COMP4650 / COMP6490
Document Analysis 2018

Info ction

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Overview of IE lectures

- Introduction to Information Extraction (IE)
  - Overview
  - Relation Extr
  - Named Entit
- Sequence labeling meth d 2
- Automatic Summarization

* Acknowledgement: Some of the content originates from the Stanford NLP course at Coursera.org

Books

Speech and Language Processing

Jurafsky and Martin

2014. Pearson.

Na age Processing

Jacob Eisenstein

2018. MIT pres.

https://github.com/jacobeisenstein/gt-nlp-class

Introduction to IE

What is IE?

Automatically extract structured information from unstructured and/or semi-structured data.

Who did what

Main goals:

- Helps natural language understanding
- Organize information for humans
- Organize information in a formal and precise form that allows further analysis and/or inferences made by computer algorithms

IE Applications

Scan documents and populate:

- Templates
- Ontologies
- Data Bases
- Knowledge Bases

Text understanding (e.g.: named entity recognition, relation extraction)

Automatic summarization

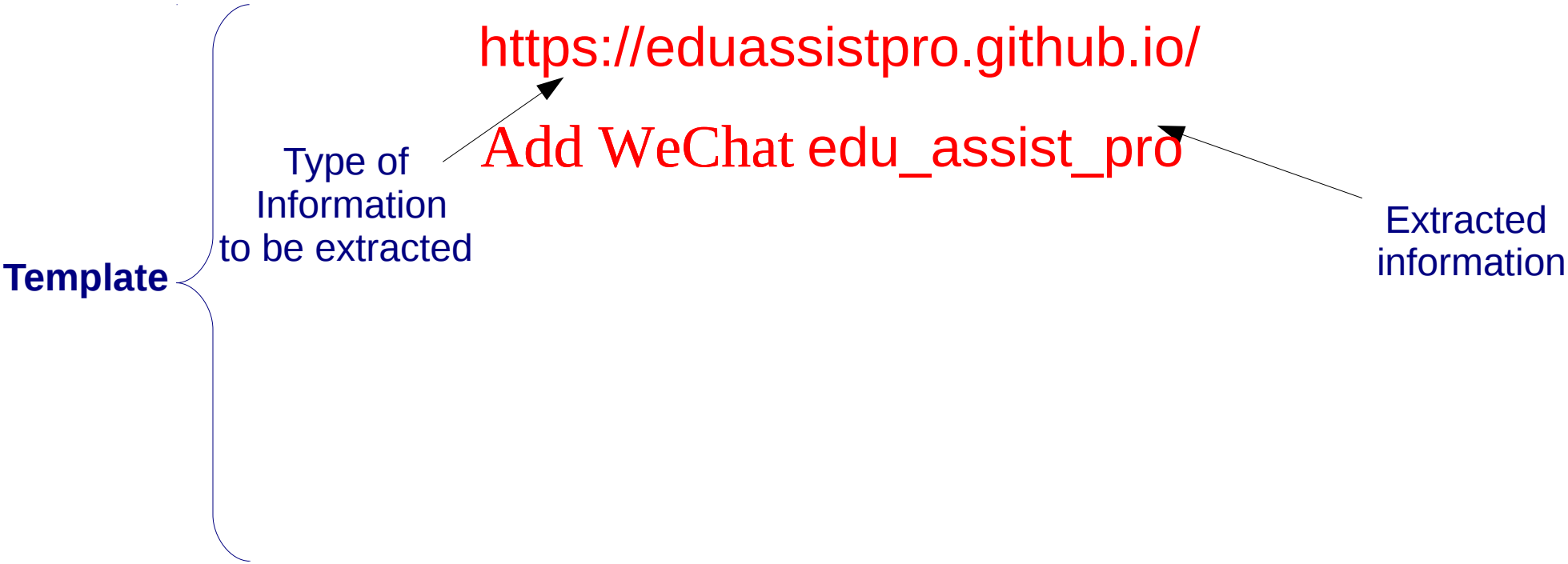
Question answering

...

etc.

IE Template based example

2008 January 17
British Airways **Flight 38**, a **Boeing 777- 200ER**, lands short of the runway at **London Heathrow Airport** in the United Kingdom. **Nine** of the 152 people on board are treated for minor injuries, but there are **no fatalities**; this is the first loss of a Boeing 777.



Extract information about aircraft accidents from news

Templates types

Slots in a template are usually filled by a substring of a document

- Some slots may **llers**


```
hysic Job type: n
```


- Some slots may allow **multiple fillers**

```
Programming language: Java, C++, Python, etc.
```

IE applications

- **Relation Extraction**

  Paris **is the capital** of France.

