EPE 2017
Towards an Infrastructure for Extrinsic Parser Evaluation

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Some Near-Authentic Quotes and Reflections

Two Decades of Progress in (Statistical) Parsing

- Parsing into PTB-style trees has been a crisp task for many years;
- great advances: representations, algorithms, probabilistic models;
- $F_1$: 84.2 (Magerman, 1995) → 91.0 (Charniak & Johnson, 2005);
- some ten years later, neural advances: 93.8 (Choe & Charniak, 2016).
To me, the ultimate goal of our new field of Computational Linguistics is to build machines that, in a suitable interpretation of that term, ‘understand’ human language.

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Parallel Contributions to Natural Language ‘Understanding’?
Extrinsic Evaluation: Motivation & Goals

Limitations in Intrinsic Evaluation

• Presupposes ‘gold-standard’ syntactico-semantic target representations;
• out of necessity, typically limited to narrow range of domains and genres;
• repeated testing (sometimes over decades) against the same benchmark;
• granular output similarity metrics (e.g. ParsEval or LAS) hard to interpret;
• and maybe mis-leading: one mis-attachment can make all the difference.
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Desiderata for Extrinsic Parser Evaluation

- Informative about downstream utility for broad range of NLU applications;
- applicable across diverse output representations and parsing approaches;
- easy to reproduce and apply with new parsers, for all parser developers.
The EPE 2017 Shared Task: What We Did
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(5) Automated re-training for each submitted parser output;
(6) Low barrier to participation: Run your parser on our text.
Extrinsic Evaluation: Methodological Challenges

Tease Apart Various Contributions

- Parser is one component in complex end-to-end systems; does it matter?
  \[\rightarrow\] pick applications ‘sensitive’ to grammatical structure: hierarchical events;
  \[\rightarrow\] contrast state-of-the-art parser outputs with ‘baseline’ dependency graphs.
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Informative & Plausible Measurements

• Evaluate at state-of-the-art performance levels (even if a moving target);
  → EPE 2017 end-to-end performances more than competitive with prior art.
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No ‘Bias’ Towards Individual Analysis Schemes

- Automatic re-training of downstream systems; input ‘pseudonymization’;
- feature engineering and tuning originally only against one type of inputs.
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Towards and Infrastructure for Extrinsic Parser Evaluation (6)
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Additional Schemes Represented in the Task

- ‘Basic’ Stanford Typed Dependencies (SB)
- CCG Word–Word Dependencies (CCD)
- ‘Mesh-Ups’ from Multiple Parses (Szeged)
- UPF Deep Syntactic Structures (DSyntS)
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Additional Schemes Represented in the Task

- CCG Word–Word Dependencies (CCD)
- UPF Predicate–Argument Structures (PredArg)
Major Dimensions of Variation

EPE 2017 Limits Itself to English Dependency Parsing
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Formal Graph Properties

- Rooted trees vs. general directed graphs: node re-entrancies; singletons;
- unique root node with zero in-degree vs. zero to n (semantic) top nodes.
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Linguistic Design Decisions
- Function vs. ‘content’ words as heads: e.g. auxiliaries and prepositions;
- directionality: e.g. determiners and adjectives as predicates semantically.
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Pushing the Notion of Lexicalization

- Relax one-to-one correspondence to tokens: ‘empty’ or overlapping nodes.
The term (bi-lexical) dependency representation in the context of EPE 2017 is interpreted as a graph whose nodes are anchored in surface lexical units, and whose edges represent labeled directed relations between two nodes. Each node corresponds to a sub-string of the underlying linguistic signal (input string), identified by character stand-off pointers. Node labels can comprise a non-recursive attribute–value matrix (or ‘feature structure’), for example to encode lemma and part of speech information. Each graph can optionally designate one or more ‘top’ nodes, broadly interpreted as the root-level head or highest-scoping predicate. [Oepen et al., 2017]
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- Allow divergent segmentations: stand-off annotations; not token-centric;
- graph serialization in JSON: human- & machine-readable; easy to extend.
Biological Event Extraction (Björne, et al., 2009)

• Hierarchically nested event triggers, each with its arguments and modifiers.
EPE 2017: Supported Downstream Applications

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Initial Set: Three (Nearly) SotA Systems Assumed to Benefit from Parsing.
Participating Teams and Approaches (1/2)

East China Normal University [5 Runs]

• Neural, transition-based parser (Kiperwasser & Goldberg, 2016)—UD.
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INRIA, Paris Diderot, Paris Sorbonne (With Stanford) [12 Runs]
- Neural, transition-based tree-to-graph parser; two sets of training data;
- systematic variation of representations: SDP & many UD ‘enhancements’.
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Charles University in Prague [5 Runs]
- Variants of UDPipe system: representations; version; pre-processing—UD.
University of Szeged [5 Runs]

- Integrating dependencies from multiple parsers and parses—CoNLL++.

Universitat Pompeu Fabre [3 Runs]

- Three strata: surface syntax, 'deep' syntax, predicate–argument structure;
- 'classic' string-to-tree parser; hand-crafted graph transduction grammars.

Stanford University (With Paris) [11 Runs]

- Neural string-to-tree parser; heuristic rules to 'enhance' and 'normalize'.

University of Washington [1 Run]

- Neural, multi-task string-to-graph parser (Peng et al., 2017)—DM (SotA).
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EPE 2017 Mechanics: Facts and Figures

Schedule

**Mid-March** Release training and development data; EPE interchange format;

**Throughout April** Data updates; pre-processed variant and format converter;

**Mid-April** Pre-evaluation trial run: Five teams submitted 14 different runs;

**Throughout June** Debugging, with some teams; a couple of re-submissions;

**Late July** Final evaluation results; application and system descriptions;

**September 20** Presentation of infrastructure, participants, and results;

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All Available: Data, Systems, Results, Scores

http://epe.nlpl.eu
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Looking for collaborators: parser and application developers.

Towards and Infrastructure for Extrinsic Parser Evaluation (15)