School of CIT –
Social Computing
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# Natural Language Processing
# IN2361

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# Chapter 17
# Information Extraction

- content is based on [1]
- certain elements (e.g. equations or tables) were taken over or taken over in a modified form from [1]
- citations of [1] or from [1] are omitted for legibility
- errors are fully in the responsibility of Georg Groh
- BIG thanks to Dan and James for a great book!

# Named Entity Recognition → see previous chapter

- Named Entity: Anything referred to by a proper name, often extended to temporal or numerical expressions

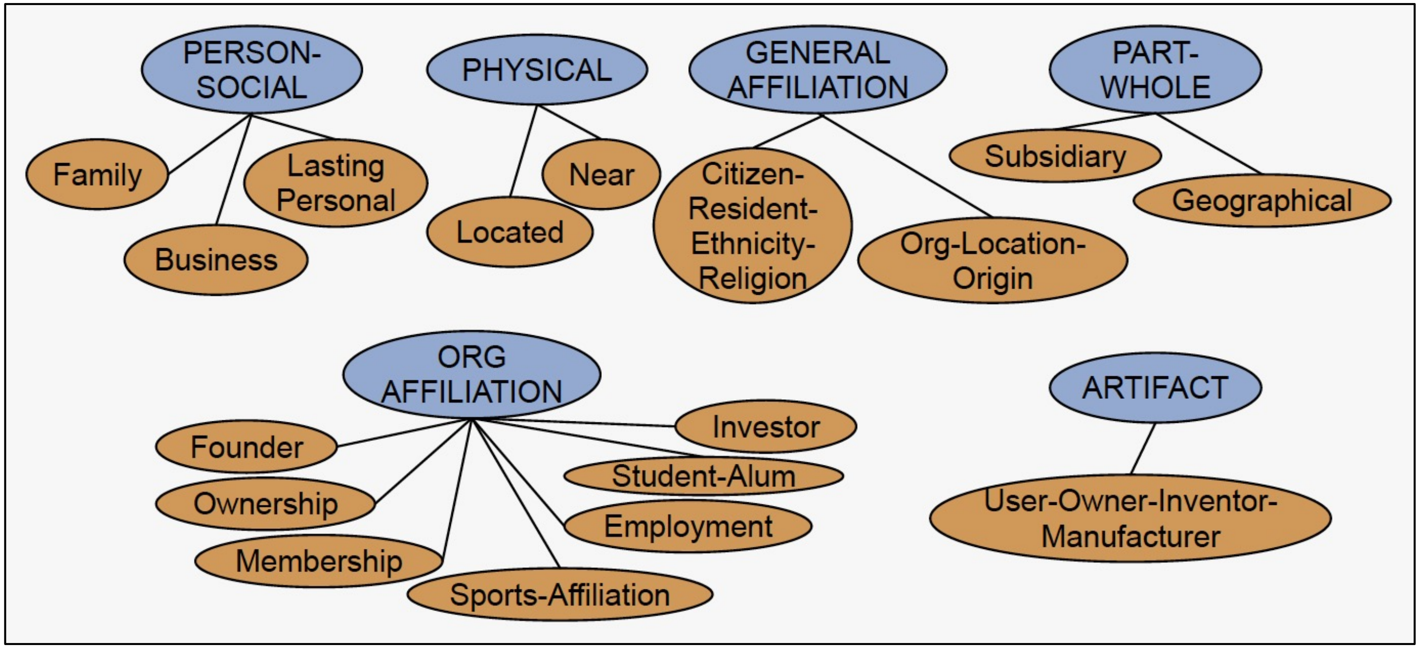
> Citing high fuel prices, [ORG **United Airlines**] said [TIME **Friday**] it has increased fares by [MONEY **$6**] per round trip on flights to some cities also served by lower-cost carriers. [ORG **American Airlines**], a unit of [ORG **AMR Corp.**], immediately matched the move, spokesman [PER **Tim 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**].

