NLP Applications using Deep Learning

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Feb 28, 2018

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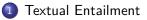
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Agenda for the day

- Entailment
- Question Answering
- Named Entity Recognition

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Overview







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What is Deep Understanding?

Students develop deep understanding when they grasp the relatively complex relationships between the central concepts of a topic or discipline. Instead of being able to recite only fragmented pieces of information, they understand the topic in a relatively systematic, integrated or holistic way. As a result of their deep understanding, they can produce new knowledge by discovering relationships, solving problems, constructing explanations and drawing conclusions. – Dept. of Education, Queensland

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That is, Deep Understanding involves Knowledge, Reasoning, Learning, and Action

Textual Entailment

- An example of a **positive TE** (text entails hypothesis) is:
 - text: If you help the needy, God will reward you.
 - *hypothesis*: Giving money to a poor man has good consequences.
- An example of a **negative TE** (text contradicts hypothesis) is:
 - text: If you help the needy, God will reward you.
 - hypothesis: Giving money to a poor man has no consequences.
- An example of a non-TE (text does not entail nor contradict) is:
 - text: If you help the needy, God will reward you.
 - *hypothesis*: Giving money to a poor man will make you a better person.

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Textual Entailment is required for many applications

- Question Answering
- Information Extraction
- Creation of Knowledge Bases

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Textual Entailment Approaches

• Build a classifier that is input [(T, H), L] sentence pairs and labels

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- Construct a seq2seq model to convert T to ${\cal H}$

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- Construct Knowledge Bases to capture semantic information (manual, not scalable)

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- Construct a seq2seq model to convert T to H
- Construct Knowledge Bases to capture semantic information (manual, not scalable)
- Try to learn a latent knowledge representation

- Parse each sentence into a parse tree
- Represent each sentence by a *composite* representation similar to Recursive Tree Model
- Use a Restricted Boltzmann Machine to jointly learn a latent representation on top of these (T,H) representations
- Given a sentence pair, look at the reconstruction error and classify if they are entailed or not

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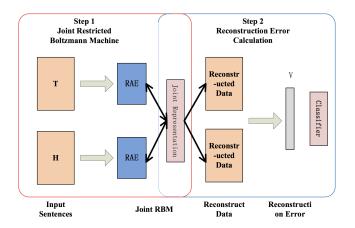


Figure: Image Source: Lyu, ICTAI 2015

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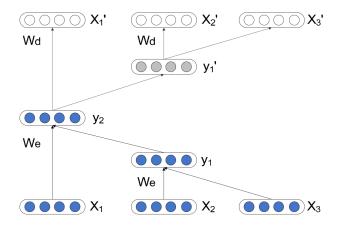


Figure: Image Source: Lyu, ICTAI 2015

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A Symmetrical, Bipartite, Bidirectional Graph with Shared Weights

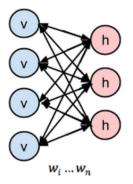


Figure: Image Source: DeepLearning4J

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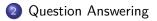
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Overview





3 Named Entity Recognition

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IBM Watson wins Jeopardy

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Application of QA Systems

- Dialog Systems
- Chatbots
- Intelligent Assistants

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- **Open** Includes General knowledge in addition to questions, whose answers are in the text
- **Closed** The answers can be found completely using the Context provided in the text and the question

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Conventional NLP Approaches to QA

- Parsing
- Part of speech tagging
- Named Entity extraction
- Encode rules. E.g. Jeopardy category, Daily Double

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Deep Learning approaches to closed QA

Closed QA task

- I: Jane went to the hallway.
- I: Mary walked to the bathroom.
- I: Sandra went to the garden.
- I: Daniel went back to the garden.
- I: Sandra took the milk there.
- Q: Where is the milk?
- A: garden
- I: It started boring, but then it got interesting.
- Q: What's the sentiment?
- A: positive

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SQuAD: Stanford Question Answering Dataset

