Deep and Broad NLP for Big Data and Knowledge Graph Generation

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NLP-Lab

https://nlp-lab.org/

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Agenda

• NLP technologies
  • RESTful Microservice Infrastructure
• JSON-NLP
• HooSIER Text to Graph
• Research Directions
Motivation for NLP Infrastructure and API

- NLP Interoperability
- NLP Complexity
- NLP Errors
Motivation

• NLP Interoperability
  • Syntactic level: output formats are incompatible
  • Semantic level: annotation standards do not exist
  • Incompatibility of outputs and annotations

• Example:
  • Stanford CoreNLP
  • FreeLing
  • Spacy
  • ...
Issues

• NLP Complexity:
  • Interpretation and processing of outputs
    • Structural information
    • Meaning of Part-of-Speech tags
    • Interpretation of Dependency Labels

• Example:
  • Constituent Parse Tree
  • Lexical Functional Grammar C- and F-structure
NLP Issues

• NLP Errors in analysis:
  • Expert knowledge and knowledge of language necessary
  • Model specific error types

• Example:
  • Allen NLP:
    • Coreference Resolution
    • Constituent Parser
    • Dependency Parser
    • Open Domain Information Extraction (OpenIE)
  • Stanford CoreNLP
  • ...

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NLP Infrastructure

• NLP Errors
  • Introduce Redundancy: Multiple NLP components for the same annotation task
  • Repair systematic output errors

• NLP Complexity
  • Build an API to simplify access, facilitate use of advanced NLP output

• NLP Interoperability
  • Normalization and standardization of output formats and annotations
  • Uniform API for NLP
NLP Services

• Functional Aspects
  • Differences in Linguistic Annotation
  • Underlying Models/Theories Differ

• Solution
  • Merging outputs from different NLP components
NLP Services

• Technical Issues
  • Configurational Complexity
  • Dependencies for libraries, modules, extensions (Python, Java, C++)
  • Memory
    • Large models
    • Runtime memory requirements
    • Storage (file, db) requirements
  • Platform limitations
  • Hardware requirements: CPU & GPU
Microservice Architecture

• Solution: RESTful Microservice architecture
  • Scalability
  • Target platform and remote access (intranet or Cloud service)
  • Flexibility
    • Replaceable components
    • Versioning
  • Open to numerous programming languages, systems, architectures
    • Dominance of Python in NLP limits engineering possibilities and integration of NLP in larger production environments
NLP Services

• Most commonly used NLP services:
  • Tokenizer
  • Sentence segmentation
  • Part-of-Speech Tagging
  • Embeddings

• Less common NLP services:
  • Morphological analysis
  • Coreference and Anaphora Resolution
  • Dependency Parsing
  • Constituent Parsing
  • Semantic Role Labeling
  • …
NLP API

• Linguistic complexity as a barrier
  • Understanding of Parse Trees and Potential Use in Applications

• API as a Translational Service
  • Mapping of Linguistic Information to Useful Services
  • Transformation of NLP Output

• Example:
  • Scope relation and syntactic trees
  • Part-of-Speech tags and morph-syntactic features
NLP Output Format

• Normalization and Interoperability via Output Standardization
• Other Standards (no real standards)
  • CONLL – text-based line to token format
  • Proprietary JSON and XML formats
  • Binary objects in Python
• Issues with other standards:
  • Lack of interoperability
  • Lack of features
  • Data size and processing complexity
JSON-NLP

• JSON:
  • Full support in most important programming languages
  • Human readable
  • Compact and efficient

• Extended normalized feature set:
  • Document level annotation: meta-info, tokens
  • Annotation of e.g. coreference types, semantic, pragmatic features
  • Translational layer: making implicit features explicit, providing features like voice, tempus, aspect
  • Annotation of discontinuities
  • Implicit, covert tokens (e.g. ellipsis, gapping, implicit arguments)
JSON-NLP

• Open and Free on GitHub (https://github.com/dcavar/JSON-NLP)
• Converters from major NLP pipelines and components to JSON-NLP
• Converters from JSON-NLP to other formats (e.g. CONLL), lossy conversion
• JSON Schema with Validation
• Translation of NLP output to extended annotations in JSON-NLP
• Enabling:
  • Middleware for NLP for abstraction
  • NLP output comparison
JSON-NLP

• Extended features
  • Encoding of time reference, duration of events, prosody, intonation, focus
  • Clause detection, identification of phrasal heads and compounds

• Unification
  • Symbolic and Probabilistic Algorithm
  • Merging of n-JSON-NLP files
  • Detection of mismatches in NLP-annotations

• Facilitates
  • Deeper comparison and evaluation of individual NLP components
  • Ensembles of NLP components or pipelines
NLP Ensemble

- HooSIER
- NLP-ensemble
NLP Infrastructure

• Python-based technologies
  • spaCy, Flair, Polyglot, Natural Language Toolkit (NLTK), Xrenner, ...

