CSCE 771: Computer Processing of Natural Language

Lecture 13: Representation (Learning, Formalized), Quiz 2

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

29TH SEPTEMBER, 2022

Carolinian Creed: "I will practice personal and academic integrity."

Acknowledgement: Used materials by Jurafsky and Martin, and online as cited

Organization of Lecture 13

- Opening Segment
  - Recent Classes
  - Project Review
- Main Lecture
- Concluding Segment
  - About Next Lecture – Lecture 14

Main Section
- Complete discussion: Word2Vec, Glove
- Formalized representation
- Quiz 2

Recent Classes

Sep 29 (Th)	Representation: Embeddings, Language Models, QUIZ
Oct 4 (Tu)	Review: Reasoning and Representation for NLP: Ontology, Knowledge Graph, PROJ REVIEW
Oct 6 (Th)	Entity extraction
Oct 11 (Tu)	Guest Lecture – Dr. Amitava Das: Using lang models to solve NLP tasks
Oct 13 (Th)	
Oct 18 (Tu)	Entity linking, Events extraction, spatio-temporal analysis
Oct 20 (Th)	Topic Analysis, QUIZ
Oct 25 (Tu)	NLP Task: Sentiment; Related papers presentation; PROJ REVIEW

Review of Lecture 12 - Invited Talk

- Historical perspective on representation, Zipf and Heap laws
- Word2Vec
  - Derivation from first principles
- Material: https://prezi.com/view/amx5hBo8UhMOn1rPyJ02/

Project Update Presentations

- W1 - Sep 26
- W2 – Oct 3
  - **Review presentation for class: 3 min each – Oct 4, 2022**
- W3 – Oct 10
- W4 – Oct 17
- W5 – Oct 24
  - **Review presentation for class: 3 min each – Oct 27, 2022**
- W6 – Oct 31
- W7 – Nov 7
- W8 – Nov 14
- W9 – Nov 21

Milestones

- Penalty: **not** ready by Sep 15, 2022 **[-20%]**
- Project report **not** ready by Nov 10, 2022 **[-20%]**
- Project presentations **not** ready by Nov 15, 2022 **[-10%]**

Format for Review Presentation Slide (2 mins)

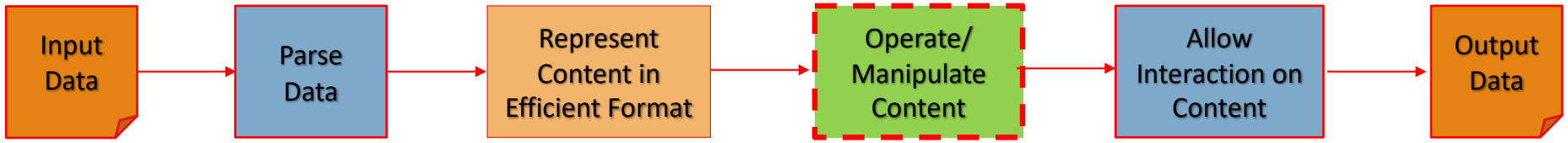
- Project Name
- Problem
- Approach
- Status (based on your project plan)
- Comment:
  - Challenges faced
  - Need help

Test Case – *how will your program be run*

- Input
- Output
- Assumptions

Main Lecture

Language Model to Manipulate Content



Where are We

- Learning representation
  - Approach 1: count-based
    - Creating word vectors in which each dimension corresponds to the frequency the word type occurred in some context.
    - Example: TF-IDF
  - Approach 2: learning-based
    - learn contexts from documents. Vector size is given as input
    - Examples: Word2Vec, Glove

Word2Vec

- Learn representation for words based on context
  - *Mikolov, Tomas; et al. (2013). "Efficient Estimation of Word Representations in Vector Space". arXiv:1301.3781 [cs.CL]. Mikolov, Tomas (2013). "Distributed representations of words and phrases and their compositionality". Advances in Neural Information Processing Systems. arXiv:1310.4546.*
  - Word-based, prediction focus
- Setup
  - Skip-gram
  - Bag-of-words

