Information Extraction

LING 570

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Outline

- What is IE?
- General process
- Relation detection
  - Supervised method
  - Lightly supervised method
- J&M Chapter 22

What is IE?

- Motivation:
  - Unstructured data hard to manage, assess, analyze
  - Many tools for manipulating structured data:
    - Databases: efficient search, agglomeration
    - Statistical analysis packages
    - Decision support systems
- Goal:
  - Given unstructured information in texts
  - Convert to structured data
    - E.g., populate DBs

An example

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

Announcement date:	10/14/2016 (Friday)
Lead Airlines:	United Airlines
Amount:	$6 round trip
Effective date:	10/13/2016 (Thursday)
Follower:	American Airlines

Applications

- Shared tasks:
  - Message Understanding Conferences (MUC)
    - Joint ventures/mergers:
      - CompanyA, CompanyB, CompanyC, amount, type
    - Terrorist incidents:
      - Incident type, Actor, Victim, Date, Location
  - BioNLP contests
- General domains:
  - Pricegrabber
  - Stock market analysis
  - Apartment finder

Approaches

- Incorporates range of techniques and tools:
  - FSAs (pattern extraction)
  - Supervised learning:
    - Classification
    - Sequence labeling
  - Semi- and un-supervised learning: clustering, bootstrapping

Common pre-processing steps

- Part-of-Speech tagging
- Named Entity Recognition
- Chunking
- Parsing
- …

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The general process (1)

- Tokenization, POS tagging, chunking, parsing, …
- NER: detect entities mentioned in a text
  - Often application-specific

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

The general process (2)

- Reference resolution: “United” refers “United Airlines”
  - Create entity equivalent classes

- Citing high fuel prices, **[$_{ORG}$ United Airlines]** said [$_{Time}$ Friday] **it** has increased fares by [$_{MONEY}$ $6] per round trip to some cities also served by lower-cost carriers. [$_{ORG}$ American Airlines], a unit of [$_{ORG}$ AMR Corp.] immediately matched the move, spokesman [$_{PER}$ Time Wagner] said**.** **[$_{org}$ United]**, a unit of [$_{ORG}$ UAL Corp.], said the increase took effect [$_{TIME}$ Thursday] an applies to most routes where **it** competes against discount carriers, such as [$_{LOC}$ Chicago] to [$_{LOC}$ Dallas] and [$_{LOC}$ Denver] to [$_{LOC}$ San Francisco].

The general process (3)

- Relation detection and classification:
  - Find and classify relations among entities in text
    - Mix of application-specific and generic relations
    - Generic relations:
      - Family, employment, part-whole, membership, geospatial
  - Generic relations:
    - United is **part-of** UAL Corp.
    - American Airlines is **part-of** AMR
    - Tim Wagner is an **employee** of American Airlines
  - Domain-specific relations:
    - United **serves** Chicago; United **serves** Denver, etc

The general process (4)

- Event detection and classification:
  - Find key events
  - Fare increase by United
  - Matching fare increase by American
  - Reporting of fare increases
    - How cued?
      - Instances of “said” and ”cite”

The general process (5)

- Temporal expression recognition
  - Finds temporal events in text
    - E.g. Friday, Thursday in example text
  - Others:
    - Date expressions:
      - Absolute: days of week, holidays
      - Relative: two days from now, next year
    - Clock times:
      - noon, 3:30pm
- Temporal analysis:
  - Map expressions to points/spans on timeline
    - Anchor: e.g. Friday, Thursday: tied to example dateline

The general process (6)

- Template filling: Texts describe stereotypical situations in domain
  - Identify texts evoking template situations
  - Fill slots in templates based on text
  - In example: fare-raise is stereo-typical event

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

The general process (recap)

- NER
- Reference resolution
- Relation detection and classification
- Event detection and classification
- Temporal expression detection and temporal analysis
- Template-filling

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Common relations

Relations		Examples	Types
Affiliations			
	Personal	*married to, mother of*	PER → PER
	Organizational	*spokesman for, president of*	PER → ORG
	Artifactual	*owns, invented, produces*	(PER | ORG) → ART
Geospatial			
	Proximity	*near, on outskirts*	LOC → LOC
	Directional	*southeast of*	LOC → LOC
Part-Of			
	Organizational	*a unit of, parent of*	ORG → ORG
	Political	*annexed, acquired*	GPE → GPE