- Entity Types:

| Type | Tag | Sample Categories | Example sentences |
|---|---|---|---|
| People | PER | people, characters | **Turing** is a giant of computer science. |
| Organization | ORG | companies, sports teams | The **IPCC** warned about the cyclone. |
| Location | LOC | regions, mountains, seas | The **Mt. Sanitas** loop is in **Sunshine Canyon**. |
| Geo-Political Entity | GPE | countries, states, provinces | **Palo Alto** is raising the fees for parking. |
| Facility | FAC | bridges, buildings, airports | Consider the **Tappan Zee Bridge**. |
| Vehicles | VEH | planes, trains, automobiles | It was a classic **Ford Falcon**. |
| … | | | |

# Relation Extraction

- 17 relations from ACE relation extraction task




| Relations | Types | Examples |
|---|---|---|
| Physical-Located | PER-GPE | **He** was in **Tennessee** |
| Part-Whole-Subsidiary | ORG-ORG | **XYZ**, the parent company of **ABC** |
| Person-Social-Family | PER-PER | **Yoko**'s husband **John** |
| Org-AFF-Founder | PER-ORG | **Steve Jobs**, co-founder of **Apple**... |

# Relation Extraction

model-based view of example text in terms of unary (←→ NER) and binary relations

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**].

| | |
|---|---|
| **Domain** | $\mathscr{D} = \{a,b,c,d,e,f,g,h,i\}$ |
| United, UAL, American Airlines, AMR | $a,b,c,d$ |
| Tim Wagner | $e$ |
| Chicago, Dallas, Denver, and San Francisco | $f,g,h,i$ |
| **Classes** | |
| United, UAL, American, and AMR are organizations | $Org = \{a,b,c,d\}$ |
| Tim Wagner is a person | $Pers = \{e\}$ |
| Chicago, Dallas, Denver, and San Francisco are places | $Loc = \{f,g,h,i\}$ |
| **Relations** | |
| United is a unit of UAL | $PartOf = \{\langle a,b\rangle, \langle c,d\rangle\}$ |
| American is a unit of AMR | |
| Tim Wagner works for American Airlines | $OrgAff = \{\langle c,e\rangle\}$ |
| United serves Chicago, Dallas, Denver, and San Francisco | $Serves = \{\langle a,f\rangle, \langle a,g\rangle, \langle a,h\rangle, \langle a,i\rangle\}$ |

# Relational / Ontological Databases

- the Semantic Web (with ontology standards OWL, RDF(S), SPARQL etc.)
  - RDF: subject-predicate-object triples:

| **subject** | **predicate** | **object** |
|---|---|---|
| Golden Gate Park | location | San Francisco |

  - DBPedia: (extensional) ontology derived from Wikipedia with > 3 billion RDF triples

- Wikipedia: semi-structured source for relations:
  example info-boxes: article about *Stanford University* →
  *state* = *"California"* , *president* = "Mark Tessier-Lavigne".

- Freebase: relations like:

people/person/nationality
location/location/contains
people/person/place-of-birth
biology/organism_classification

# Relational / Ontological Databases

- WordNet:
  - hyponym hypernym relation:
    Giraffe is-a ruminant is-a ungulate is-a mammal is-a vertebrate is-a animal …
  - instance-of relation:
    San Francisco instance-of city .

- domain specific ontologies: example: Unified Medical Language System (UMLS): 134 broad subject categories, entity types, and 54 relations between the entities

| 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 |

*Doppler echocardiography can be used to diagnose left anterior descending artery stenosis in patients with type 2 diabetes*

→ UMLS relation: *Echocardiography, Doppler* Diagnoses Acquired stenosis

# Relational / Ontological Databases

- TACRED (2017): 41 general relation types, hand-labeled

| Example | Entity Types & Label |
|---|---|
| Carey will succeed Cathleen P. Black, who held the position for 15 years and will take on a new role as chairwoman of Hearst Magazines, the company said. | PERSON/TITLE<br>Relation: *per:title* |
| Irene Morgan Kirkaldy, who was born and reared in Baltimore, lived on Long Island and ran a child-care center in Queens with her second husband, Stanley Kirkaldy. | PERSON/CITY<br>Relation: *per:city_of_birth* |
| Baldwin declined further comment, and said JetBlue chief executive Dave Barger was unavailable. | Types: PERSON/TITLE<br>Relation: *no_relation* |

# Relation Extraction Using Patterns

- *Agar is a substance prepared from a mixture of red algae, such as Gelidium, for laboratory or industrial use.*
  → without detailed knowledge we can infer: hyponym(Gelidium, red-algae)

- → lexico-syntactic patterns (Hearst patterns) e.g.

  if: $NP_0 \text{ such as } NP_1\{,NP_2\ldots,(and|or)NP_i\}, i \geq 1$

  then: $\forall NP_i, i \geq 1, \text{hyponym}(NP_i, NP_0)$

| | |
|---|---|
| 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 |

- patterns using NE types:

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

# Relation Extraction Using Patterns

- *Agar is a substance prepared from a mixture of red algae, such as Gelidium, for laboratory or industrial use.*
  → without detailed knowledge we can infer: hyponym(Gelidium, red-algae)

- → lexico-syntactic patterns e.g.