Sample Code: Word2Vec

Notebook:
https://github.com/biplav-s/course-nl-f22/blob/main/sample-code/l12-llm/Gensim-Word2Vec.ipynb

Glove

- Learning representation for words based on context
  - Word-based, count
  - https://nlp.stanford.edu/projects/glove/, Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation. [pdf] [bib]

Sample Code: Glove

Notebook:
https://github.com/biplav-s/course-nl-f22/blob/main/sample-code/l13-llm-quiz/Glove%20usage.ipynb

Evaluation – Language Model

- **Intrinsic evaluation**: measure the quality of a model independent of any application
- E**xtrinsic evaluation**: situate model in an application and evaluate the whole application for improvement. Also called in-vivo evaluation

Perplexity

- Intrinsic evaluation
- **Definition**: perplexity of a language model on a test set is the inverse probability of the test set, normalized by the number of words

$$\begin{aligned} \text{PP}(W) &= P(w_1 w_2 \ldots w_N)^{-\frac{1}{N}} \\ &= \sqrt[N]{\frac{1}{P(w_1 w_2 \ldots w_N)}} \end{aligned}$$

Of bi-grams

$$\text{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i | w_{i-1})}}$$

Example: digits – 0 ..9, assuming equal probab. of 0.1

$$\begin{aligned} \text{PP}(W) &= P(w_1 w_2 \ldots w_N)^{-\frac{1}{N}} \\ &= \left(\frac{1}{10}^{N}\right)^{-\frac{1}{N}} \\ &= \frac{1}{10}^{-1} \\ &= 10 \end{aligned}$$

From Jurafsky & Martin

Perplexity

- Suppose
  - P('X') = 0.25
  - P('Y') = 0.5
  - P('Z') = 0.25
- Perplexity
  - ('XXX') = (0.25 x 0.25 x 0.25) ^ (-1/3) = 3.94
  - Perplexity ('XYX') = (0.25 x 0.5 x 0.25) ^ (-1/3) =
- Lower the number, the better is the model

Transformer

- RNN/ LSTM with
  - Attention
    - attention layer can access all previous states and weighs them according to some learned measure of relevancy to the current token, providing sharper information about far-away relevant tokens
    - **Query** vector, **Key** vector, and **Value** vectors introduced during encoding and decoding phase
  - Parallelization of learning
  - See Dr. Amitava Das's slide for Attention/ BERT video

Source and details: https://en.wikipedia.org/wiki/Transformer_(machine_learning_model), http://jalammar.github.io/illustrated-transformer/

BERT - **B**idirectional **E**ncoder **R**epresentations from **T**ransformers

Learns with two tasks

- Predicting missing words in sentences
  - mask out 15% of the words in the input, predict the masked words.
- Given two sentences A and B, is B the actual next sentence that comes after A, or just a random sentence from the corpus?

(12-layer to 24-layer Transformer) on (Wikipedia + BookCorpus)