Relations and entities from the example

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	$Serves = \{\langle a,f\rangle, \langle a,g\rangle, \langle a,h\rangle, \langle a,i\rangle\}$

Supervised Approaches to Relation Analysis

- Two-stage process:
  - Relation detection:
    - Detect whether a relation holds between two entities
      - Positive examples:
        - » Drawn from labeled training data
      - Negative examples:
        - » Generated from within-sentence entity pairs with no relation
  - Relation classification:
    - Label each related pair of entities by type
      - Multi-class classification task

Some Example Features

[$_{ORG}$ American Airlines], a unit of [$_{ORG}$ AMR Corp.] immediately matched the move, spokesman [$_{PER}$ Time Wagner] said.

Entity-based features	
$Entity_1$ type	ORG
$Entity_1$ head	*airlines*
$Entity_2$ type	PERS
$Entity_2$ head	*Wagner*
Concatenated types	ORGPERS
Word-based features	
Between-entity bag of words	{ *a, unit, of, AMR, Inc., immediately, matched, the, move, spokesman* }
Word(s) before $Entity_1$	NONE
Word(s) after $Entity_2$	*said*
Syntactic features	
Constituent path	$NP \uparrow NP \uparrow S \uparrow S \downarrow NP$
Base syntactic chunk path	$NP \rightarrow NP \rightarrow PP \rightarrow NP \rightarrow VP \rightarrow NP \rightarrow NP$
Typed-dependency path	$Airlines \leftarrow_{subj} matched \leftarrow_{comp} said \rightarrow_{subj} Wagner$

Lightly Supervised Approaches

- Supervised approaches is highly effective, **but**
  - require large manually annotated corpus for training
- Unsupervised approaches interesting, **but**
  - may not yield results consistent with desired categories
- Lightly supervised approaches:
  - Build on small seed sets of patterns that capture relations of interest
    - E.g. manually constructed regular expressions
  - Iteratively generalize and refine patterns to optimize

Bootstrapping Relations

- Create seed patterns and instances
  - Example: finding airline hub cities
    - Initial pattern: / * has a hub at * /
    - In a large corpus finds examples like:
      - Delta has a hub at LaGuardia.
      - Milwaukee-based Midwest has a hub at KCI.
      - American airlines has a hub at the San Juan airport
    - Instances:
      - (Delta, LaGuardia), (Midwest, KCI), (American, San Juan)

Patterns ➔ more tuples

ORG has a hub at LOC

Milwaukee-based Midwest has a hub at KCI.

Delta has a hub at LaGuardia.

Bulgaria Air has a hub at Sofia Airport, as does Hemus Air.

American Airlines has a hub at the San Juan airport.

No frills rival easyJet, which has established a hub at Liverpool...

Ryanair also has a continental hub at Charleroi airport (Belgium).

