Open Domain Information Extraction

Günter Neumann, DFKI, 2012

Improving TextRunner

- Wu and Weld (2010) Open Information Extraction using Wikipedia, ACL 2010
- Fader et al. (2011) Identifying Relations for Open Information Extraction, EMNLP 2011

Wu and Weld (2010) Open Information Extraction using Wikipedia

- Novel form of **self-supervised learning** for open extractors: heuristic matches between Wikipedia infobox attribute values and corresponding sentences to construct training data

- Like TextRunner: avoid lexicalized features and handles unbounded set of semantic relations

- System WOE (Web-based Open Information Extraction):
  - WOE^{pos} : POS tag features → as fast as TextRunner but better P & R
  - WOE^{parse} : dependency-parse features → even higher P & R, but 30times slower

Open Extractor - Problem Definition

- An open information extractor is:
  - a function from a document d to a set of triples {<**arg_1**, **rel**, **arg_2**>}, where
  - **arg_i** is a noun phrase and **rel** is a textual fragment indicating an implicit, semantic relation between **arg_1** and **arg_2**
- Restriction: Triples represent facts stated *explicitly* in the text, no inference of implicit facts
- Assumption: all relational instances are stated within a single sentence

Self-Supervision using Wikipedia

- Goal: Learn an open extractor without direct supervision !
- Input: Wikipedia (as source for sentences) and DBpedia (as source for cleaned infoboxes)
- Output: unlexicalized and relation-independent open extractor
- Objection: Extractor should generalize beyond Wikipedia, e.g., that can handle the general Web

Wikipedia-based Open IE

- Key idea: automatic construction of training examples by heuristically matching Wikipedia infobox values and corresponding text.

- Used to generate generalized relation-independent extractors.

From infoboxes to a training set

Clearfield County, Pennsylvania	
Statistics	
Founded	March 26, 1804
Seat	Clearfield
Area	
- Total	2,988 km² (1,154 mi²)
- Land	sq mi (km²)
- Water	17 km² (6 mi²), 0.56%
Population	
- (2000)	83,382
- Density	28/km²

Clearfield County was created in 1804 from parts of Huntingdon and Lycoming Counties but was administered as part of Centre County until 1812.

Its county seat is Clearfield.

2,972 km² (1,147 mi²) of it is land and 17 km² (7 mi²) of it (0.56%) is water.

As of 2005, the population density was 28.2/km².

Architecture of WOE

- Preprocessor converts raw Wikipedia text into a sequence of sentences
- The matcher constructs training data from attribute-value pairs of infoboxes and matching sentences
- Learner acquires the open extractors using either parser features or POS features.