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high precision, low recall

- patterns using NE types:

PER, POSITION of ORG:
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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

# Relation Extraction Using Supervised ML

- 3 sub-classifiers necessary:

  (unfortunately: hand labelling is very costly here, and resulting classifiers are brittle (do not generalize well across domains)

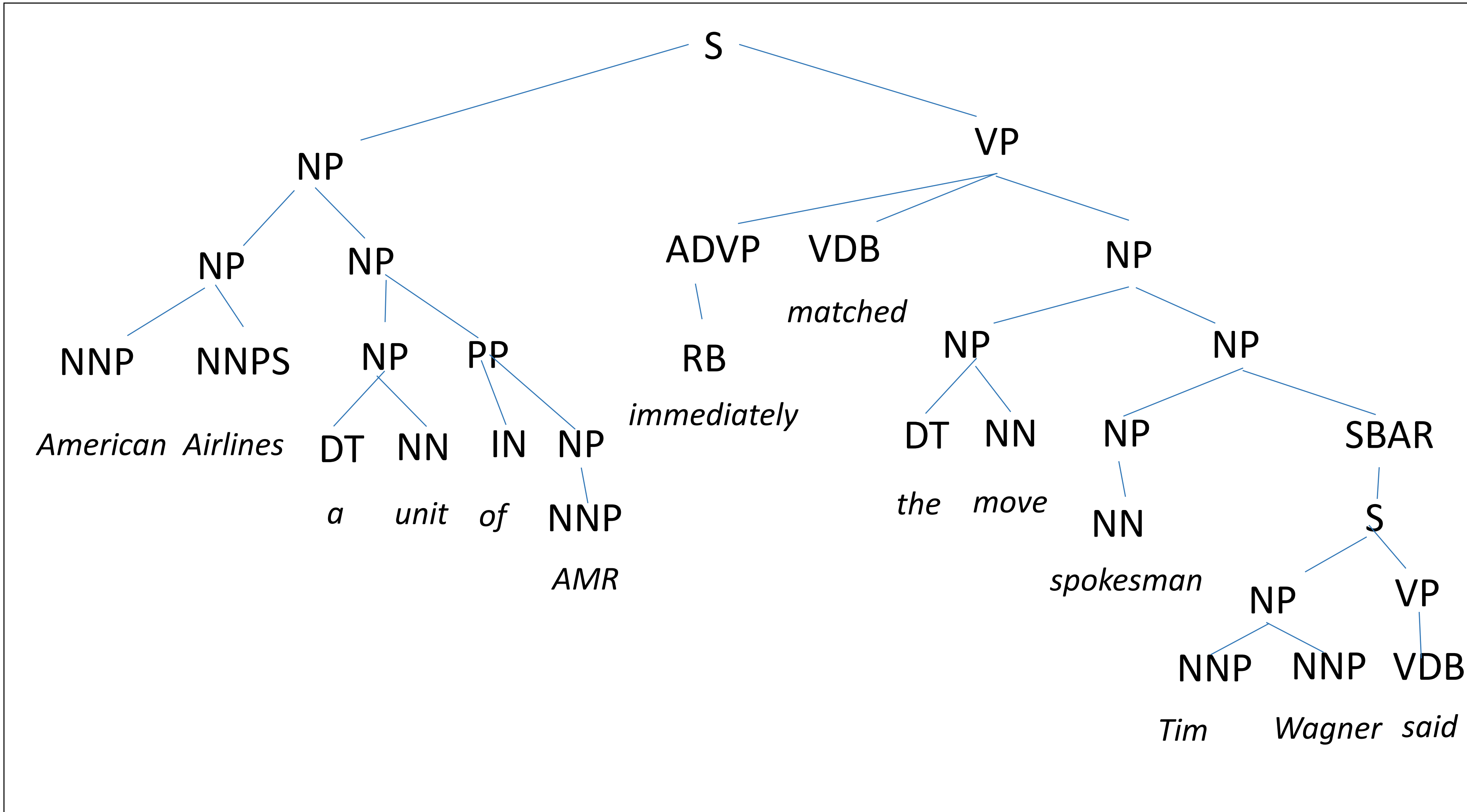
```
function FINDRELATIONS(words) returns relations

    relations ← nil
    entities ← FINDENTITIES(words)
    forall entity pairs ⟨e1, e2⟩ in entities do
        if RELATED?(e1, e2)
            relations ← relations+CLASSIFYRELATION(e1, e2)
```

