Open Information Extraction using Wikipedia

Soraya Nikousokhan

Department of Computer Science
Albert-Ludwigs-University Freiburg, Germany

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Overview

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Motivation

- **IE systems** extract semantic relations from natural language text
- Use **supervised learning**
  - availability of training data
  - Can not scale to the web
- Open IE systems aim to handle **the unbounded number of relations**
  - self-supervised learning
  - Automatic heuristics generate labeled data
- **How well** can these open systems perform?

Wikipedia-based Open Extractor

- Improves dramatically on text runner's ***precision*** and ***recall***.
- **A self-supervised learning**
  - heuristic matches between Wikipedia infobox attribute values and corresponding sentences
- **Operate in two modes**:
  - Restricted to POS
  - Dependency parse features

Open Information Extractor

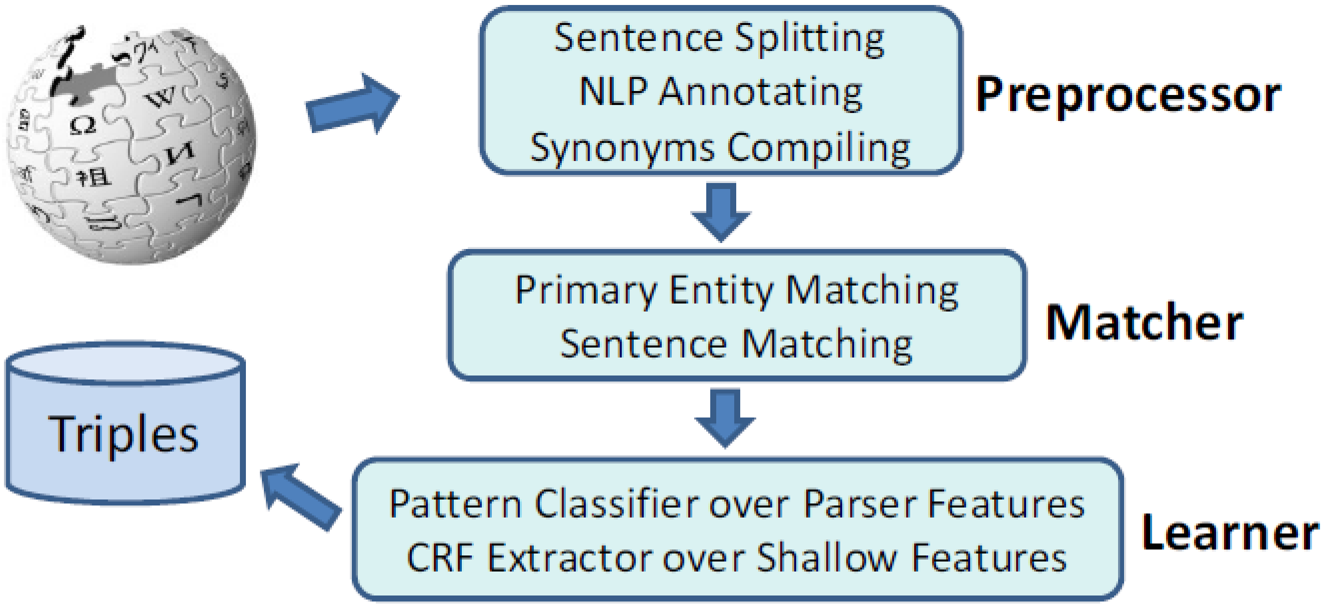
- A function from a document ***d***, to a set of triples,***{<arg1,rel,arg2>}***, where the ***args*** are ***noun phrases*** and ***"rel"*** indicating a semantic ***relation*** between the two noun phrases

- The extractor should produce **one triple** for **every relation** stated explicitly in the text

Open Information Extractor
Example

- Article: “Stanford university”
- Infobox: <estabilished,1891>
- Sentence: ” the university was founded in 1891 by… ”
- The triple would be:
  - <arg1,rel,arg2>
  - <Stanford university,estabilished,1891>

Architecture of WOE



Preprocessor

- **Sentence Splitting**
  - Transform each Wikipedia article into HTML
  - Splits into sentences by OpenNLP
- **NLP annotation**
  - OpenNLP to supply POS tags and NP-chunk annotations
  - Stanford Parser to create a dependency parse
- **Compiling synonyms**
  - The preprocessor build a set of synonyms
  - Uses Wikipedia redirection pages and backward links

Matcher

- Constructs **training data** for the learner component
- Given a **Wikipedia page** with an **infobox**
  - the matcher **iterates** through all **infobox attributes**
  - looking for sentence that contains **references to** both the **subject of the article** and the **attribute value**
  - These noun phrases will be annotated in the training set.