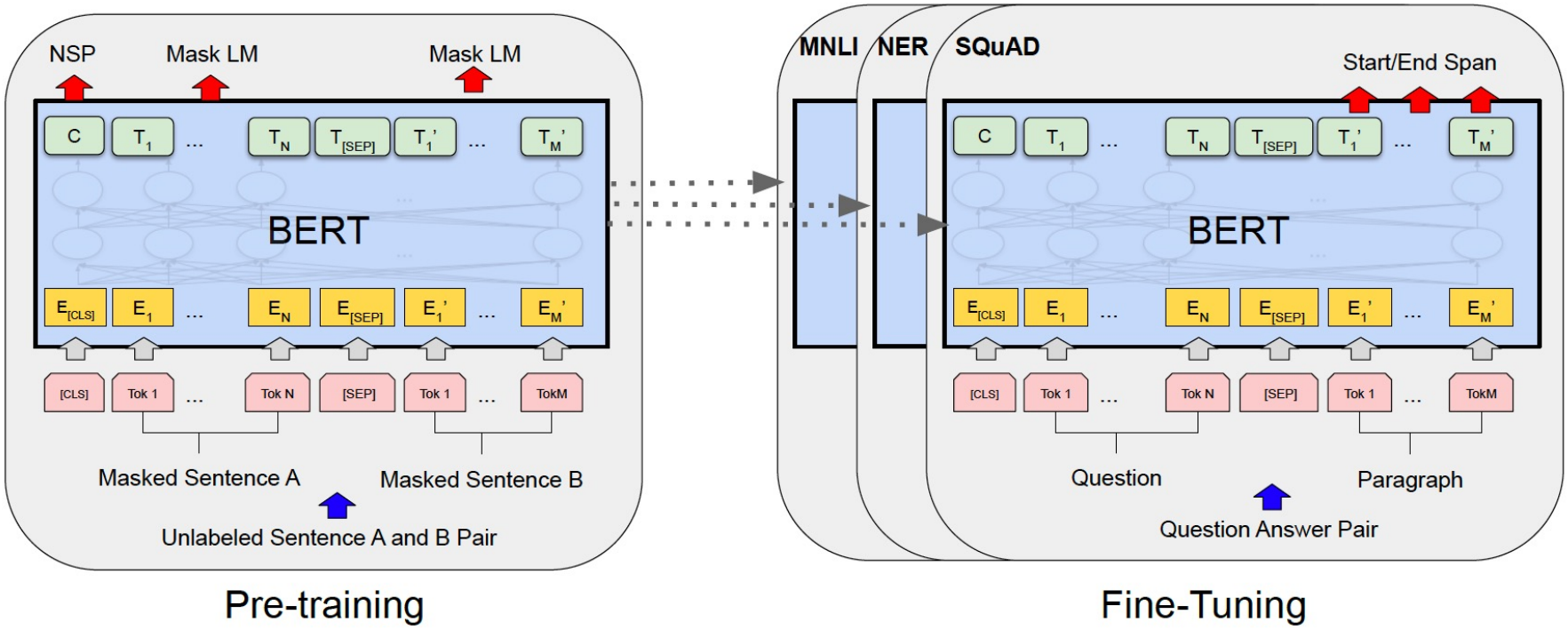
Input: the man went to the [MASK1] . he bought a [MASK2] of milk.
Labels: [MASK1] = store; [MASK2] = gallon

Sentence A: the man went to the store .
Sentence B: he bought a gallon of milk .
Label: IsNextSentence

Sentence A: the man went to the store .
Sentence B: penguins are flightless .
Label: NotNextSentence

Credit and details: https://github.com/google-research/bert

BERT: Before and During Usage



Credit and details: **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**
Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova, 2018

Using BERT in Practice – Huggingface Libraries

- Transformers – https://github.com/huggingface/transformers
- APIs to download and use pre-trained models, fine-tune them on own datasets and tasks
  - Code Sample

```
# Loading BERT
model_class, tokenizer_class, pretrained_weights =  (ppb.DistilBertModel, ppb.DistilBertTokenizer, 'distilbert-base-uncased')

# Load pretrained model/tokenizer
tokenizer = tokenizer_class.from_pretrained(pretrained_weights)
model = model_class.from_pretrained(pretrained_weights)
```

- Provides pretrained models in 100+ languages.
- Use with popular deep learning libraries, PyTorch and TensorFlow,
  - Possible to train / fine-tune models with one, and load it for inference with another

Using BERT in Practice – Huggingface Libraries

- DistilBERT
  - Details: https://medium.com/huggingface/distilbert-8cf3380435b5
  - Teacher-student learning, also called model distillation
    - Teacher: bert-base-uncased
    - Student: dstilBERT - BERT without *the token-type embeddings and the pooler* , and half the layers
  - **"DistilBERT,** has **about half** the total number of parameters of BERT base and retains 95% of BERT's performances on the language understanding benchmark GLUE"

- Sample code of usage for sentiment classification: https://github.com/biplav-s/course-nl/blob/master/l12-langmodel/UsingLanguageModel.ipynb