- possible features:

  *American Airlines* [mention M1]*, a unit of AMR, immediately matched the move, spokesman Tim Wagner* [mention M2] *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** = (chunk sequence) | $NP \rightarrow NP \rightarrow PP \rightarrow NP \rightarrow VP \rightarrow NP \rightarrow NP$ |
| **Typed-dependency path** | $Airlines \leftarrow_{subj} matched \leftarrow_{comp} said \rightarrow_{subj} Wagner$ |

# Relation Extraction Using Supervised ML




| | |
|---|---|
| **Concatenated types** | ORG-PERS |
| **Constituent path** | $NP \uparrow NP \uparrow S \uparrow S \downarrow NP$ |
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| **Typed-dependency path** | $Airlines \leftarrow_{subj}$ $matched \leftarrow_{comp}$ $said \rightarrow_{subj}$ $Wagner$ |

# Neural Relation Extraction

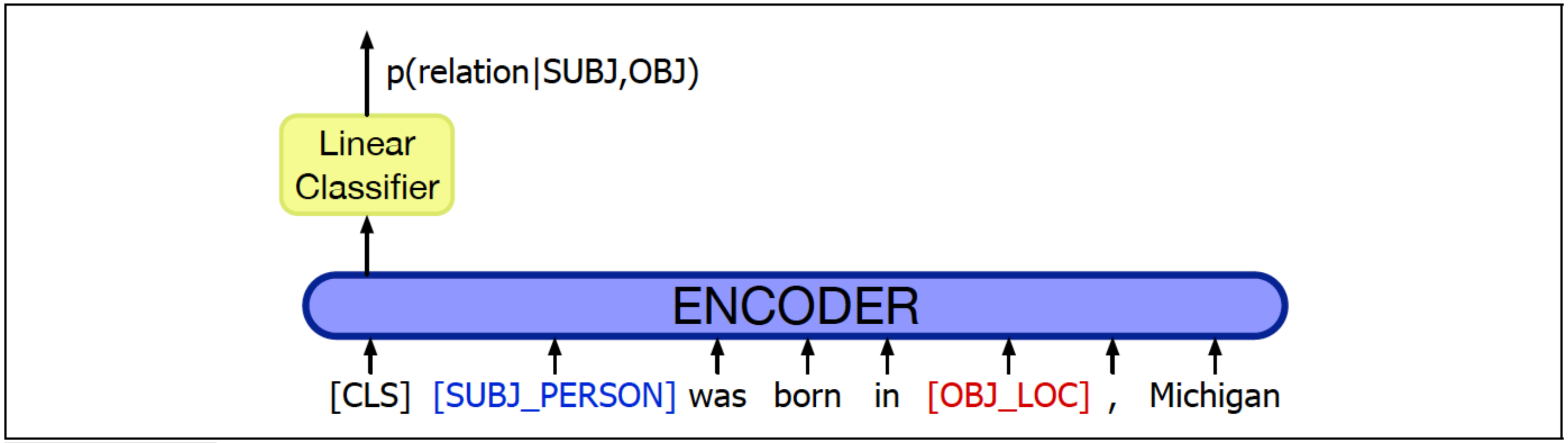



**Figure 17.7** Relation extraction as a linear layer on top of an encoder (in this case BERT), with the subject and object entities replaced in the input by their NER tags (Zhang et al. 2017, Joshi et al. 2020).

