first and use results
 - Hand-annotated (“true”) entity mentions
- Example System: Zhou, et al. 2005 (using “true” entity mentions)
 - <http://www.aclweb.org/anthology/P05-1053>
 - Support Vector Machines – ML algorithm, details omitted
 - Features similar to those used for semantic role labeling:
 - words in arguments, entity types, nearby words, chunking features, parsing features, dependency features, name features from gazetteers, WordNet features ...
 - Observation: Parsing (and dependency) features helped very little
 - Probably because most relations are between nearby words
 - Results: Precision = **63.1**, Recall = **49.3**, F-score = **55.5**
 - F-scores vary by type from **36.4** (Physical.near) to **72.6** (Gen-Aff.CRRE)



ACE Events

- Event Entity: set of coreferential event mentions
 - Nonconflicting arguments
 - A mention may include a subset of the arguments
 - Refer to same predication (event, state, etc.)
- Event types
 - Life: be-born, marry, divorce, injure, die
 - Movement: transport
 - Transaction: transfer-ownership, transfer-money
 - Business: start-org, end-org, merge-org, declare-bankruptcy
 - Conflict: attack, demonstrate
 - Contact: meet, phone-write
 - Personnel: start-position, end-position, nominate, elect
 - Justice: arrest-jail, release-parole, sue, appeal, pardon, ...



ACE Event Example

- *On Thursday, Pippi sailed the ship from Sweden to the South Seas*
 - EVENT-TYPE = Movement
 - ANCHOR = sailed
 - ARTIFACT-ARG = Pippi
 - VEHICLE-ARG = the ship
 - ORIGIN-ARG = Sweden
 - DESTINATION-ARG = the South Seas
 - TIME-ARG = Thursday
- Similar to Semantic Role Labeling, but limited to several Frames
 - Like FrameNet
 - fewer frames
 - annotation-based instead of lexicon based
 - Targeted towards specific tasks (unlike PropBank/NomBank)



ACE Event Detection

- Very few published system descriptions
 - Official ACE scores are hard to understand
 - Much more complex than F-score
 - Includes (subjective) weights based on utility value (e.g., names are weighted higher than common nouns because they carry more info)
 - Task is complex including entity detection, coreference, event coreference, etc.
 - Only for ACE years 2004 (English) and 2005 (English and Chinese)
 - Scores tended to be low
- Best performing systems use parsing features, e.g.,
 - Parsing or Dependency Paths:
 - ***NP ↑S ↓VP ↓VBD***
 - **ARG(word), ARG1 (word), ARGO(ARG1(word))**
- Task often broken down into subtasks
 - Identify event anchor, identify arguments, coreference, ...



Example System: Ahn 2006

- <http://anthology.aclweb.org/W/W06/W06-0901.pdf>
- Maximum Entropy Based System
- Detecting and Classifying Event Anchors:
 - Features: word, regularized (upper/lower, lemma, POS, depth in parse tree, WordNet features, left/right context (case, POS), dependency relations (info about words/relations above and below anchor, path features, etc.)
 - Precision = .735, Recall = .513, F-score = .601
- Argument Identification
 - Features: anchor word (with/without regularization), Event type, argument (determiner, head, POS, class, depth in parse tree, mention type, same info about sibling arguments, dependency path from anchor to argument
 - Precision = .689, Recall = .490, F-score = .573
- Other subtasks: time, +/-generic, modality, polarity



NYU 2016 system for KBP Event Nugget: A Deep Learning Approach

- <https://tac.nist.gov/publications/2016/participant.papers/TAC2016.NYU.proceedings.pdf>
- Nguyen, et. al. 2016
- Represents each word w as a 2-D matrix of surrounding words: $w_n, w_{n-1}, \dots, w_{-1}, w, w_1, \dots, w_n$
- Vector of each word in the window concatenates
 - word embedding (pre-trained) – represents meaning
 - dependency embedding – like word embedding, but trained on dependency graph
 - position embedding – represents number of words from w



