Semantic Information Extraction and Generation of Dynamic Knowledge Graphs

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Agenda

• Goals
• Knowledge Graphs
• Information Extraction
• NLP now and then
• Issues
• HooSIER Knowledge Graph Extractor
• Demo
Goals

• Information Extraction:
  • Entities and Relations from text
    • Open domain and domain specific
  • Description of concepts, relations, detailed semantic properties using
    • Description Logic approach
    • Knowledge Graph approach
    • Linking and Typing of entities and relations

• Natural Language Processing:
  • Semantic and Pragmatic processing
    • Implicatures and Presuppositions
    • Reasoning and Common Sense
  • Linguistic Processing

• Scalable and High-Performance Big-Data NLP for Text 2 Data
Knowledge Graphs

• Assumption:
  • First mention of term in a Google Blog
    • Amid Singhal (2012), Introducing the Knowledge Graph: things, not strings
      https://www.blog.google/products/search/introducing-knowledge-graph-things-not

• Reality:
  • Use of Graphical Knowledge Representation is older
    • Description Logic
    • RDF, OIL and DAML to OWL
    • Applications
Knowledge Graphs back in 2000

- RDB-based SemNet
  - Prior to OWL
  - OIL, DAML were around
  - No GraphDB
  - No NLP technologies (Stanford CoreNLP, OpenNLP, spaCy, Polyglot, GATE, etc.)
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>Falmouth, KY</td>
</tr>
<tr>
<td>DOB</td>
<td>06/06/1944</td>
</tr>
<tr>
<td>gender</td>
<td>male</td>
</tr>
<tr>
<td>year</td>
<td>1993</td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
</tbody>
</table>

Phillip Sharp

George W. Bush

Studyed at University of Illinois at Urbana-Champaign

Received Nobel Prize

honor

studiedAt

received
Formal Semantics

- Meaning and Compositionality as Formal Mapping from Syntax to Semantic Representation

a. David yawned.

\[
\begin{align*}
\text{NP} & \quad \text{I}' \\
\text{N} & \quad \text{VP} \\
\text{David} & \quad \text{V} & \quad \text{yawned}
\end{align*}
\]

\[\phi \quad \text{PRED} \quad \text{‘YAWN(SUBJ)’} \quad \text{SUBJ} \quad \text{PRED} \quad \text{‘DAVID’} \quad \text{yawn’(david’)} : [ ] \]
Knowledge Graphs

• No computation or interpretation of logic equations
• Direct mapping of knowledge from text

• Description of Knowledge
  • Directed Graph: encoding concept, events, domain specific knowledge...
  • Attribute-Value encoded features like size and shape, but also event time references (start, end, duration), etc.

• Reasoning
• Prediction
• Machine Learning of concepts and concept properties
State-of-the-Art

• Information Extraction
  • Open IE
  • Language Agnostic IE
    • Entity detection
    • Entity-Relation extraction

• Knowledge Graphs and Knowledge Representations
  • Ontology learning
  • Entity and Relation Linking
OpenIE

• Unstructured natural language expressions to structured representations (Banko et al., 2007)
  • Structured representation:
    • Relational tuples of semantic relations: argument – predicate – argument
    • Relations are not a priori specified (not domain specific)
    • Extraction of all entities and relations
    • Domain agnostic entity and relation discovery

• Example:
  • Tim Cook, the CEO of Apple and a board member of Alphabet Inc., announced that he will no longer serve in any function for Apple Inc.
OpenIE

• Underlying goal:
  • Tim Cook, the CEO of Apple and board member of Alphabet Inc. (...)
    • Tim Cook – isA – CEO of Apple
    • Tim Cook – isA – board member of Alphabet Inc.
    • Not in the last relation ignored completely!

• Reality:
  • Tim Cook – CEO of – Apple
    • No relation to Alphabet Inc.
  • He – serve in – function for Apple Inc.
    • No anaphora resolution
    • No processing of Negation
OpenIE Issues

• Underlying NLP ranks between “acceptable” and “of limited use at best.”

• Entity recognition is broad
  • Coreference analysis not reliable

• Lack of Linking
  • Entities identified via Linking to concepts in Knowledge Graphs (e.g. YAGO, DBpedia)
NLP Technologies

• Back in 2000
  • Regular expressions and pattern matching
  • Template-based text generation
  • Finite State Dialog modeling
  • Knowledge Graphs (SemNets) on RDBs
  • Text2Speech
  
• Part-of-speech tagging
• Parsing
• Machine Translation

• Rule-based systems, probabilistic models, knowledge-based NLP
NLP Technologies

• 2019: Focus on limited model types and technologies:
  • Data driven and usage based modeling, ignoring knowledge, rules, universals
  • Dependency Parse Trees from treebanks
  • Treebank-derived Constituent Tree Parsers
  • Label/Tag-based Semantic Role Labeling
  • ...
  • Pipeline-architecture as such:
    • Isolated modules with very limited NLP-focus chained in an input-output pipeline
      • CoreNLP, spaCy, OpenNLP, LingPipe, GATE, NLTK, UIMA, ...