Other modern idea:

- use Hearst rules to formulate „queries" to language models or encoders (BERT):

*„Man, I was so full after our visit to Hofbräuhaus"* artificially expand:

*„Man, I was so full after our visit to Hofbräuhaus. <$X_h$> such as Hofbräuhaus are…"*

let BERT predict <$X_h$>

# Semi-Supervised Relation Extraction via Bootstrapping

- learning new rules / patterns from seed rules or seed tuples

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

*tuples* ← Gather a set of seed tuples that have relation *R*

*newpairs* ← *tuples*

**iterate**

*sentences* ← find sentences that contain entities in *newpairs*

*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

# Semi-Supervised Relation Extraction via Bootstrapping

example:

- we know: Ryanair has a hub at Charleroi → seed: hub(Ryanair, Charleoi)
- find other sentences with *Ryanair, hub, Charleroi*:
  - Budget airline Ryanair, which uses Charleroi as a hub, scrapped all weekend flights out of the airport.
  - All flights in and out of Ryanair's Belgian hub at Charleroi airport were grounded on Friday...
  - A spokesman at Charleroi, a main hub for Ryanair, estimated that 8000 passengers had already been affected.
- use context of words between entity mentions, words before mention one, word after mention two, NE types of the two mentions, … → extract general patterns:

```
/ [ORG], which uses [LOC] as a hub /
/ [ORG]'s hub at [LOC] /
/ [LOC] a main hub for [ORG] /
```

# Semi-Supervised Relation Extraction via Bootstrapping

*Sydney has a ferry hub at Circular Quay* → (Sydney, Circular Quay) ∈ hub?

→ assign confidence values to new tuples to avoid semantic drift:

- given :
  - document collection D,
  - current set of tuples T,
  - proposed pattern p

- define:
  - hits : set of tuples in T that p matches while looking in D
  - finds : total set of tuples that p finds in D

- then

$$Conf_{RlogF}(p) = \frac{|hits(p)|}{|finds(p)|} log(|finds(p)|)$$

·eliability" * "frequency")

- using noisy or: combine evidence for new instance tuple t from all rules P' supporting it in D

$$Conf(t) = 1 - \prod_{p \in P'} (1 - Conf(p))$$

assumptions:

- for a proposed tuple to be false, all of its supporting patterns must have been in error
- the sources of their individual failures are independent.

# Distant Supervision for Relation Extraction

hand-labelled training data is expensive → use relation databases to produce large number of seeds

**function** DISTANT SUPERVISION(*Database D, Text T*) **returns** *relation classifier C*

**foreach** relation $R$
  **foreach** tuple ($e1$,$e2$) of entities with relation $R$ in $D$
    $sentences \leftarrow$ Sentences in $T$ that contain $e1$ and $e2$
    $f \leftarrow$ Frequent features in $sentences$
    $observations \leftarrow$ observations + new training tuple ($e1$, $e2$, $f$, $R$)
$C \leftarrow$ Train supervised classifier on $observations$
**return** $C$

also learn a “no –relation”-relation using tuples not in database

# Distant Supervision for Relation Extraction

example: learn place-of-birth relationship between people and their birth cities

- DBPedia or Freebase: over 100,000 tuples of place-of-birth: <Edwin Hubble, Marshfield> , <Albert Einstein, Ulm>, …
- find all sentences in T with two NEs matching one of those tuples
  - ...Hubble was born in Marshfield...
  - ...Einstein, born (1879), Ulm...
  - ...Hubble's birthplace in Marshfield...
- for each tuple (e.g. <born-in, Albert Einstein, Ulm>: from all sentences matching the tuple extract conjunctions of features (e.g. NE types of the two mentions, words and dependency paths in between the mentions, neighboring words etc.)
  - example sentence: American Airlines, a unit of AMR, immediately matched the move, spokesman Tim Wagner said
    → conjunction of features:
    M1 = ORG & M2 = PER & nextword="said"& path= NP↑NP↑S↑S↓NP

# Distant Supervision for Relation Extraction

- very large training sets → rich features that are conjunctions of individual features
- uses hand-created knowledge (although in a distant way) → high-precision evidence for the relation between entities
- able to use large number of features simultaneously → unlike iterative expansion of patterns in seed-based systems, there's no semantic drift.
- doesn't use a labeled training corpus of texts directly → no genre bias
- only useful if large extensional database for sought relations exists

# Unsupervised Relation Extraction

( x, r, y )

example: ReVerb (2001):

- POS tag and chunk sentence s
- For each verb in s, find the longest sequence of words w that start with a verb and satisfy syntactic and lexical constraints, merging adjacent matches.
- For each phrase w , find the nearest NP x to the left which is not a relative pronoun, wh-word or existential "there". Find the nearest NP y to the right.
- assign confidence c to the relation instance r = (x, w, y) using a confidence classifier and return it.