NYU 2016 IE system – Slide 2

- Uses Neural Network Classifiers for tasks
 - Identifying Event Anchors and their arguments
 - Coreference between events
 - Realis (whether or not an event happened, didn't happen or might have happened)
 - Used some GLARF features (Next Lecture)
- Scores (essentially f-measure):
 - 27.07% on Coreference task
 - 35.24% on Realis task
- State of the Art Results (beat previous results)



Time

- Timex
 - Identifying Absolute Time Expressions
 - Regularization
 - Relative Time Expressions
 - Regularization
 - Relation to document time
- TimeML – temporal relations between 2 args
 - Event and Time [Event \approx ACE Event Mention]
 - Event is before/after/at/during/.... Time
 - Event1 and Event2
 - Time(Event1) is before/after/at/during/.... Time(Event2)



TIMEX (TIMEX2, TIMEX3, ...)

- Identifies several types of time expressions in text
 - Absolute Time (January 3, 2011 at 5:00 AM)
 - Relative Time (last Thursday)
 - Duration (5 days)
- 2 Types of Markup (XML)
 - Inline:
 - `<TIMEX3 tid="t18" type="DATE" temporalFunction="true" functionInDocument="NONE" value="1990-01-02" anchorTimeID="t17">Jan. 2</TIMEX3>`
 - Offset: `<TIMEX3.... start="2015" end="2021"/>`
 - Other than start and end, all the same features



value in ISO 8861 Standard TIMEX3

- Fills the XML *value* slot
- Time values: month, day, year, hour, second, quarter, half, week, ...
- Examples:
 - *December 14, 2011 at 10:49:01AM* → *2011-12-14-T10:49:01*
 - *3:49PM* → *T15:49*
 - *December 14* → *XXXX-12-14*
 - *A Sunday in November* → *XXXX-11-SU*
 - *2011, 3rd Quarter* → *2011-Q3*
- Values of relative times are calculated
 - *Last Thursday* → *2011-12-08* if the publishing date is 12/14/2011
- Values of absolute times are looked up and filled in
 - *December 14* → *2011-12-14* (from context, e.g., past tense, before 12/14/2012, ...)
- Duration values: numbers and units
 - *5 months* → *P5M*
 - *5 minutes* → *P5TM*



Timex Systems

- Identifying Time Expressions
 - Manual rules, HMM, etc.
- Encoding values already in the text
 - Manual rules: very small number of terms with clear values – simple regular expressions or patterns with look up table
- Calculating values relative to
 - Document Time: publication date (news articles)
 - Other times found in the text [not always implemented]
- Examples for article published Wed, Dec 14, 2011
 - *Yesterday* → **2011-12-13**
 - *Last Thursday* → **2011-12-08**
 - *November 3* → **2011-11-03**
 - may be 2012 depending on month and modifiers (next, last, ...)



Sample Times Rules from NYU Proteus

- Look at Ralph's JET file: `time_rules.yaml`



TimeML Relations

- There are several different TimeML Relations
 - **Tlink:** [We will focus on this one]
 - Link between time and event
 - Link between time(event1) and time(event2)
 - Overlaps with Penn Discourse Treebank Relations (PDTB)
 - PDTB
 - » PDTB also covers non-temporal relations
 - » But only links sentences (verbs), not temporal phrases (NPs)
 - **Slink:**
 - Link between event and event (subordination)
 - **Alink**
 - Link between aspectual marker (start, end, etc.) and event



Arguments of TLink Relations

- Event (different than in ACE):
 - Word anchoring something that has a time
 - All verbs (event those that represent states)
 - PDTB uses sentences (phrase vs. dependency representation)
 - For TimeML, coordinated verbs counted separately
 - Some nouns (though not consistently marked)
 - Not in PDTB
- Time:
 - Temporal Expression
 - Document Time
 - Time(Event) – only one used in comparable PDTB relations