• No parallel architectures!
NLP Technologies

• State of the Art: (Sebastian Ruder’s overview)
  • Part-of-Speech Tagging:
    • Use: word-level part of speech annotation with a limited set of tags that encode some morphosyntactic features
    • **F1 score: 95% - 97%** based on WSJ portion of Penn Treebank, more than 100 treebanks for UD
    • Best performing: Deep Learning Approaches (alternatives not evaluated)
NLP Technologies

• State of the Art: (Sebastian Ruder’s overview)
  • Constituent Tree Parsing:
    • Use: phrasal structure; relations, hierarchies and ambiguities between phrases; semantic scope relation; ...
    • **F1 score:** 92% - 95% based on Penn Treebank
    • Best performing: Deep Learning Approaches (alternatives not evaluated)
  • Dependency Parsing:
    • Use: dependency relations between elements in the sentence; simplified annotation of functional relations: Subject, Object, Modifier, ...
    • **F1 score** on labels and relations: 91% - 94% based on Stanford Dependency conversion of the Penn Treebank
    • Best performing: Deep Learning Approaches (alternatives not evaluated)
NLP Technologies

• State of the Art: (Sebastian Ruder’s overview)
  • Named Entity Recognition:
    • Use: entity labeling – person, institution, location, time, currency, ...
    • **F1 score: 90% - 92%** based on Reuters RCV1 corpus with **four** NE-types (PER, LOC, ORG, MISC) using BIO notation
    • Best performing: Deep Learning Approaches (alternatives not evaluated)
  • Semantic Role Labeling:
    • Use: Label predicate argument structure (Who gave what to who): Predicate, Subject, Object, entity and relation extraction
    • **F1 score: 81% - 84%** based on OntoNotes benchmark of the Penn Treebank
    • Best performing: Deep Learning Approaches (alternatives not evaluated)
NLP Technologies

• F1 score margins and error rates:
  • Basic token-level classification: error of approx. 4%
  • Word-level annotation, syntactic parsing: 10%
  • Semantic-level annotation: 30%

• What has changed since 2000?
  • Cross-linguistic Coverage
  • Speed

• Situation check:
  • Mono-culture of training/test-datasets for data driven ML/DL-methods
  • Limitation to weak linguistic models (e.g. Constituent Trees, NE-classes, Semantic roles), annotation standards (e.g. Dependencies)
NLP Technologies

• Situation check:
  • Limited use of NLP-pipelines: PoS-tagging, Lemmatization
    • CoreNLP: Constituent Parser; Dependency Parser; Coreference Analysis; ...
    • spaCy: Dependency Parser
    • NLTK: WordNet
  • Lack of APIs that interface to linguistic output data structures
    • NLP developers lack understanding of the linguistic annotations generated by pipelines or tools
NLP Example

• Stanford Open IE (paper and website)

• Lack of intuition of dependency relations
  • Modification of ROOT (took) by “born in a small town” is counterintuitive

• Lack of:
  • Clause level hierarchical relation analysis (subordinate clauses and scope)
  • Tempus, Mood, ... annotation
  • Pragmatic and semantic properties (and relevant linguistic features)
Issues

• Transparency
  • Lack of understanding of linguistic annotations
  • No abstraction layer and API
  • Blackbox models without introspection
    • Deep Learning

• Data-driven Systems
  • Knowledge driven engineering impossible
    • Lacking grammar engineering interface
  • Large data sets necessary
  • Monoculture of data sets

• Error rate in a pipeline
Issues

• NLP Technologies and Language Resources
  • More than 7,100 estimated languages
  • 300 estimated to be written
  • 1% is well resourced (data and technology wise)

• Language Resources
  • Mono-culture
    • Limited data set or corpora as “standard”
    • Evolutionary model of technologies that are tuned to excel on the “standard”
  • Half-life of resources
    • Corpora use value
  • Annotation
    • Errors
    • Theoretically motivated
NLP Example

• Scope between clauses:
  • Reuters reported [ that [ Google bought Apple ] ]
  • Reuters did not report [ that [ Google bought Apple ] ]
  • Reuters did not deny [ that [ Google bought Apple ] ]

• Tense:
  • Tim Cook bought Google.
  • Tim Cook will buy Google one day.
NLP Technologies

• Applied to real text:
  • Sentence length over 10 to 15 tokens breaks common probabilistic or NN parsers (Dependency parsers, in particular)

• Problematic domains, for example:
  • SEC, Financial, or Business Reports
  • Case-law and legal documents
  • Medical text (patient reports, documentations)

• Current free and open NLP-pipelines are of limited use.