- example for a constraint specification (e.g. satisfied by *have a hub in*):

V | VP | VW*P
V = verb particle? adv?
W = (noun | adj | adv | pron | det )
P = (prep | particle | inf. marker)

# Unsupervised Relation Extraction

- confidence classifier:
  - run system on 1000 random web sentences, hand labelling each extracted relation as correct or incorrect → training data
  - train confidence classifier on this training data using features of the relation and the surrounding words such as

| |
|---|
| (x,r,y) covers all words in s |
| the last preposition in *r* is *for* |
| the last preposition in *r* is *on* |
| len(s) $\leq$ 10 |
| there is a coordinating conjunction to the left of *r* in *s* |
| *r* matches a lone V in the syntactic constraints |
| there is preposition to the left of *x* in s. |
| there is an NP to the right of *y* in *s*. |

- advantage of unsupervised relation extraction: ability to handle large number of relations without having to specify them in advance.

- example: *United has a hub in Chicago, which is the headquarters of United Continental Holdings*

```
→  r1:  <United, has a hub in, Chicago>
   r2:  <Chicago, is the headquarters of, United Continental Holdings>
```

# Evaluating Relation Extraction

- supervised RE: as usual

- semisupervised / unsupervised RE:
  - estimate precision by sampling the output and labelling the sample (ignore number of times a relation has been discovered):

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

  - estimate recall indirectly: compare estimated precision at different sample sizes ( the top 1000 new relations, the top 10,000 new relations, the top 100,000, and so on )

# Extracting Temporal Expressions

- Absolute points in time, durations, and relations between them

| Absolute | Relative | Durations |
|---|---|---|
| April 24, 1916 | yesterday | four hours |
| The summer of ’77 | next semester | three weeks |
| 10:15 AM | two weeks from yesterday | six days |
| The 3rd quarter of 2006 | last quarter | the last three quarters |

- Temporal expressions: grammatical constructions with temporal triggers as heads.
  Lexical triggers: nouns, proper nouns, adjectives, or adverbs; temporal expressions: noun phrases, adjective phrases, and adverbial phrases

| 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* |

# Extracting Temporal Expressions

- TimeML:

  *A fare increase initiated* <TIMEX3>*last week*</TIMEX3> *by UALCorp's United Airlines was matched by competitors over* <TIMEX3>*the weekend*</TIMEX3>*, marking the second successful fare increase in* <TIMEX3>*two weeks*</TIMEX3> .

- Rule-based approaches: automata, regExs etc.

```
# yesterday/today/tomorrow
$string =˜ s/(($OT+(early|earlier|later?)$CT+\s+)?(($OT+the$CT+\s+)?$OT+day$CT+\s+
$OT+(before|after)$CT+\s+)?$OT+$TERelDayExpr$CT+(\s+$OT+(morning|afternoon|
evening|night)$CT+)?)/<TIMEX2 TYPE=\"DATE\">$1<\/TIMEX2>/gio;

$string =˜ s/($OT+\w+$CT+\s+)
<TIMEX2 TYPE=\"DATE\"[^>]*>($OT+(Today|Tonight)$CT+)<\/TIMEX2>/$1$2/gso;

# this/that (morning/afternoon/evening/night)
$string =˜ s/(($OT+(early|earlier|later?)$CT+\s+)?$OT+(this|that|every|the$CT+\s+
$OT+(next|previous|following))$CT+\s*$OT+(morning|afternoon|evening|night)
$CT+(\s+$OT+thereafter$CT+)?)/<TIMEX2 TYPE=\"DATE\">$1<\/TIMEX2>/gosi;
```

# Extracting Temporal Expressions

- supervised sequence labelling with any ML seq. classifier using IOB:

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

- features that may be used:

| Feature | Explanation |
|---|---|
| Token | The target token to be labeled |
| Tokens in window | Bag of tokens in the window around a target |
| Shape | Character shape features |
| POS | Parts of speech of target and window words |
| Chunk tags | Base-phrase chunk tag for target and words in a window |
| Lexical triggers | Presence in a list of temporal terms |

- challenge: false positives:

*1984* tells the story of Winston Smith...
...U2's classic *Sunday* Bloody *Sunday*

# Temporal Normalization

- → map to ISO8601 standard

week 26 of 2007

July 2nd 2007

duration of
one weekend

```
<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>.
```

giving the one weekend
an absolute reference

duration of
two weeks

giving the two weeks
an absolute reference

- further examples:

| Unit | Pattern | Sample Value |
|---|---|---|
| Fully specified dates | YYYY-MM-DD | 1991-09-28 |
| Weeks | YYYY-Wnn | 2007-W27 |
| Weekends | PnWE | P1WE |
| 24-hour clock times | HH:MM:SS | 11:13:45 |
| Dates and times | YYYY-MM-DDTHH:MM:SS | 1991-09-28T11:00:00 |
| Financial quarters | Qn | 1999-Q3 |

# Temporal Normalization

- document or communication act has a logical temporal anchor (e.g. time of creation, time of publication, today, now, etc.)