  France's **capital** is Paris.

  Paris <is-a-capital-of> France

- **Name Entity Recognition ification**

  Paris is the capital of

  <LocationEntity> <...> <LocationEntity>

- **Combined**

  <LocationEntity> <is-a-capital-of> <LocationEntity>

IE methods

Hand written patters

Supervised m

Semi-supervised and un ed learning

Relation Extraction

How relations are express in natural language?

- Relations are instantiated by predicates
- Predicates have arguments
- Verbs are the most productive predicate form


```
predicate(arg1, arg2, ..., argn)
```

*Mery **likes** cake.*

```
likes(Mery, cake)
```

*Mery **rent** a boat for 2 weeks for 300 dolars.*

```
rent(Mery, boat, 2 weeks, 300 dolars)
```

Why Relation Extraction?

Create new structured knowledge, e.g., facts

- Augment current knowledge bases

  Adding wor[illegible] us. facts to FreeBase o[illegible]

- Support question answering

  `Which actor starred in the film BATMAN 3?`

  `acted-in(?x, BATMAN)`

  `is-a(?y, actor)`

But which relations should we extract? And how?

Which relations to extract?

- A pre-defined set of relations
- All relations (e.g., all verbs and their arguments)
- Ontological relations

Example of a pre-defined set of relations

17 relations from SemE 2008 “Relation Extraction Task

Example of extracting ALL relations

Use sytactic dependency trees to extract predicates and their arguments

Ontological relations

Examples from the WordNet Thesaurus http://wordnetweb.princeton.edu/perl/webwn

Hypernym (is-a): subsumption between classes

- Giraffe **IS--A** ruminant **IS--A** ungulate **IS--A** mammal **IS--A** vertebrate **IS--A** animal…

Hyponym relation or I en individual and class

- Dog → Terrier → Bull-terrier → St ll terrier...

- San Francisco **instance-of** city

Synonym relation

- **Car** Sense 1 => auto, automobile, motorcar, machine
- **Man** Sense 1 => adult men
- **Man** Sense 2 => homo, human being, human

Relation extraction projects

Resource Description Framework (RDF) triples

```
Golden Gate Park location San Francisco
```

Dbpedia: +1 billion

```
dbpedia:Golden_Gat                    tion
dbpedia:San_Francisco
```


Freebase relations: well-known people, places, and things
https://www.freebase.com/

```
Total RDF riples: 2.1M
```

How to build relation extractors

Hand written patters

Supervised m

Semi-supervised and un ed learning

Hand written rules: Hearst's Patterns for extracting IS-A relations

Marti A. Hearst. 1992. Automatic acquisition of hyponyms from large text corpora. In Proceedings of the 14th conference on Computational linguistics - Volume 2 (COLING '92), Vol. 2. Association for Computational Linguistics, Stroudsburg, PA, USA, 539-545.

Extracting Richer Relations Using Rules

Intuition: relations often holds between specific entities

- **located-in**(ORGANIZATION, LOCATION)
- **founded**(P , N)
- **cures**(DRUG, DISEASE)

Start with Named Entity tags to help relation extraction

Which relations hold between 2 entities?

Which relations hold between 2 entities?

Summary: Hand written patterns for Relation Extraction

- **Plus**
  - Human patterns tend to be high-precision
  - Can be tailored to specific domains
- **Minus**
  - Human patterns are often quite
  - A lot of work to think of all possible patterns
  - Don't want to have to do this for every relation
  - We would like better accuracy

Supervised machine learning for Relation Extraction

Training

- Choose the set of relations you want to extract
- Find and label data* = training set creation
- Extract relevant features = training set
- Train a classifier on the training set

Testing

- Tuned the classifier parameters on the dev. set
- Test the classifier on the test set

* Available RE datasets: SemEval7; BioNLP, etc.

Supervised relation extraction between entities

- Find all pairs of named entities (`person, location, organization`)
  - Decide if 2 entities are related
  - If yes, classify t types (`is-a, instance-of`

- You can use any classifier you like
  - MaxEnt, Naive Bayes, CRF, SVM, CNN, etc.

RESIDE: Improving Distantly-Supervised Neural Relation Extraction using Side Information

(Vashishth et al., 2018)

Summary: Supervised machine learning for Relation Extraction

- **Plus**
  - Can get high accuracy with enough hand-labeled training data, if test data is similar enough to training data
- **Minus**
  - Labeling a large training set is expensive
  - Supervised models are brittle, don't generalize well to different genres

Semi supervised Relation Extraction

No training set? Maybe you have:

- A few **seed** tuples
- A few high-pre

Can you use those **seeds** to do something useful?