• Java-based technologies
  • OpenNLP, LingPipe, Stanford CoreNLP, Malt Parser, ...

• Hybrid technologies
  • E.g. C(++) Foma in Java with JNI, in Python

• Included models:
  • Word embeddings: word2vec, GloVe, Numberbatch, FastText, Flair, ELMo, BERT

• All available as: RESTful Microservices with JSON-NLP output
NLP Infrastructure

• Facilitating research
  • Evaluation and comparison of NLP components, models, embeddings
  • Ensembles of NLP components solving problems that cannot be solved end-to-end using Deep Learning alone
    • Example: Coreference and anaphora resolution with semantic relevance
      • Take the knife, cut the lime in two halves, and put it down.
      • Take the knife, cut the lime in two halves, and squeeze it.
  • Generating ambiguities to work around lack of interactive parallelism:
    • *John met Peter. He likes him a lot.*
    • *He could be John and him could be Peter or He could be Peter and him could be John or*
      …
  • Deep NLP for any kind of text or language processing
Semantic Processing

• Meaning and Compositionality as Formal Mapping from Syntax to Semantic Representation (Bresnan, LFG)

a. David yawned.

b. 

```
  IP  
    NP     I'
    |     |  
    N     VP
```

```
  PRED  'YAWN(SUBJ)'  SUBJ  [ PRED  'DAVID' ]
  yawn'(david'): [ ]
```

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Lexical entries with associated meaning constructors

<table>
<thead>
<tr>
<th>Name</th>
<th>Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>John</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>(↑ PRED) = ‘JOHN’</td>
</tr>
<tr>
<td></td>
<td>john : ↑σ</td>
</tr>
<tr>
<td>Mary</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>(↑ PRED) = ‘MARY’</td>
</tr>
<tr>
<td></td>
<td>mary : ↑σ</td>
</tr>
<tr>
<td>meets V</td>
<td>(↑ PRED) = ‘MEET’</td>
</tr>
<tr>
<td></td>
<td>(λy, x.\text{meet}(x, y) : (↑ OBJ)σ \rightarrow (↑ SUBJ)σ \rightarrow ↑σ)</td>
</tr>
<tr>
<td>often ADV</td>
<td>(↑ PRED) = ‘OFTEN’</td>
</tr>
<tr>
<td></td>
<td>(λP, x.\text{often}(P(x)) : ((↑ ADJ)σ \rightarrow ↑σ) \rightarrow (↑ ADJ \rightarrow ↑σ) \rightarrow (↑ ADJ \rightarrow ↑σ))</td>
</tr>
</tbody>
</table>

Instantiated meaning constructors

- \(john : gσ\)
- \(mary : hσ\)
- \(λy, x.\text{meet}(x, y) : hσ \rightarrow (gσ \rightarrow fσ)\)
- \(λP, x.\text{often}(P(x)) : (gσ \rightarrow fσ) \rightarrow (gσ \rightarrow fσ)\)

Leaning derivation

\[
\begin{align*}
\lambda y, x.\text{meet}(x, y) : h - \rightarrow (g - \rightarrow f) & \quad \text{mary} : h \\
\lambda x.\text{meet}(x, \text{mary}) : g - \rightarrow f & \\
\lambda P, x.\text{often}(P(x)) : (g - \rightarrow f) - \rightarrow (g - \rightarrow f) & \\
\lambda x.\text{often}(\text{meet}(x, \text{mary})) : g - \rightarrow f & \\
\text{often}(\text{meet}(\text{john, mary})) : f
\end{align*}
\]
Description Logic Approach

• Direct mapping of sentence and clause content to graph of concepts and relations
• Accumulating properties in concepts or nodes, and for relations or links:
  • Attribute-Value table
• OWL for semantic check and validity
Knowledge Graphs

• Concepts and Relations
  • Mostly unconstrained
  • Domain specific or free

• Attributes and Values
  • encoding properties, time reference, ...

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birth place</td>
<td>LA, CA</td>
</tr>
<tr>
<td>DOB</td>
<td>08/07/1933</td>
</tr>
<tr>
<td>gender</td>
<td>female</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>year</td>
<td>2009</td>
</tr>
</tbody>
</table>

Norwegian University of S&T

Indiana University

Nobel Prize

Elinor Ostrom

honored

workedAt

received
Semantic Relations

• Extraction of core semantic relations: predicate and arguments

• Example:
  • While travelling in Africa, John Smith, the CEO of Talora Inc. bought surprisingly a farm in Kenya.