- → logical temporal arithmetic:
  - *tomorrow* = anchor of today + 1d , *yesterday* = anchor of today - 1d
  - anchor: 2007W26 → *50 weeks later* = week (((26 + 50) mod 53) + 1) of 2008

- but: complexity of absolute referencing may be high:
  - *...was matched by competitors over the weekend...* → "last weekend" (relative to anchor)
  - *Security checks will continue at least through the weekend* → "coming weekend" (relative to anchor)

    for both cases: indicator: tense of verb
  - *...next Friday...* : "immediate next Friday" or "Friday next week"? → heuristic: the closer today's anchor is to "immediate next Friday" the more probable is "Friday next week"

# Event Extraction

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

- most events: verbs / VP; also possible: NP
  - VP counterexamples:
    - *…took effect…*,
    - light verbs such as *make*, *take*, or *have*: event is expressed by their object: *took a flight*

# Event Extraction

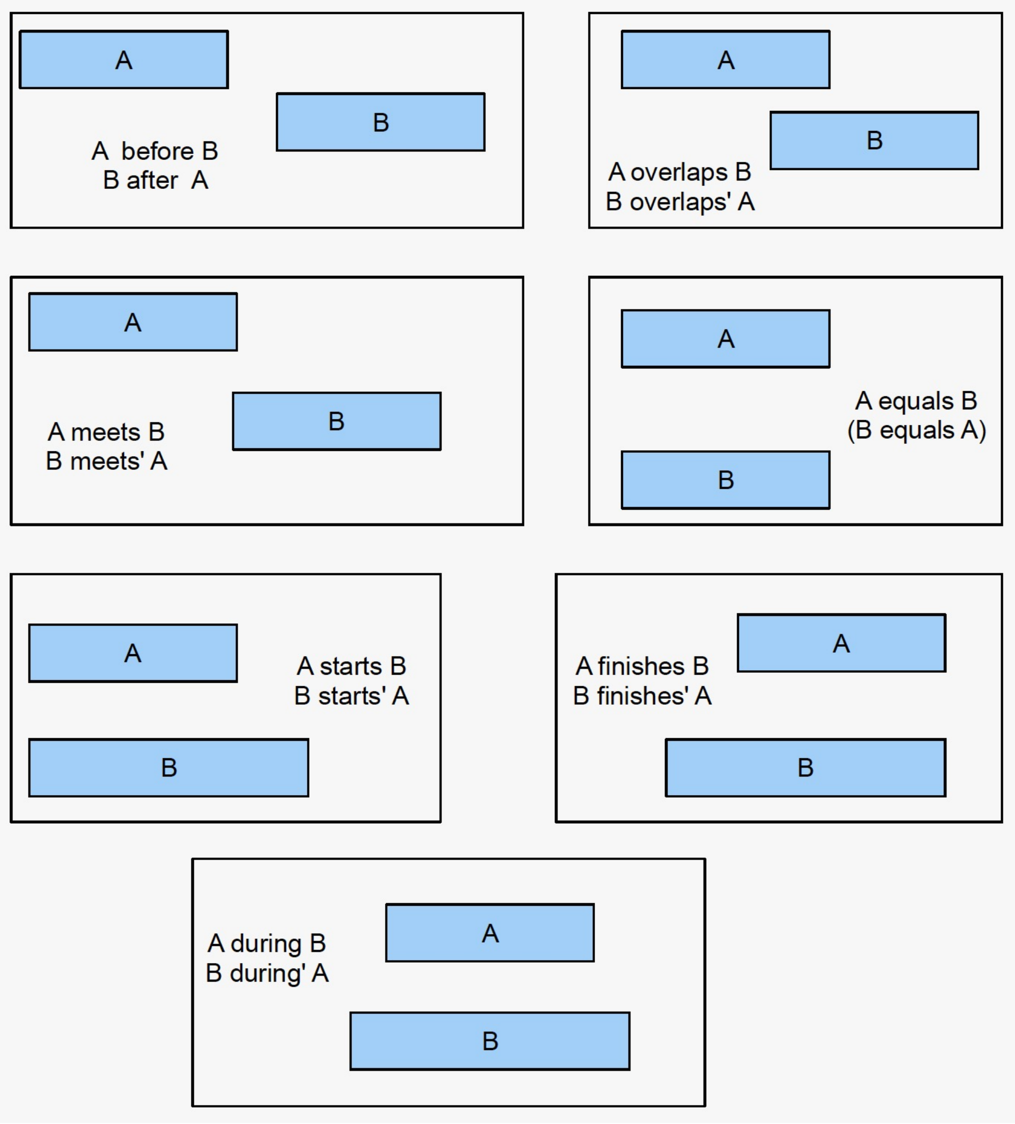
- classes of events: actions, states, reporting events (say, report, tell, explain), perception events etc.
  and further sub-classes: example: said events in example text: (class=REPORTING, tense=PAST, aspect=PERFECTIVE)