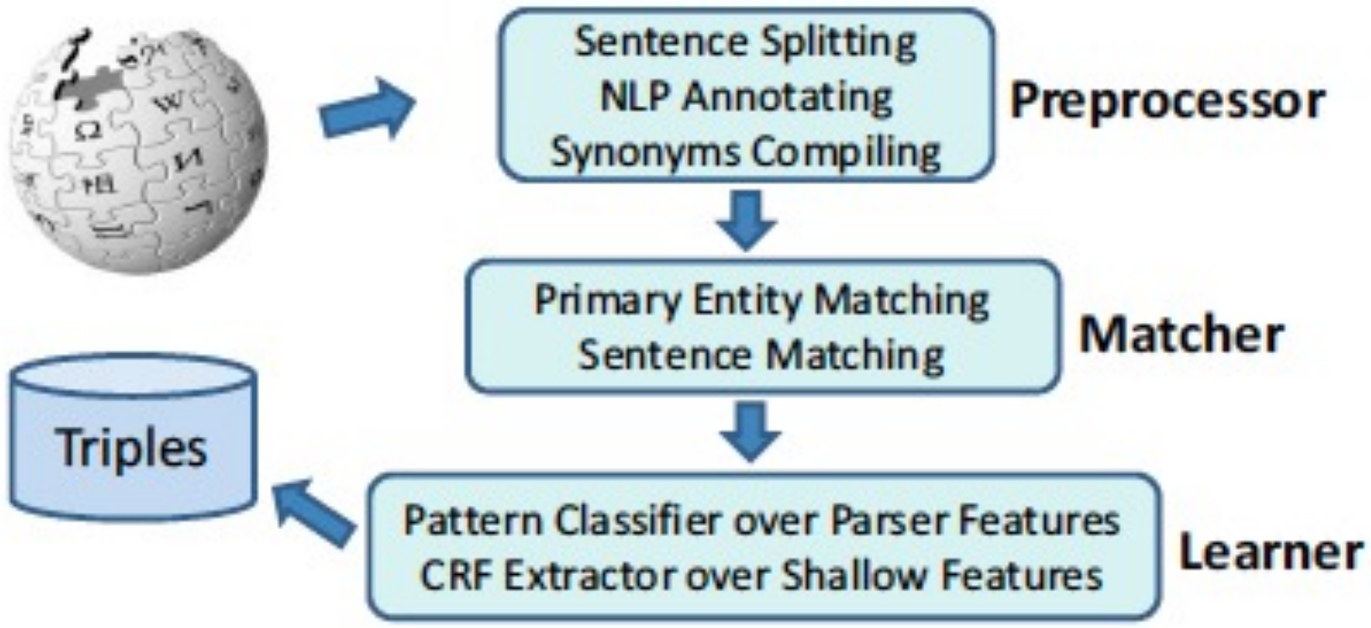


Figure 1: Architecture of WOE.

Preprocessor

- OpenNLP for sentence splitting
- NLP annotation:
  - OpenNLP for POS tagging and NP chunks
  - Stanford Parser for dependency parse; hyperlinked anchor text handled as a single token (using underscore)
- Compiling synonymies (to increase recall of the matcher)
  - Wikipedia articles contain different mentions of same entities (across pages and between infobox and Wikipedia page)
  - Wikipedia redirection pages and backward links are used to construct automatically synonym sets.

Matcher - Constructing Training Data from Infoboxes

- Given a Wikipedia page with an infobox - assumption here: such a page describes an entity - iterate through all its attributes looking for a unique sentence that contain references to both the subject of the article and the attribute value (or its synonym).

- „Stanford University“ article:
  match <established, 1891> with „The university was founded in 1891 by ...“
  → <arg_1=Stanford University, rel=???, arg_2=1891>

- Ordered heuristics for matching the subject, e.g.,
  full match, *synonym match*, *partial match* (prefix/suffix of the entity‘s name), *patterns of „the <type>“* (type identification using simple patterns from Wikipedia), *article‘s most frequent pronoun*.

- Use **DBpedia‘s** cleaned infobox data (1,027,744 articles) as basis for attribute-value pairs → leads to **301,962 labeled sentences**

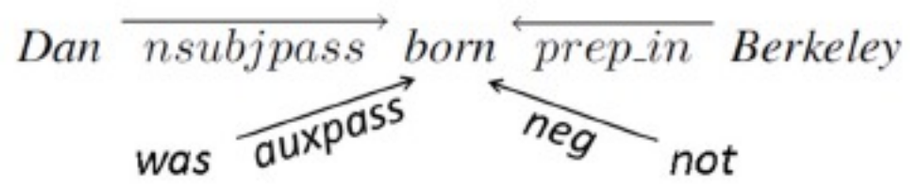
Extraction with Parser Features

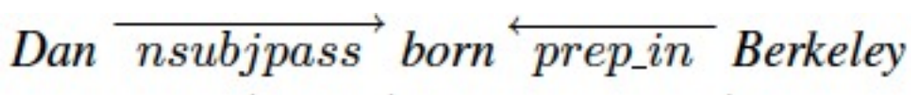
- Construction of relation text:
  - corePath = shortest dependency path between arg_1 and arg_2 (expandPath = adding all adverbial and adjectival modifiers, „neg“ and „auxpass“ labels of the root node)
  - select all tokens of expanded Path as value for rel („was not born“ in our example)
- Generalization of patterns:
  - ignoring corePaths that don‘t start with subject like dependencies, s.a. nsubj, nsubj-pass → 259,046 corePaths
  - generalized-corePaths: substitute lexical words by their POS; map all noun tags to N, verb tags to V, prep tags to prep etc.
  - yields a database $\mathbf{DB_p}$ of 29,005 distinct patterns
  - each pattern receives its number of matching sentences as frequency p (311 patterns have $f_p \geq 100$, and 3,519 have $f_p \geq 5$)

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)
prep_in(born-4, Berkeley-6)





“*N* $\overrightarrow{nsubjpass}$ *V* $\overleftarrow{prep}$ *N*”.