- Bootstrapping: use the seeds to directly learn to populate a relation

Relation Bootstrapping (Hearst, 1992)

- Gather a set of ***seed pairs*** that have relation ***R***
- Iterate:
  - Find sentenc
  - Look at the context betwe nd the pair and generalize the context to create patterns
  - Use the patterns for *grep* for more pairs

Bootstrapping

Unsupervised relation extraction

- Extract relations from with no training data, thus no pre-defined list of relations

- Single-past: extra NPs

- Assessor ranks relations based ndancy

Elsahar et al., 2018

Evaluation of unsupervised relation extraction

- Since it extracts totally new relations...

  there is no gold set of correct relations

  - cannot compute precision (don't know which ones are correct)
  - cannot compute recall (don't know which ones were missed)

- Instead, we can approximate **precision**

  draw a random sample of relation from output, check precision manually

Name Entity Recognition

Name Entity Recognition

Named Entity Recognition (NER)
Find and classify names in texts,
e.g.: person, location, organization, number, currency, etc.

Designated **S/2004** own moon to circle the giant planet.

It also appears to be the smallest moon in the **Neptunian** system, measuring just **20 km** (**12 miles**) across, completing one revolution around **Neptune** every **23 hours**.

US astronomer **Mark Showalter** spotted the tiny dot while studying segments of rings around Neptune.

proper name
quantity
location
person
Time
Other

NER Applications

- Machine Translation
- Question Answering
- Automatic S
- Relation Extraction

NER as learning

- **Training**
  - Collect a set of representative training documents
  - Label each token for its entity class or other
  - Design feature to the text and classes
  - Train a sequence classifier to labels from the data
- **Testing**
  - Receive a set of testing documents
  - Run sequence model inference to label each token
  - Appropriately output the recognized entities

NER Task: the training data

US	**LOC**
astronomer	
Mark	
Showalter	**PER**
spotted	**O**
that	**O**
:	**:**

Standard evaluation is per Entity not per token

cision, recall and F-measure

NER Task: example features

Numbers

- twoDigitNum (90) = Two-digit year
- fourDigitNum (1990) = Four-digit year
- containsDigitA duct code
- containsDigitAndDash (09-96)
- containsDigitAndSlash (11/9/8
- containsDigitAndComma (23,000.00) = Monetary amount
- containsDigitAndPeriod (1.00) = Monetary amount, percentage

NER Task: example features

- Person
  - capPeriod (M.) = Person name initial
  - initCap (Sally d
  - lowerCase (c word

- Organization
  - allCaps (IBM) = Organization

* Gazzeters (list with persons, organizations, abbreviations, etc.)

NER challenges

Ambiguity problems:

- **Paris** (city vs. person)
- **May** (person vs. month)
- **2013** (date vs. quantity)
- **Ferrari** (person vs.

Multi-language NER:

- Language independent features (position, suffix, prefix, digits, POS-tags)
- Lack of capitalization (Chinese, Indian lang., etc.)
- Too much capitalization (German)
- Free word order languages (Hungarian, Russian, etc.)
- Languages with rich morphology (Czech, Spanish, etc.)

Evaluation in IE

How much relevant information has been extracted

Precision = # of correct answers given by the system /

total # of possible correct answers in the text

How much of the extracted information is correct

Recall = # of corstem /

# of answers given

How good is the system in ignoring spurious information

Fall out = # of incorrect answers given by the system /

# of spurious facts in the text

Combination of Precision and Recall

F-Measure = 2 * (Precision * Recall / Precision + Recall)

IE take away

IE deals with processing human language texts by means of natural language processing techniques

- **Rule based methods**
  - Use lexical patterns, e.g.: `X was born in Y`;
  - Use syntactic patt
- **Supervised method**
  - Sequential labeling algorithms as HMM, CRF
  - Required training data
- **Semi-supervised and unsupervised methods**
  - Semi: required seed examples, e.g. lexical patterns
  - Unsupervised: require unlabeled data
  - Evaluation is not straightforward

Conclusion

- In the future, IE from cross-website pages will become more important as we move towards the Semantic

- IE new challenges are: domain independent solutions, data integration and multilingualism
  - Lots need to be done!

Resources/Tools

KnowItAll

https://github.com/knowitall

Stanford Named Ent **, McCallum, and Pereira, 2001)**

http://nlp.stanford.edu/software/CR l

OpenIE

https://nlp.stanford.edu/software/openie.html