- approach: supervised ML with IOB tagging; features:

| Feature | Explanation |
|---|---|
| Character affixes | Character-level prefixes and suffixes of target word |
| Nominalization suffix | Character level suffixes for nominalizations (e.g., *-tion*) |
| Part of speech | Part of speech of the target word |
| Light verb | Binary feature indicating that the target is governed by a light verb |
| Subject syntactic category | Syntactic category of the subject of the sentence |
| Morphological stem | Stemmed version of the target word |
| Verb root | Root form of the verb basis for a nominalization |
| WordNet hypernyms | Hypernym set for the target |

# Temporal Ordering of Events

- absolute positioning of events in anchored timeline or partial ordering of events (after, before etc.) (useful in e.g. question answering)
- example for partial ordering: determining that fare increase by American Airlines came after fare increase by United
- partial ordering: binary relation detection and classification task; target relations: Allen temporal logic relations



# Temporal Ordering of Events

- TimeBank corpus: 183 news articles

```
<TIMEX3 tid="t57" type="DATE" value="1989-10-26"  functionInDocument="CREATION_TIME">
10/26/89  </TIMEX3>

Delta Air Lines earnings <EVENT eid="e1" class="OCCURRENCE"> soared </EVENT> 33% to a
record in  <TIMEX3 tid="t58" type="DATE" value="1989-Q1" anchorTimeID="t57"> the
fiscal first quarter </TIMEX3>, <EVENT eid="e3"  class="OCCURRENCE">bucking</EVENT>
the industry trend toward <EVENT eid="e4" class="OCCURRENCE">declining</EVENT>
profits.
```

- in addition to events and temporal expressions, corpus also includes Allen relations btw these

*Delta Air Lines earnings soared 33% to a record in the fiscal first quarter, bucking the industry trend toward declining profits*

- Soaring$_{e1}$ is **included** in the fiscal first quarter$_{t58}$
- Soaring$_{e1}$ is **before** 1989-10-26$_{t57}$
- Soaring$_{e1}$ is **simultaneous** with the bucking$_{e3}$
- Declining$_{e4}$ **includes** soaring$_{e1}$

# Template Filling

- template: "scripts" of common stereotypical situations / event sequences with fixed set of slots

- template filling task: detect presence of template and fill slots with slot filler values

| | | |
|---|---|---|
| FARE-RAISE ATTEMPT: | LEAD AIRLINE: | UNITED AIRLINES |
| | AMOUNT: | $6 |
| | EFFECTIVE DATE: | 2006-10-26 |
| | FOLLOWER: | AMERICAN AIRLINES |

  - template recognition: supervised text classification task; usual set of features: tokens, word shapes, part-of-speech tags, syntactic chunk tags, NE tags etc.
  - role filler extraction: detect roles (either via supervised classifier on NPs or as sequence labelling task) and fill roles (again via supervised ML)

# Bibliography

(1) Dan Jurafsky and James Martin: Speech and Language Processing (3rd ed. draft, version Jan 2022); Online: https://web.stanford.edu/~jurafsky/slp3/ (URL, Oct 2022); this slide-set is especially based on chapter 17

# Recommendations for Studying

- minimal approach:

  work with the slides and understand their contents! Think beyond instead of merely memorizing the contents

- standard approach:

  minimal approach + read the corresponding pages in Jurafsky [1]

- interested students

  == standard approach