WOE^{parse} - A Simple Pattern Classifier

- Lookup the generalized-corePath of a test triple in DB_p , and compute normalized logarithmic frequency as the probability:

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

- f_{max} = max. freq. of patterns in DB_p , f_{min} = a controlling threshold

- Example: „Dan was not born in Berkeley“
  let f_{max} = 54,274, f_{min} = 1, and f_p = 31,767, where p= $\text{“}N \xrightarrow{nsubjpass} V \xleftarrow{prep} N\text{”}.$

- then w(p) = 0.95

- Performance: 79% to 90% higher F-measure than TextRunner ! But:
  TextRunner is still 30X faster !

WOE^{pos} - Extraction with Shallow Patterns

- Like TextRunner learn a CRF extractor WOE^{pos} based on shallow features. (CRF -conditional random fields - classifier from the Mallet ML toolkit.)

- However, use **generated labeled examples**, where TextRunner learns from a small set of hand-written labeled sentences.

- Use same matching sentence set behind DB_p :

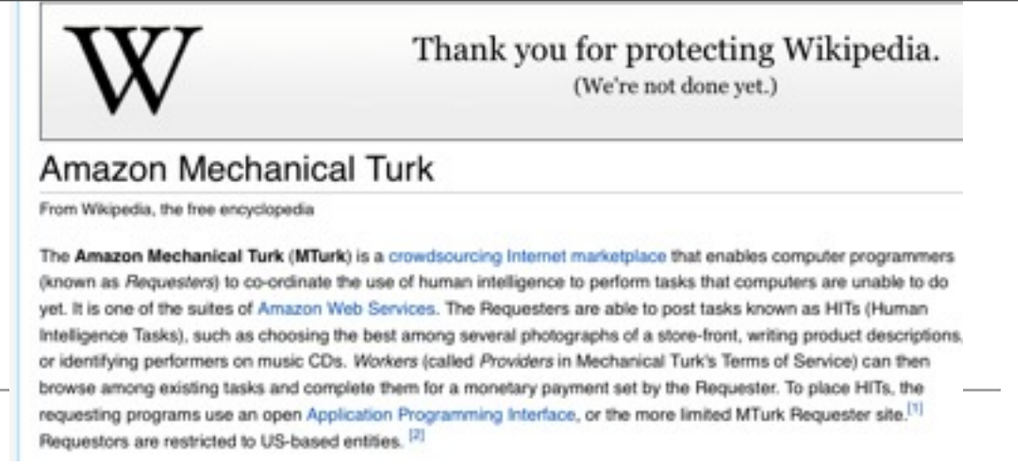
  - positive examples: use matching arg_1 and arg_2 as ends of text sequences, rel used from expandedPath

  - negative examples: random NP pairs in other sentences which are not covered via DB_p

- Features: POS-tags, regular expressions, combined features from 6-sized window

- Performance: 15% to 34% higher F-measure than TextRunner ! And: as fast as TextRunner !!

Experiments



- 300 randomly selected sentences form three corpora:
  - WSJ from Penn Treebank
  - Wikipedia
  - general Web

- Each sentence was examined by two people to label all reasonable triples. These triples are mixed with pseudo-negative ones.

- Using Amazon Mechanical Turk for verification: each triple was examined by 5 workers, and was labeled positive when more than 3 workers marked it as positive.