Example Pre-Trained Models

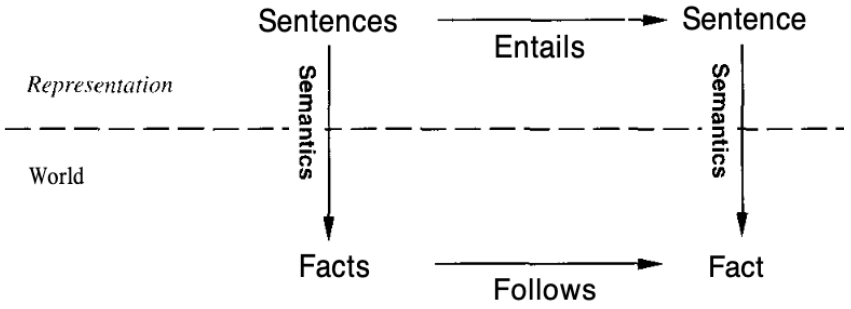
1. ALBERT (from Google Research and the Toyota Technological Institute at Chicago) released with the paper ALBERT: A Lite BERT for Self-supervised Learning of Language Representations, by Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, Radu Soricut.
2. BART (from Facebook) released with the paper BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension by Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov and Luke Zettlemoyer.
3. BERT (from Google) released with the paper BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding by Jacob Devlin, Ming-Wei Chang, Kenton Lee and Kristina Toutanova.
4. BERT For Sequence Generation (from Google) released with the paper Leveraging Pre-trained Checkpoints for Sequence Generation Tasks by Sascha Rothe, Shashi Narayan, Aliaksei Severyn.
5. CamemBERT (from Inria/Facebook/Sorbonne) released with the paper CamemBERT: a Tasty French Language Model by Louis Martin*, Benjamin Muller*, Pedro Javier Ortiz Suárez*, Yoann Dupont, Laurent Romary, Éric Villemonte de la Clergerie, Djamé Seddah and Benoît Sagot.
6. CTRL (from Salesforce) released with the paper CTRL: A Conditional Transformer Language Model for Controllable Generation by Nitish Shirish Keskar*, Bryan McCann*, Lav R. Varshney, Caiming Xiong and Richard Socher.
7. DeBERTa (from Microsoft Research) released with the paper DeBERTa: Decoding-enhanced BERT with Disentangled Attention by Pengcheng He, Xiaodong Liu, Jianfeng Gao, Weizhu Chen.
8. DialoGPT (from Microsoft Research) released with the paper DialoGPT: Large-Scale Generative Pre-training for Conversational Response Generation by Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, Bill Dolan.
9. DistilBERT (from HuggingFace), released together with the paper DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter by Victor Sanh, Lysandre Debut and Thomas Wolf. The same method has been applied to compress GPT2 into DistilGPT2, RoBERTa into DistilRoBERTa, Multilingual BERT into DistilmBERT and a German version of DistilBERT.
10. DPR (from Facebook) released with the paper Dense Passage Retrieval for Open-Domain Question Answering by Vladimir Karpukhin, Barlas Oğuz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih.
11. ELECTRA (from Google Research/Stanford University) released with the paper ELECTRA: Pre-training text encoders as discriminators rather than generators by Kevin Clark, Minh-Thang Luong, Quoc V. Le, Christopher D. Manning.
12. FlauBERT (from CNRS) released with the paper FlauBERT: Unsupervised Language Model Pre-training for French by Hang Le, Loïc Vial, Jibril Frej, Vincent Segonne, Maximin Coavoux, Benjamin Lecouteux, Alexandre Allauzen, Benoît Crabbé, Laurent Besacier, Didier Schwab.
13. Funnel Transformer (from CMU/Google Brain) released with the paper Funnel-Transformer: Filtering out Sequential Redundancy for Efficient Language Processing by Zihang Dai, Guokun Lai, Yiming Yang, Quoc V. Le.
14. GPT (from OpenAI) released with the paper Improving Language Understanding by Generative Pre-Training by Alec Radford, Karthik Narasimhan, Tim Salimans and Ilya Sutskever.