Tlink Features

- Signal: word or phrase that anchors relation
 - Same as predicate for Penn Discourse Treebank
 - Optional
- RelType: Classification of temporal relation
 - BEFORE, AFTER – before or after
 - INCLUDES, IS_INCLUDED – time spans event
 - DURING – duration
 - SIMULTANEOUS – at same time
 - IBEFORE, IAFTER – Immediately Before/After
 - IDENTITY – same event
 - BEGINS, ENDS, BEGUN_BY, ENDED_BY – marks boundary



Simple Cases: Signals and Modification

- Relation **from** Event Instance (red) **to** Time/Event (white)
 - PDTB: ARG1 = **from**, ARG2 = **to** due to **Signal** (blue)
- Prepositions and subordinate conjunction signals
 - *They **left** the room **after** 5 o'clock.* (AFTER)
 - *They **left** the room **while** the mayor was **announcing** the new law.* (During)
- Discourse adverb signal
 - *The mayor **announced** the law. **Simultaneously**, they **sang** the song.* (Simultaneous)
- Modification
 - *The mayor **announced** it **Last Thursday**.* (IS_INCLUDED)



Sequences of Simple Tenses

- Two instances of simple past tense
 - *John **had** a headache. He **took** two aspirin.* (BEFORE)
 - *The lamp **fell**. It **shattered** into a million pieces.* (IBEFORE)
 - *They **ate** steak. They **drank** wine.* (SIMULTANEOUS)
 - *He **slept** for hours. He **dreamed** about monsters.* (INCLUDES)
- Two instances of simple present tense
 - *I **have** a big problem. I **have** a headache.* (IDENTITY)
 - *The fish **swims**. The bird **flies**.* (SIMULTANEOUS)
- Different Tenses
 - *Mary's head **hurts**. She **left** school early.* (AFTER)
 - *Mary **left** school early. Her head **hurts**.* (BEFORE)



+/-Progressive and +/-Perfective

- Progressive: – *be* + *-ing* (continuous action)
- Perfective: *have* + *-en* (past relative to a reference point)
- Examples:
 - *I **see** a ghost. I am **leaving**.* (IBEFORE)
 - *They are **laughing**. They **see** the ghost.* (SIMULTANEOUS)
 - *He was **leaving**. He **saw** a ghost.* (IAFTER)
 - *They **saw** a ghost. They were **leaving**.* (SIMULTANEOUS)
 - *I am **leaving**. They have **won** the game.* (AFTER)
 - *They have **won** the game. I am **leaving**.* (BEFORE)
 - *She **left**. She had **eaten** a sandwich.* (AFTER)
 - *She had **eaten** a sandwich. She **left**.* (BEFORE)
 - *She **left**. She had been **eating** a sandwich.* (AFTER)
 - *She had been **eating** a sandwich. She **left**.* (BEFORE)



Vendler's Aspectual Verb Classes

- States: *be, know, love, have, own, ..*
- Process: *run, eat, fly, ...*
 - Process describes all subevents
- Accomplishment: *draw a circle, run a race, ...*
 - Time period measures entire event duration
- Achievement: *won, die, ...*
 - Time measures end point
- Interaction: aspect classes and aspect
 - Progressive: state → process, process → state, ...
- Vendler, Zeno “Verbs and Times”
 - Originally published in 1957 in *The Philosophical Review*, but easier to find in Vendler (1967) *Linguistics in Philosophy*
 - <http://www.jstor.org/stable/pdf/2182371.pdf>



Factors in the Ordering of Events

- Signals
- Sequence of Tenses
- Sequences of Aspect
- Sequences of Aspectual Verb Classes
 - Sense disambiguation-like problem
- Real world knowledge
 - e.g., breaking tends to occur after falling



