Chatbots and NLP

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Agenda

• Chatbots then
• and now
• NLP and Chatbots
• Issues
• Modest Prediction of Sensible R&D Directions
From Verbmobil to Chatbots

• Speech2Speech MT
  • Dialog Models
  • ASR
  • Machine Translation
  • NLP

• Chatbots and Avatars
  • Text input
  • Text to speech output
  • Virtual communication partner with lip-synchronization
Avatar

• Web-based
• Terminals in stores

Valerie (Charamel GmbH)
Knowledge Graphs

- RDB-based SemNet
- (before OWL, etc.)
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
NLP Technologies

• Focus on limited models and technologies:
  • Dependency Parse Trees
  • 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, NLTK, UIMA, ...
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%

• Not much has changed since 2000!

• 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)
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 most 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 Chatbot 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
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
Directions

• Speech
  • Prosodie – Semantics / Pragmatics interface

• Semantics and Pragmatics
  • Entailment
  • Quantifiers
  • Scope
  • Implicatures
  • Presuppositions
Prosodie – Semantics / Pragmatics

• Suprasegmental speech properties
  • Intonation Contour
    • ASR output: what did you buy
    • Speech properties:
      • interrogative or rhetorical, echo question
  • Pitch Accent (in specific languages)
    • Simple accent detection:
      • White board vs. whiteboard
      • HOtel vs. hoTEL
  • Focus Stress:
    • Contrastive Stress: I bought THAT CAR. I BOUGHT that car.
    • Verum Focus: I DID buy that car.
Prosodie – Semantics / Pragmatics

• Data sources
  • Limited corpora for a few languages
    • Richer documentation without audio data component
  • Creation of corpora with relevant speech properties and linguistic annotation
    (mapping of content to some semantic and pragmatic level)

• Efficient speech signal level processing:
  • librosa
  • OpenSMILE
  • Etc.
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”
NLP and Future Chatbots

• Technology trends might include:
  • Speech signal properties that relate to:
    • Sentiment, Emotions
    • Prosodie and Semantics/Pragmatics Interface
    • Properties of speakers, general and temporary
  • Pragmatics and Semantics
    • Implicatures and Presuppositions, Natural Logic, Entailment
    • Irony, Humor, Sarcasm, Deception...
  • Knowledge Representation
    • Dynamic, Cascaded or Interconnected KRs
  • Multi-Modal systems (speech/language, image, gesture, mimic)
  • NLP
    • Deep Learning and hybrid systems, knowledge-based engineering and data-driven (M|D)L