15. GPT-2 (from OpenAI) released with the paper Language Models are Unsupervised Multitask Learners by Alec Radford*, Jeffrey Wu*, Rewon Child, David Luan, Dario Amodei** and Ilya Sutskever**.
16. LayoutLM (from Microsoft Research Asia) released with the paper LayoutLM: Pre-training of Text and Layout for Document Image Understanding by Yiheng Xu, Minghao Li, Lei Cui, Shaohan Huang, Furu Wei, Ming Zhou.
17. Longformer (from AllenAI) released with the paper Longformer: The Long-Document Transformer by Iz Beltagy, Matthew E. Peters, Arman Cohan.
18. LXMERT (from UNC Chapel Hill) released with the paper LXMERT: Learning Cross-Modality Encoder Representations from Transformers for Open-Domain Question Answering by Hao Tan and Mohit Bansal.
19. MarianMT Machine translation models trained using OPUS data by Jörg Tiedemann. The Marian Framework is being developed by the Microsoft Translator Team.
20. MBart (from Facebook) released with the paper Multilingual Denoising Pre-training for Neural Machine Translation by Yinhan Liu, Jiatao Gu, Naman Goyal, Xian Li, Sergey Edunov, Marjan Ghazvininejad, Mike Lewis, Luke Zettlemoyer.
21. MMBT (from Facebook), released together with the paper a Supervised Multimodal Bitransformers for Classifying Images and Text by Douwe Kiela, Suvrat Bhooshan, Hamed Firooz, Davide Testuggine.
22. Pegasus (from Google) released with the paper PEGASUS: Pre-training with Extracted Gap-sentences for Abstractive Summarization> by Jingqing Zhang, Yao Zhao, Mohammad Saleh and Peter J. Liu.
23. Reformer (from Google Research) released with the paper Reformer: The Efficient Transformer by Nikita Kitaev, Łukasz Kaiser, Anselm Levskaya.
24. RoBERTa (from Facebook), released together with the paper a Robustly Optimized BERT Pretraining Approach by Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, Veselin Stoyanov. ultilingual BERT into DistilmBERT and a German version of DistilBERT.
25. SqueezeBert released with the paper SqueezeBERT: What can computer vision teach NLP about efficient neural networks? by Forrest N. Iandola, Albert E. Shaw, Ravi Krishna, and Kurt W. Keutzer.
26. T5 (from Google AI) released with the paper Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer by Colin Raffel and Noam Shazeer and Adam Roberts and Katherine Lee and Sharan Narang and Michael Matena and Yanqi Zhou and Wei Li and Peter J. Liu.
27. Transformer-XL (from Google/CMU) released with the paper Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context by Zihang Dai*, Zhilin Yang*, Yiming Yang, Jaime Carbonell, Quoc V. Le, Ruslan Salakhutdinov.
28. XLM (from Facebook) released together with the paper Cross-lingual Language Model Pretraining by Guillaume Lample and Alexis Conneau.
29. XLM-RoBERTa (from Facebook AI), released together with the paper Unsupervised Cross-lingual Representation Learning at Scale by Alexis Conneau*, Kartikay Khandelwal*, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer and Veselin Stoyanov.
30. XLNet (from Google/CMU) released with the paper XLNet: Generalized Autoregressive Pretraining for Language Understanding by Zhilin Yang*, Zihang Dai*, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, Quoc V. Le.