Matcher

- **Matching primary entities**

  Use heuristics :
  - Full match
  - Partial match: “Amherst ” matches “Amherst, Mass”
  - Patterns of “the<type>”: “City” for ” Ithaca”
  - The most frequent pronoun: ” he” for the page on “Albert Einstein”
- **Matching sentence**
  - The matcher seeks a **unique** sentence to match the attribute value

Learning Extractors

- **Extraction with parser features**
  - WOE^{Parse} using features from dependency-parse trees.
  - It uses a pattern learner to classify whether the shortest dependency path between two noun phrase indicate a semantic relation
- **Extraction with shallow features**
  - WOE^{POS} limited to shallow features like POS tags
  - Trains a conditional random field(CRF) to output certain text between noun phrases when the text denotes such a relation.

Extraction with Parser Features

Shortest Dependency Path as Relation

"Dan was not born in Berkeley."

- **The Stanford parser dependencies are**:

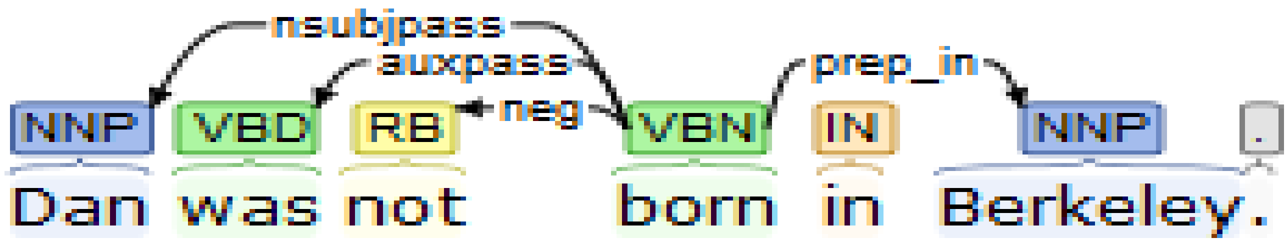
nsubjpass(born-4, Dan-1)

auxpass(born-4, was-2)

neg(born-4, not-3)

root(ROOT-0, born-4)

prep_in(born-4, Berkeley-6)



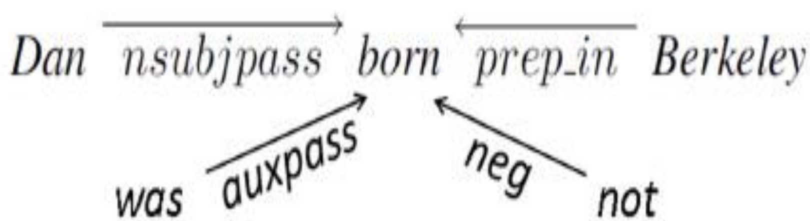
Extraction with Parser Features

Shortest Dependency Path as Relation

- “Dan was not born in Berkeley.”
- **CorePath:**

$$\textit{Dan}\ \overrightarrow{\textit{nsubjpass}}\ \textit{born}\ \overleftarrow{\textit{prep\_in}}\ \textit{Berkeley}$$

- **ExpandPath:**



Extraction with Parser Features

Building a Database of Patterns

- Learner generates a **corePath** between the tokens denoting the **subject** and the **infobox attribute value**.
- To improve **learning performance**:
  - **Generalized–corePaths:** eliminate irrelevant relations
  - Lexical words in corePaths are replaced with their POS tags
  - Extraction pattern "$N \xrightarrow{nsubjpass} V \xleftarrow{prep} N$".

- WOE builds a **database** (named $\mathbf{DB}_p$) of 15,333 distinct patterns
- Each **pattern *p*** associated with **a frequency**

Extraction with Parser Features

Learning a Pattern Classifier

- WOE^{parse} checks whether the **generalized-corePath** from a test triple is present in DB_p and computes the **normalized logarithmic frequency** as the probability:
- $\boldsymbol{f_p}$:associated frequency of the pattern
- $\boldsymbol{f_{max}}$: maximal frequency of patterns in DB_p
- $\boldsymbol{f_{min}}$:controlling threshold, minimal frequency of a valid pattern

$$w(p) = \frac{max(log(f_p) - log(f_{min}), 0)}{log(f_{max}) - log(f_{min})}$$

Extraction with Parser Features
Learning a Pattern Classifier

- Example:
- "Dan was not born in Berkeley "
- Dan as arg1 , Berkeley as arg2
- Computes corePath $Dan\ \overrightarrow{nsubjpass}\ born\ \overleftarrow{prep\_in}\ Berkeley$
- Abstracts to "$N\ \overrightarrow{nsubjpass}\ V\ \overleftarrow{prep}\ N$"
- Queries $DB_p$to retrieve the frequency f_p=29112 and assigns probability of 0.95(f_m : 50.259)
- WOE^{parse} traverses the triple's expandPath to out put the final expression $\langle Dan, wasNotBornIn, Berkeley\rangle$