Manual Rules

- Lexical signals
 - Most common signals (subord conj/preps) easy
 - Others (adverbs) may require a lexicon (manually or automatically created)
- Tense and Aspect Sequences
 - There is some descriptive work
 - General rules may only describe typical cases
 - (Past | Perfective) + Present → Before
 - Present + (Past | Perfective) → After
 - Past + Past-Participle → After [reliable rule]
 - *Mary left. She had eaten her dinner.*
 - Past + Past → Before [not reliable]
 - *Mary left. She ate dinner.*
 - Exception: *The dish broke. It fell.*



Machine Learning

- TimeBank – Annotation for Supervised Methods
- Patterns to Acquire
 - Rare signals → Relation Type
 - Lexical information
 - Ex: whence → SIMULTANEOUS, ...
 - Predicate/Predicate Pairs → Relation Type
 - Modeling real world knowledge
 - Ex: fall/break → BEFORE, ...
 - Tense/Aspect Pair Probabilities
 - Past/Past → BEFORE relation with 72% probability



TimeML Systems

- 2010 Shared task: <http://www.timeml.org/tempeval2/>
 - Best System Performance for English:
 - Task A (recognition/regularization of timex3)
 - Recall/Precision/F-score – all about 85%
 - Task B (identifying events)
 - Best Recall: 81%, Precision: 86%, F-score: 83%
 - Best F-scores for Relation Tasks
 - Task C (relation betw timex and event in 1 sentence): 63%
 - Task D (relation betw event and document time): 82%
 - Task E (relation betw main events in adjacent sentences): 56%
 - Task F (relation betw superordinate/subordinate events): 60%
- Other TimeML Tasks:
 - 2013 Task: <https://www.cs.york.ac.uk/semeval-2013/task1/>
 - 2017 Clinical Docs: <http://alt.qcri.org/semeval2017/task12/>



Other High Level IE-like Tasks

- Detect Attribution
 - Whose view does a given sentence represent
 - John said that Mary said [Author:John:Mary]
- Factivity
 - Is the statement reported to be true/false/other
 - Implemented in several ways in connection with ACE and other IE tasks
 - According to whom



Other Types of Entities to Extract

- Terminology
 - Terms that are specific to particular genres
 - genes, chemicals, species, formulas, ..
- Numeric terms
 - Numbers, Money, Percent
- Commercial
 - Product Names, Brand Names, ...
 - ID numbers, ...



Summary

- Information Extraction:
 - The automatic extraction of information from text to produce structured output that, e.g., can be put into a database
- Named Entities: classified instances of names
- ACE Relations and Events: predications with entities and other nouns as arguments
- Timex: An NE-like classification for temporal expressions, with missing information filled in.
- TLink: Temporal relation (before, after, etc.) between 2 events



Events and Relations Readings

- J & M Chapters 22.2 to 22.4 (required)
- ACE Relation Guidelines (optional):
 - <https://www ldc.upenn.edu/sites/www ldc.upenn.edu/files/english-relations-guidelines-v6.2.pdf>
- ACE Event Guidelines (optional):
 - <https://www ldc.upenn.edu/sites/www ldc.upenn.edu/files/english-events-guidelines-v5.4.3.pdf>
 - <https://www ldc.upenn.edu/sites/www ldc.upenn.edu/files/english-values-guidelines-v1.2.4.pdf>
- ACE Relation and Event System papers (read 1 paper)
 - <http://www.aclweb.org/anthology/P/P05/P05-1053.pdf>
 - <http://nlp.cs.nyu.edu/publication/papers/ACE05-NYUEnglishSysDescrDec10.pdf>
 - <http://www.aclweb.org/anthology-new/W/W06/W06-0901.pdf>



Time Annotation and Documentation

- TimeBank corpus (optional)
 - <http://timeml.org/site/timebank/timebank.html>
 - TimeBank1.1 Corpus – I may be able to make this available if needed
- A good resource (optional)
 - Mani, Pustojovsky and Gaizauskas (2005).
Language of Time: A Reader.
Oxford University Press.
 - Includes reprint
 - Vendler (1967) “Verbs and Times”
- Trips/Trio – An Example TimeML system (read):
 - <http://www.aclweb.org/anthology/S10-1062>