• Are they of any use for serious NLP-based technologies?
State of the Art

• Δ between 2000 – 2018
  • ASR improvements
  • Knowledge Graphs, Ontologies
  • Integration
    • Data sources
    • Interfaces, multi-modal interaction
    • Device architecture

• Is there any significant progress in ___?
  • Dialog management
  • NLP at the utterance and discourse level
  • Semantics and Pragmatics
NLP Ensemble

- HooSIER
Knowledge Representations

• Practical use cases:
  • Dialogs
    • Topic and concepts in focus (conversational example)
  • Common Sense
    • Anaphora resolution using semantic properties
      • “Take the knife, cut the lime into two halves, and squeeze it.” (p.c. Matthias Scheutz)
  • ...

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Pipeline

• Knowledge Graph Generation
Concept Relation Mapping

• Input:
  • Tim Cook sold Apple.
  • He bought Google.
  • He likes apples.

• 1st level typing using:
  • Named Entity Recognition
Linking

• Identification of the unique entity in a large Knowledge Graph
  • E.g. YAGO, DBpedia, ConceptNet, ...

• Our approach:
  • Disambiguation using word and graph embeddings

• Language Independent
  • Language agnostic entity extraction
Typing

• Identification of the closest Hypernym
  • WordNet lookup
  • Microsoft Concept Graph
  • Using Linking results
Word and Graph Embeddings

• Distributional Semantics approach
  • Words are represented by vectors of a fixed length
  • Vectors are prediction models (e.g. Word2Vec):
    • Maximize the predicted likelihood of the words in their context

• Graph embeddings:
  • Semantic and conceptual: concepts and relations in graph context
  • Topological: shape of a conceptual sub-graph
Knowledge Representations

• General World Knowledge
  • From static to dynamic, with inferencing, reasoning

• Domain Specific Knowledge
  • Medical, Financial, Business, Legal, etc.

• Discourse specific Knowledge
  • Simple dialog memory (concepts and their linguistic features, relevant for anaphora resolution, coreference analysis)
  • Knowledge Graph or Ontology of semantic concept space in encapsulated discourse
Speech Acts, Implicatures, Presuppositions

• Deep Linguistic Processing:
  • A to B: “I bought the blue car.”
  • Implicature:
    • A and B talked about the event earlier.
    • There is a set of cars, at least 2 that was in the range of A’s action.
    • None of the other cars in the set is blue.
  • Linguistic indicators:
    • Definiteness via “the”
    • Specificity of the Noun Phrase
Speech Acts, Implicatures, Presuppositions

• Deep Linguistic Processing:
  • “Peter fed his cat.”
  • Presupposition:
    • Peter owns a cat.
    • Peter owns cat food.
    • ...
  • Linguistic indicators:
    • Possessive

• Types:
  • Universal linguistic properties (see Grice Maxims, Relevance Theory)
  • Language specific properties (dependency to cultural and sociological aspects)
  • Domain specific: e.g. “to be like milk”
HooSIER IE Approach

- Advanced NLP technologies
  - Deep linguistic processing
    - Tense, Voice, Mood detection
    - Hierarchical relations of elements in the clause, clause detection, scope reconstruction
  - Identification of phrasal heads of arguments, compound structure, and modifiers
  - Normalization of words and phrases
  - Extraction of core semantic relations
  - Extraction of modifiers and meta-information
  - Mapping of relations into complex Graphs (towards Description Logic representations)
  - Linking of entities and relations to Knowledge Graphs and Ontologies
HooSIER IE Approach

• Deep Linguistics
  • Tense, Voice, Mood detection
    • Tim Cook left Apple.
    • Tim Cook will leave Apple.
    • Apple was bought by Google.
  • Scope relations
    • Tim Cook did not leave Apple.
    • Tim Cook left, not Apple, but the board of Alphabet Inc.
  • Clause detection and scope
    • I wish [ Tim Cook left Apple ]
    • I did not claim [ that Tim Cook left Apple ]
HooSIER IE Approach

• Identification of phrasal heads of arguments, compound structure, and modifiers
  • The former president of the United States, Barak Obama...
  • Head: Obama
  • Compound component: Barak
  • Modification or Specification: “the former president of the United States”

• Mapping into complex Graphs
  • Concepts or entities
  • Relations between entities
  • Attribute-value pairs associated with entities and relations
HooSIER IE Approach