Overall Performance Analysis

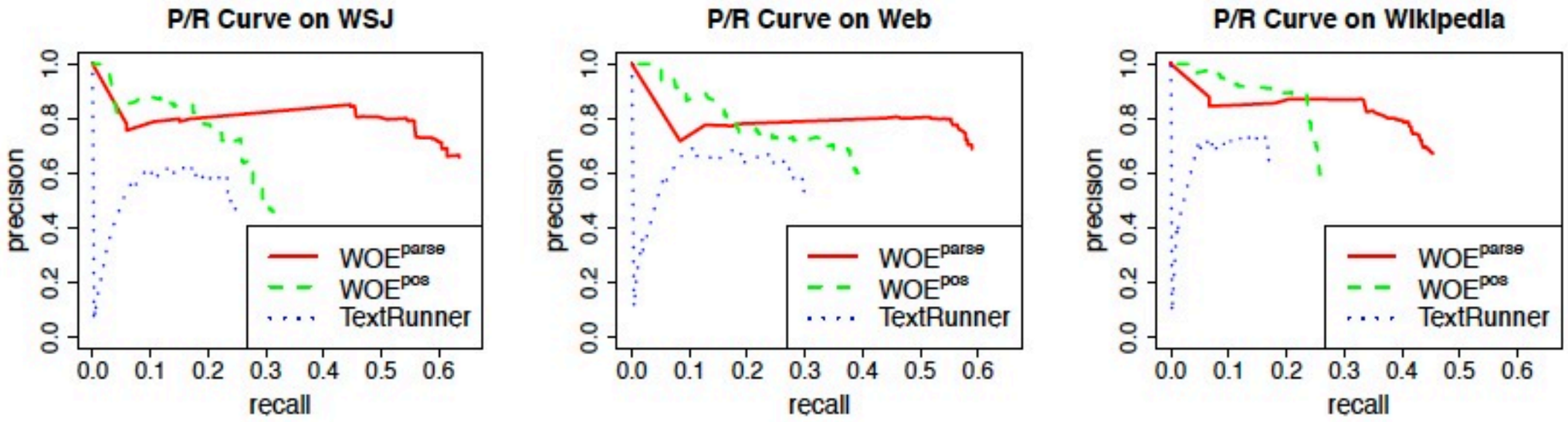


Figure 2: WOE^{pos} performs better than TextRunner, especially on precision. WOE^{parse} dramatically improves performance, especially on recall.

- WOE^{pos} is better than TextRunner, especially on precision
- WOE^{parse} performed best, especially in recall; parser helps to handle complicated and long-distance relations in difficult sentences; further experiments showed that parser errors have negligible effect !
- Extraction errors (numbers based on WSJ corpus) : 1) incorrect args from NP chunking (18,6%), 2) erroneous parses (11.9%), 3) inaccurate meaning (27,1%), 4) a pattern inapplicable for the test sentence (42,4%)

Further Performances

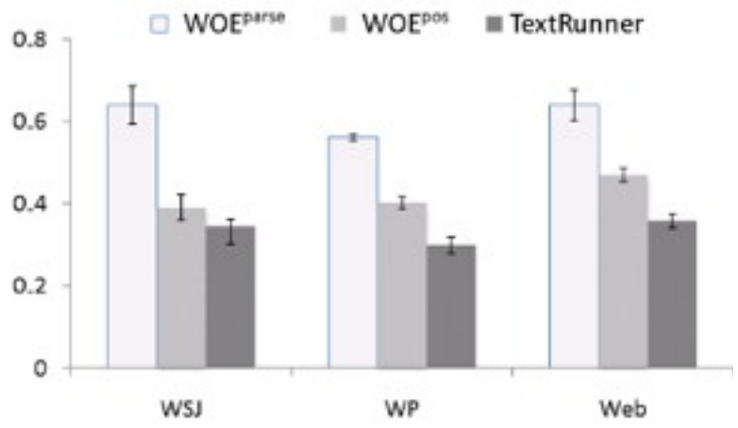


Figure 3: WOE^{pos} achieves an F-measure, which is between 15% and 34% better than TextRunner's. WOE^{parse} achieves an improvement between 79% and 90% over TextRunner. The error bar indicates one standard deviation.