    John Smith – buy – a farm
    PERS TRANS INDEF
    SUBJ PRED OBJ

• Required components
  • Deep NLP
Information Extraction

• Basic NLP: tokenization, lemmatization, Part-of-Speech tagging, split into sentences
• More advanced: Clause level segmentation
• Parsing: Dependency and Constituent Structure

• Problems:
  • Margin of Error
• Solution:
  • Parallelization and NLP ensembles
NLP Issues and IE

• Scope (missing in NLP technologies)
  • John bought a car.
  • Peter said that John bought a car.
  • It is not true that John bought a car.

• Ellipsis
  • John bought a car and Mary bought a car.
  • John bought a car and John drove to Canada.

• Gapping
  • John liked to read books and Mary liked to read newspapers.

• Implicit arguments:
  • John wants PRO to read a book.
  • Got it!
NLP Extensions

• Knowledge representations
  • WordNet
  • VerbNet
  • PropBank
  • FrameNet
  • Knowledge Graphs

• Predict required arguments

• Extract advanced properties of concepts, predicates, events from knowledge representations

• Integrated in HooSIER NLP Infrastructure
  • Wrapped in JSON-NLP
NLP Extensions

• Implicatures:
  • John to Peter: I bought the blue car.
    • John and Peter talked about cars earlier.
    • There should be a set with at least one more car the John could have bought, but did not, and
    • None of the cars in the set is blue.
  • Clues: Definiteness of NP via the, and specificity of NP

• Presuppositions:
  • John fed his cat this morning.

• Assumptions:
  • John owns/has a cat/pet.
  • John owned cat-food this morning.

• Clues: Possessive pronoun as modifier of Direct Object.
Semantic Mapping and Reasoning

• Type of Predicative Arguments: Typing
  • Named Entity Recognition
  • Closes possible Hypernym in a Taxonomy or Ontology of isA relations

• Identity of entity: Linking
  • Named Entity Recognition
  • Link to unique identifier of entity in some knowledge representation, Ontology, Wikipedia, Knowledge Graph

• Issues: Ambiguity
Linking Disambiguation

• Vector-based computation over text and graphs

• Context prediction:
  • Compute the prediction of the context words in text with entity for all link-candidates

• Similarity:
  • Vectorize the sub-net of all concepts in Knowledge Graph and compute the similarity to the text with entity

• Example
Pipeline

- Knowledge Graph Generation
NLP Infrastructure

• Knowledge Graphs as RESTful Microservices
  • YAGO integrated in Apache Jena with TDB, SPARQL interface, Lucene index
  • ConceptNet using remote API
  • Microsoft Concept Graph via interface to MongoDB
  • DBpedia using remote API, possible setup as for YAGO
  • SPARQL-based n-hop search and string-similarity search (multi-lingual)

• Generated Graphs
  • Neo4J using Cypher
  • Stardog using SPARQL
  • Open format based on abstract graph class
Other systems

• **FRED Graph Extraction**
  - [http://wit.istc.cnr.it/stlab-tools/fred/](http://wit.istc.cnr.it/stlab-tools/fred/)
  - [http://wit.istc.cnr.it/stlab-tools/fred/demo/](http://wit.istc.cnr.it/stlab-tools/fred/demo/)

• **FreeLing**
  - [http://nlp.lsi.upc.edu/freeling/demo/demo.php](http://nlp.lsi.upc.edu/freeling/demo/demo.php)

• **Limitations:**
  • NLP restricted
  • Graphs or Networks limited or restricted
Research Directions

• Encoding of Events and Event Types using graphs
• Link Prediction or computation of Paradigmatic relations
• Network representation of typed concepts
• Forensic Research: with implicatures and presuppositions
• News article comparison
• Abstract semantic search over typed and linked concepts and entities
• Information validation, knowledge mapping
• Etc.
Resources

• JSON-NLP and Wrappers on GitHub repo
• KG Linking Disambiguator
  • Graph storage and SPARQL interface: YAGO, ConceptNet, DBpedia, Microsoft Concept Graph
• NLP RESTful Microservice Modules (Java, Python, C(++)
  • JSON-NLP output conversion
  • RESTful wrappers for: Stanford CoreNLP, Apache OpenNLP, LingPipe, spaCy, Flair, Polyglot, NLTK, Xrenner, etc.

• Apache License 2.0
NLP Infrastructure

• Estimated Server Requirements without stress-test
  • WildFly 16 and Java 11
  • Python 3.x
  • GPU recommended
  • Disk space for data, models, DBs: min. 2 TB (possibly more with DBpedia)
  • RAM for daemons, services, runtime: min. 128 GB