• Normalization of words and phrases
  • Lemmatization
    • chatting, went, hired → chat, go, hire
  • Reduction to core properties (semantic normalization)
    • X was chatting with Y → X – talk – Y
• Multi-lingual normalization:
  • Machine translation prior to extraction of entity-relation tuples
  • Linking of entities and relations to a language neutral representation
    • More later (using YAGO, MS Concept Graph, VerbNet, PropBank etc.)
HooSIER IE Approach

• Extraction of core semantic relations
  • Predicate argument structures:
    • Tim Cook left Apple.
      • Predicate: leave
      • Argument 1 (subject, agent): Tim Cook
      • Argument 2 (object, patient or beneficiary): Apple
    • Tim Cook, who lives in San Francisco, left yesterday suddenly Apple without further explanation.

• Extraction of modifiers
  • Tim Cook – livesIn – SF

• Extraction of time references:
  • One day before document production time
HooSIER IE Approach

• Entities and relations as Graphs
  • Entities
    • String representation
    • Label = type
    • All other information:
      • Attribute-Value tuples associated with entity
  • Relations
    • String representation
    • Label – predicate type (e.g. PropBank ID)
    • All other information:
      • Attribute-Value tuples associated with entity
    • Relations have directionality, domain, and range
    • Domain and Range can be entities (and relations in some Graph DBs)
HooSIER IE Approach

• Linking of entities and relations to Knowledge Graphs and Ontologies
  • Large Knowledge Graphs as Link targets
    • Language independent URI/specification
    • Detailed concept properties
    • Multi-lingual representations or realizations of concept names
    • Example: DBpedia, YAGO, MS Concept Graph, Google KG, etc.
  • Ontologies (domain specific models, taxonomies)
    • Core taxonomy relations: isA hierarchy essential for efficient reasoning
    • Semantic type and consistency checking with assertions into graphs
    • Reasoning
  • Identification of the most specific hypernym for any entity/concept
    • THING – … – MAMMAL – DOG – POODLE
    • THING – … – FRUIT – APPLE
    • apple isA fruit
    • poodle isA dog
HooSIER IE Approach

• Typing of entities:
  • NLP-based pre-typing
    • Named Entity Recognition (NER) types: PERSON, ORGANIZATION, PLACE, DATE, TIME, CURRENCY, TITLE, ... (5 to 7 core types of onomastic entities)
  • Knowledge Graph based typing
    • YAGO more than 17,000 types
  • Domain specific NER or Taxonomy-based typing
    • Our own model of types and potentially sub- or co-types
    • Develop own NER components
      • (Weighted) Finite State Transducers for (multi-) word analysis
      • Trained NER models using own corpora and data-sets
HooSIER IE Approach

• Linking Disambiguation
  • Multiple types (hypernyms) for an entity in a given KG
  • NER types reduce the ambiguity
    • NLP components introduce error with NER
  • Use word embeddings and vector based models for disambiguation
    • Using Google, FastText, or GloVe vectors
    • Given vector for the target entity word (or multi-word expression) \( X \)
      • Tim Cook like apples. \( \rightarrow \) \( X = \) apples/apple
    • For every hypernym candidate (and its hypernym, synonyms, and hyponyms) \( Y \) compute the probability of the observed context
    • Pick the one hypernym (and its semantic context) that best predicts the context of \( X \)
HooSIER IE Approach

• Expand Graph Representations (multiple graphs or linked sub-graphs)
  • Propositions represented as multiple entity-relation graphs
    • True propositions
    • Projected future related propositions
    • Assumed false propositions
  • Graph representation of Implicatures and Presuppositions
  • Entity identification and typing
    • Detailed semantic properties
    • Most specific type from isA taxonomy
    • Induction of types from Edge2Vec, predicate argument structures (e.g. VerbNet, PropBank), Graph similarity etc.
      • Syntagmatic vs. Paradigmatic relations
HooSIER IE Approach

• Applications:
  • Event identification and extraction (types: political event, pandemic outbreaks, civil unrest, security related events, etc.)
    • Agents, locations, time, timeline, causalities, victims, etc.
  • Graph-similarity as document similarity
  • Summarization using graph-based text generation
  • Search and query
    • Graph-search, e.g. query to graph and similarity search, graph navigation
  • Ontology or Knowledge Graph generation
    • Forensic, investigative
    • AI or chatbot related
Technologies

• Environment
  • Microservices using isolated RESTful modules
  • Mainly Java, Scala, Apache Spark
    • Wrapping C(++) , Python
  
• Databases
  • MongoDB, PostgreSQL hosting Knowledge Graphs (DBpedia, YAGO, MS Concept Graph)
  • Neo4J (Cypher), Stardog (SPARQL & OWL)
  • Docker Containers
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