Tuples ➔ more patterns

(hub, Ryanair, 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.

```
/ [ORG], which uses [LOC] as a hub /
/ [ORG]'s hub at [LOC] /
/ [LOC] a main hub for [ORG] /
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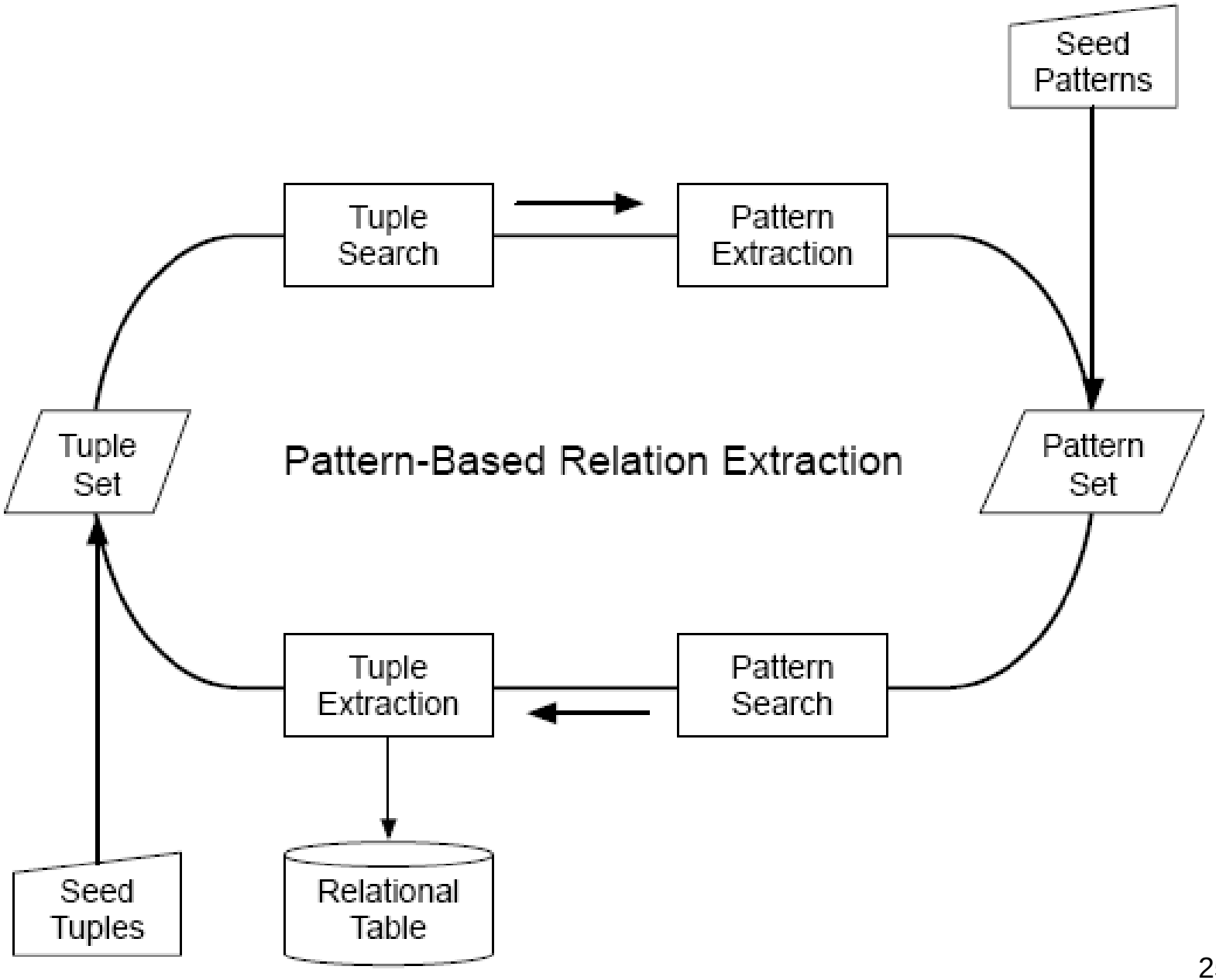
Seed Patterns
Tuple Search
Pattern Extraction
Tuple Set
Pattern-Based Relation Extraction
Pattern Set
Tuple Extraction
Pattern Search
Seed Tuples
Relational Table

Bootstrapping Relations

- Issues:
  - False alarms:
    - Some matches aren't valid relations
      - The catheter has a hub at the very end of the hall.
    - Fix? Change the pattern to /[ORG] has hub at [LOC]/
  - Misses:
    - Some instances are narrowly missed by pattern
      - No frills rival easyJet, which has established a hub at Liverpool.
      - Ryanair also has a continental hub at Charleroi airport.
    - Fix?
      - Relax patterns – see the 1st issue
      - Add new high-precision patterns

Bootstrapping

- How can we obtain more high quality patterns?
  - Human labeling? Expensive
  - Use tuples identified by seed patterns
  - Find other occurrences of tuples
  - Extract patterns from those occurrences

- E.g. tuple: (hub, Ryanair, Detroit)
  - Occurrences:
    - Budget airline Ryanair, which uses Detroit as a hub
    - All flights in and out of Ryanair's Belgian hub at Detroit
  - Patterns:
    - /[ORG], which uses [LOC] as a hub /
    - /[ORG]'s hub at [LOC] /

Relation Analysis Evaluation

- Approaches:
  - Standardized, labeled data sets
    - Precision, recall, f-measure
      - ‘Labeled’ precision: test both detection and classification
      - ‘Unlabeled’ precision: test only detection
  - No fully labeled corpus
    - Evaluate retrieved tuples (e.g. DB contents)
      - Don’t care how many times we find the same tuple