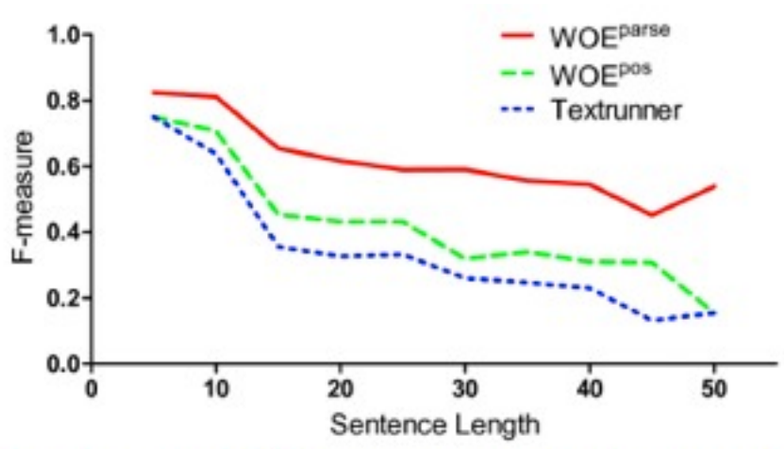


Figure 4: WOE^{parse}'s F-measure decreases more slowly with sentence length than WOE^{pos} and TextRunner, due to its better handling of difficult sentences using parser features.

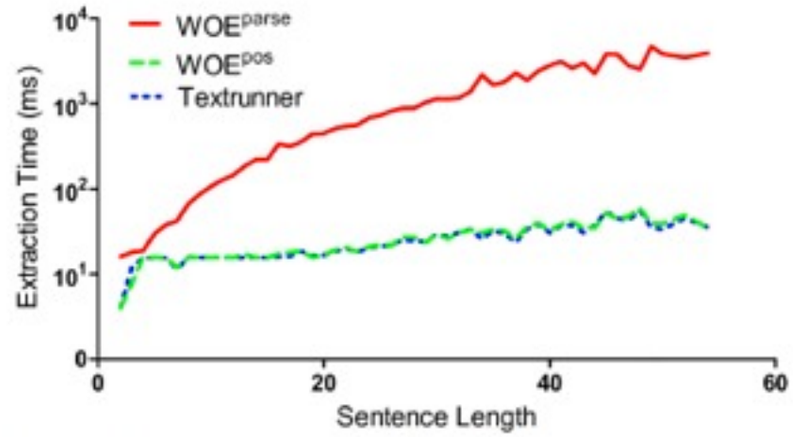


Figure 5: Textrnner and WOE^{pos}'s running time seems to grow linearly with sentence length, while WOE^{parse}'s time grows quadratically.

- WOE^{parse} achieves best results (Figure 3), due to deeper parsing, however also has highest costs (Figure 5; 0.679 sec/sent vs. 0.022 sec/sent)

- WOE^{parse} decreases more slowly with sentence length, also due to deeper parsing (figure 4)