The Normans (Norman: Nourmands: French: Normands; Latin: Normandiy were the people who in the **10th and 11th centuries** gave their name to Normandy, a region in France. They were descended from Norse (Norman" comes from "Norseman") raiders and pirates from Denmark, Iceland and Norway who, under their leader Rollo, agreed to swear fealty to King Charles III of West Francia. Through generations of assimilation and mixing with the native Frankish and Roman-Gaulish populations, their descendants would gradually merge with the Carolingian-based cultures of West Francia. The distinct cultural and ethnic identity of the Normans emerged initially in the first half of the 10th century, and it continued to evolve over the succeeding centuries. In what country is Normandy located? Ground Truth Answers: France France France France

When were the Normans in Normandy?

Ground Truth Answers: 10th and 11th centuries in the 10th and 11th centuries 10th and 11th centuries 10th and 11th centuries

From which countries did the Norse originate?

Ground Truth Answers: Denmark, Iceland and Norway Denmark, Iceland and Norway Denmark, Iceland and Norway Denmark, Iceland and Norway

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Figure: Source - Rajpurkar 2016

GRU for QA

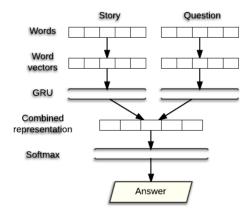


Figure: Source - Stroh, Mathur cs224d Report

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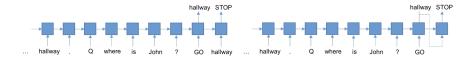


Figure: Source - Stroh, Mathur cs224d Report

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Dynamic Memory Networks for QA

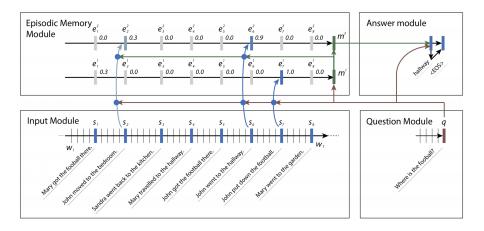


Figure: Source - Kumar et. al 2016

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Match-LSTM for QA

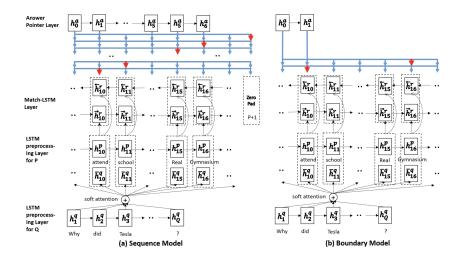


Figure: Source - Wang, Jiang ICLR 2017

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Match-LSTM for QA

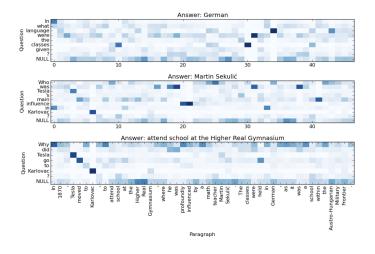


Figure: Source - Wang, Jiang ICLR 2017

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Overview







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- Names (e.g. John Smith, New York Times)
- Places (e.g. Boston, Seattle, Sarajevo)
- Titles (e.g. Dr., PhD, Justice)
- Dates (e.g. Sept 11th, Veterans Day, Memorial Day)

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- Hand-crafted features
- Domain-specific knowledge
- Gazetteers for each domain, language etc
- Capitalization patterns

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biLSTM+CRF for NER

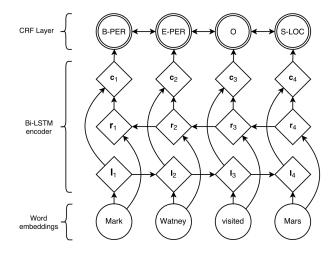


Figure: Source - Lample et al, 2016

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- Start with GloVe / word2vec embeddings
- Capture both left and right contexts for each word using LSTMs
- Impose adjacency constraints using CRF that learns a transition matrix between adjacent states

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