https://github.com/huggingface/transformers

Introduction to Reasoning (for NLP)

Formal Logic – 1/3

- An automaton for manipulating symbols and drawing conclusions
- Consists of a knowledge base with:
  - a set of true statements (sentences). Sentences have
    - Syntax
    - Semantics – compositional property
  - Proof theory: a set of rules for deducing the entailments / interpretations of the sentences

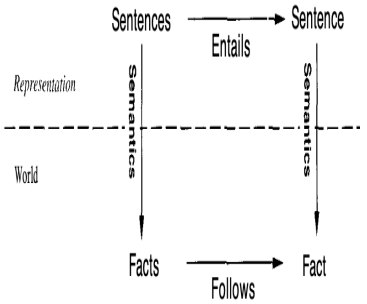


- Properties of sentences
  - **Valid**: A sentence is **valid** or necessarily true if and only if it is true under all possible interpretations in all possible worlds. Also called a **tautology**
  - **Satisfiable:** A sentence is satisfiable if and only if there is some interpretations in some possible worlds where it is true.

Credits:
- Russell & Norvig, AI - A Modern Approach
- Deepak Khemani - A First Course in AI

Formal Logic – 2/3

- Levels at which sentences are encoded
  - Epistemic (also called knowledge): what agents knows or believes
  - Logical: how sentences are encoded to allow inferencing. E.g., symbols
  - Executional: how sentences are encoded during execution. E.g., vectors, symbols
- Properties of sentences
  - **Valid**: A sentence is **valid** or necessarily true if and only if it is true under all possible interpretations in all possible worlds. Also called a **tautology**
  - **Satisfiable:** A sentence is satisfiable if and only if there is some interpretations in some possible worlds where it is true.



Credits:
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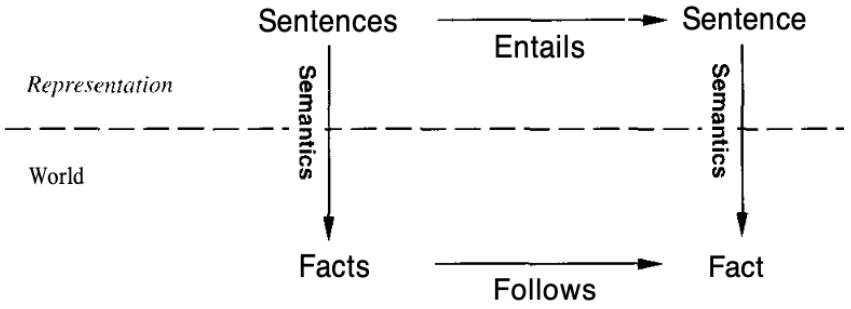
Formal Logic – 3/3

- Properties of Logic System
  - **Soundness**: if it produces only true statements
  - **Completeness**: if it produces all true statements
  - **Consistency**: if it does not produce a sentence and its negation



Language	Ontological Commitment (What exists in the world)	Epistemological Commitment (What an agent believes about facts)
Propositional logic	facts	true/false/unknown
First-order logic	facts, objects, relations	true/false/unknown
Temporal logic	facts, objects, relations, times	true/false/unknown
Probability theory	facts	degree of belief 0…1
Fuzzy logic	degree of truth	degree of belief 0…1

Credits:
- Russell & Norvig, AI - A Modern Approach
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Major Types of Reasoning

- Inference: From premises to conclusions
  - Major types
    - **Deduction**: deriving logical conclusions from premises known or assumed to be true
    - **Induction**: deriving from particular premises to a universal conclusion.
    - **Abduction**: from an observation, find the most likely conclusion from the observations
- Usage
  - Deduction is useful to build knowledge bases from parts
  - Induction: to generalize
  - Abduction is a good source for hypothesis / priors in Bayesian learning

Sample Notebook on GitHub

Logical Reasoning in NLTK
https://github.com/biplav-s/course-nl/blob/master/l10-logic-review/Logic%20Review%20-%20NLTK.ipynb

Lecture 13: Concluding Comments

- We discussed word representation and Word2Vec, Glove
- Further reading
  - Transformers - slides
  - Paper reading - Language models
    - Hang Li, Language Models: Past, Present, and Future, Communications of the ACM, July 2022, Vol. 65 No. 7, Pages 56-63 10.1145/3490443
    - A Primer in BERTology: What We Know About How BERT Works (Rogers et al., TACL 2020)
- We discussed reasoning and the approach of formal knowledge representation

Quiz 2

Concluding Segment

About Next Lecture – Lecture 14

Lecture 14 Outline

- Reasoning - continued
- Ontology and Knowledge graph
- Project reviews