Self-supervision with Wikipedia Results in Better Training Data

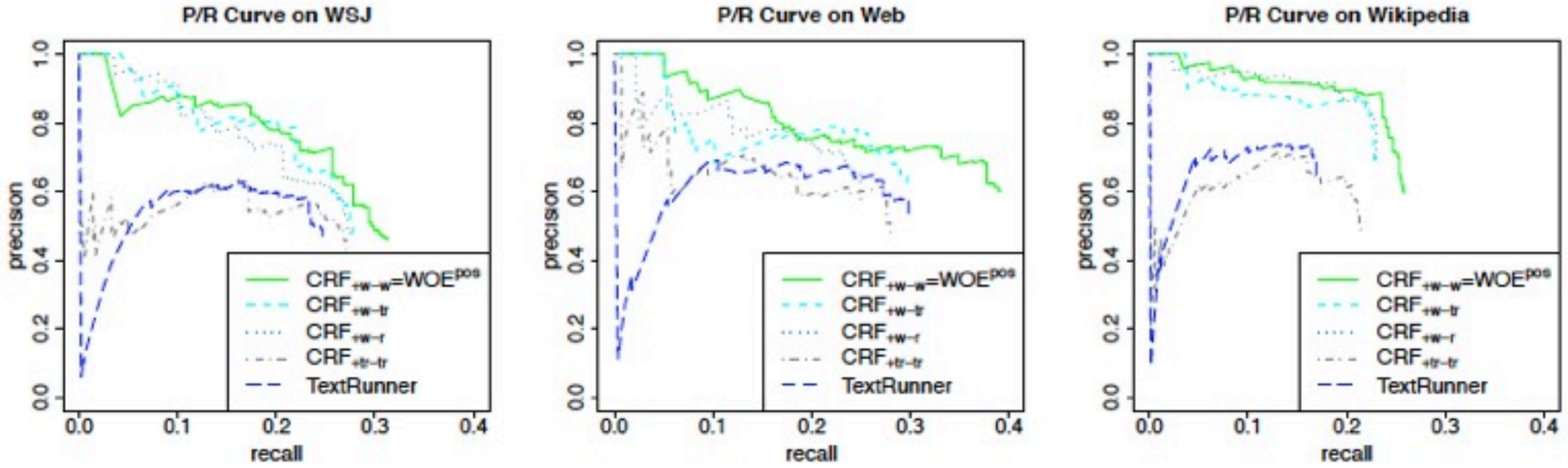


Figure 6: Matching sentences with Wikipedia infoboxes results in better training data than the hand-written rules used by TextRunner.

- Generating training examples from Wikipedia differently: 1) tr = pos/neg examples selected using TextRunners patterns, 2) w = WOE‘s heuristic infobox matchers, 3) r = randomly

- CRF_{+h1-h2}, where h_i = {tr,w,r}; using same feature set as TextRunner

Design Criteria for WOS^{parse}

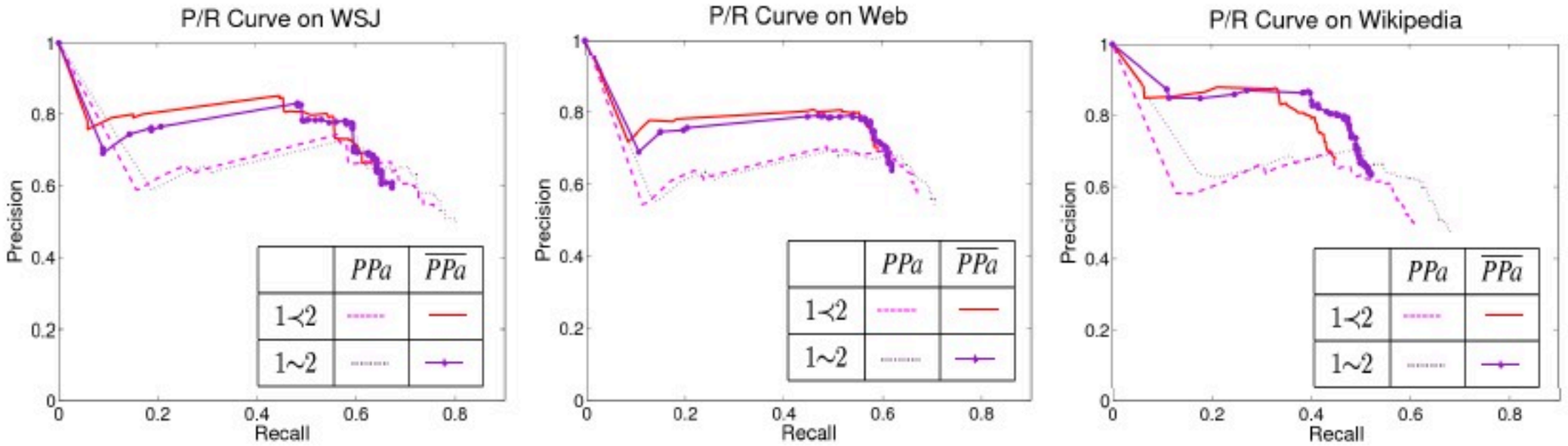


Figure 7: Filtering prepositional phrase attachments ($\overline{PPa}$) shows a strong boost to precision, and we see a smaller boost from enforcing a lexical ordering of relation arguments ($1 \prec 2$).

- two interesting design choices:
- require arg_1 to appear before arg_2 ($1 < 2$)
- allow corePath to contain PP-attachment (PPa)

Conclusion

- Novel self-supervised method using automatically generated training examples from Wikipedia

- CRF extractor trained with shallow features (WOE^{pos}) and dependency-parse features (WOE^{parse})

- Much better P&R compared to TextRunner

- Two sources of WOE's strong performance:
  1) the Wikipedia heuristic is responsible for the bulk of WOE's improved accuracy

  2) dependency-parse features are highly informative when performing unlexicalized extraction.