Extraction with Shallow Features

- **High speed** can be **crucial** when processing web-scale corpora
- Shallow features like **POS-tags**
- Use the same matching sentence set behind $\boldsymbol{DB_P}$ to generate **positive examples**
- **Negative examples** are generated from **random** noun-phrase pairs
  - generalized-corePaths which are **not in** $\boldsymbol{DB_P}$
- **Learning algorithm** and selection features as textrunner
  - A two-order CRF chain model is trained with Mallet package

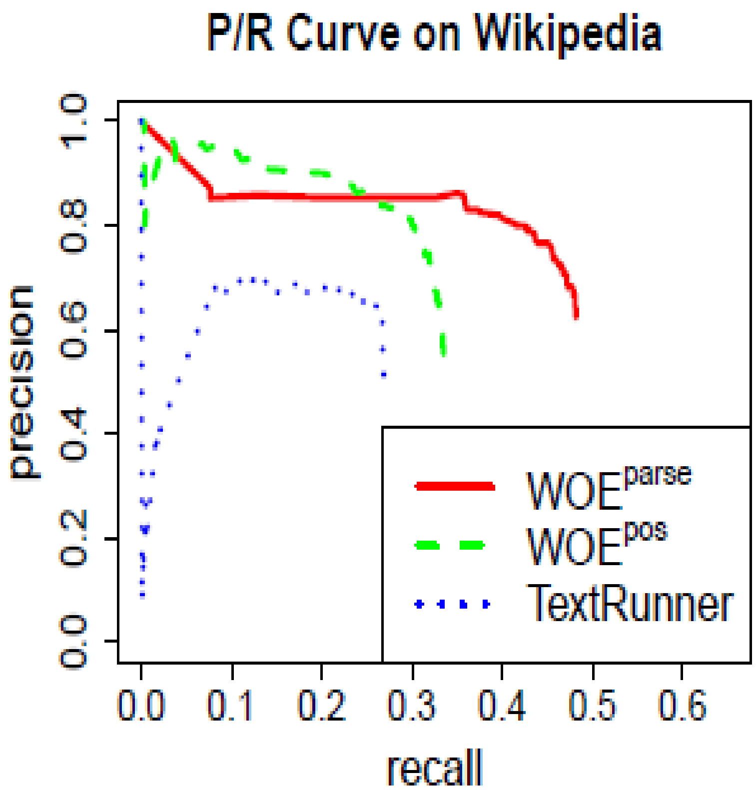
Experiments

- **Three corpora** for experiments:
  - WSJ from Penn Treebank
  - Wikipedia
  - Web
- Randomly selected **300 sentences** for each
- Examined by two people to **label** all **reasonable triples**
- Submitted to **Amazon Mechanical Turk** for **verification**
- Each triple examined by **5 Turkers**
- **Positive** when more than **3 Turkers** marked them as positive

Overall Performance Analysis

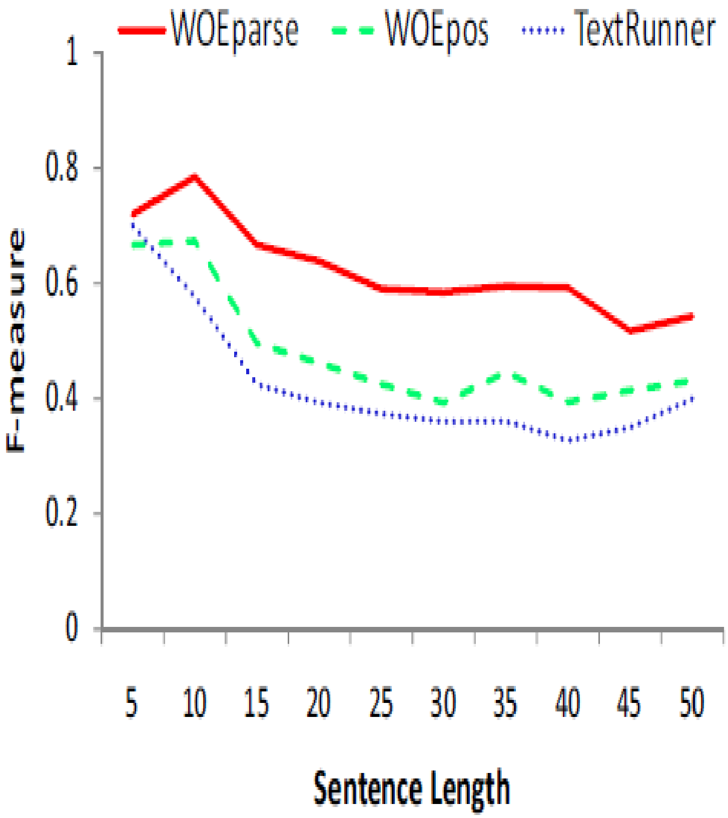
- How do these systems ***perform*** against each other?
- How does ***performance*** vary w.r.t ***sentence length***?
- How does ***extraction speed*** vary w.r.t ***sentence length***?

Overall Performance Comparison



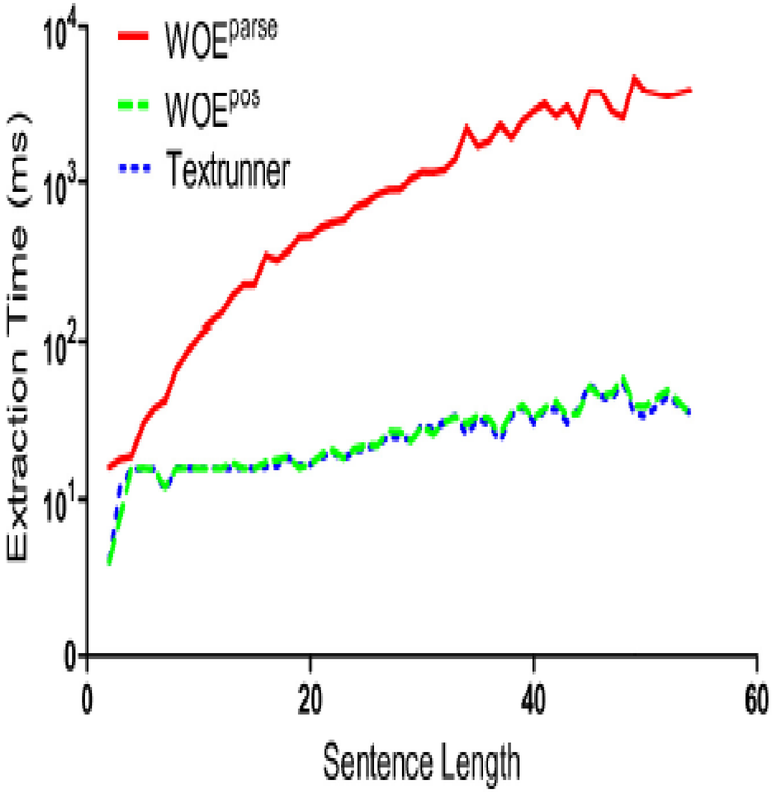
- WOE^{pos} is better than TextRunner on precision
  - Better training dataset
- WOE^{parse} is the best on recall
  - Parser features

Extraction Performance vs. Sentence Length



- Long sentence have long-distance relations
  - Difficult for shallow feature

Extraction Speed vs. Sentence Length



- WOE^{parse}'s extraction time grows quadratically
  - Reliance on parsing

Shallow or Deep Parsing

- Shallow features like **POS tags** enable **fast extraction** over large-scale corpora
- Deep features are derived from **parse trees**
  - **training better** extractors
- Abstracted dependency path features are **highly informative**
- In Web, many sentences contain **complicated long-distance relations**
  - **Parser features** are more **powerful**

Conclusion

- **WOE** a new approach that uses **self-supervised learning** over **unlexicalized features**, based on **heuristic match** between Wikipedia infoboxes and corresponding text
- Runs in **two** modes
  - $\boldsymbol{WOE^{pos}}$: a CRF extractor trained with shallow features like POS tags
  - $\boldsymbol{WOE^{parse}}$: a pattern classifier learned from dependency path patterns
- In comparison with textrunner
  - $\boldsymbol{WOE^{pos}}$ runs at **the same speed**, but achieves an **F-measure** which is between 9% and 23% **greater**
  - $\boldsymbol{WOE^{parse}}$ achieves an **F-measur**e which is between %51 and 70%, but runs about 30X times **slower** due to it reliance on parsing.

Reference

- *Open Information Extraction* using *Wikipedia*. ,Fei Wu ,Daniel S. Weld, University of Washington .