CSCE 590-1: Trusted AI

Lecture 15: Unstructured Text – Common NLP Tasks

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

12TH OCT, 2021

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

Organization of Lectures 15

- Introduction Segment
  - Recap of Lecture 14

- Main Segment
  - Common NLP Tasks
    - Sentiments
    - Question Answering
    - Text Summarization
  - Pretrained embedding and NLP Tasks

- Concluding Segment
  - About next lecture – Lecture 16
  - Ask me anything

Introductory Segment

Schedule Snapshot

Sep 28 (Tu)	**Review: AI Fairness, Project presentations, Discussion**	Quiz 2
Sep 30 (Th)	AI - Unstructured (Text): Processing and Representation	
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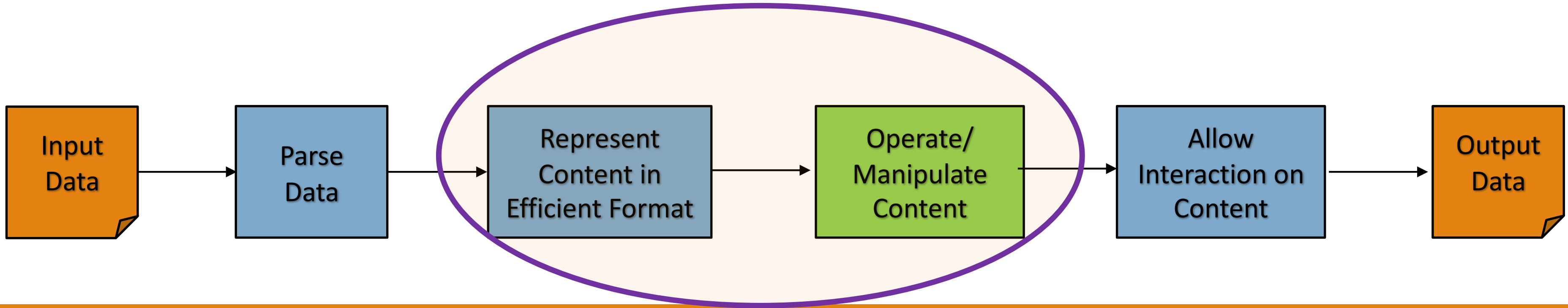
Recap of Lecture 14

- We looked at contextual word representation methods
  - Vector representation:
    - with dimensions having meaning or without
    - Dimension given as input or decided from data

- Started with basic NLP tasks: string similarity and sentiment detection

Main Segment



Common NLP Tasks

- **Text similarity**
- Event Extraction
- **Sentiment detection**
- **Question Answering**
- **Summarization**
- Machine translation
- Natural Language Interface to Databases
- Natural Language Generation

Sentiment Detection

Types of Sentiment Tasks

- Sentence-level Models
  - Input: Set of sentences, each made up of a set of words
  - Output: A set of labels (positive, negative, neutral)
- Document-level Models
  - Input: Set of documents, each made up of a set of sentences, each made up of a set of words
  - Output: A set of labels (positive, negative, neutral)
- Fine-grained sentiment labels
  - (e.g., sentiment strength)
- Sentiment-oriented Word Embedding

Scherer's Typology of Affective States

Emotion: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance

angry, sad, joyful, fearful, ashamed, proud, desperate

Mood: diffuse affect state …change in subjective feeling, of low intensity but relatively long duration, often without apparent cause

cheerful, gloomy, irritable, listless, depressed, buoyant

Interpersonal stance: affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange

distant, cold, warm, supportive, contemptuous

Attitudes: relatively enduring, affectively colored beliefs, preferences predispositions towards objects or persons

liking, loving, hating, valuing, desiring

Personality traits: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person

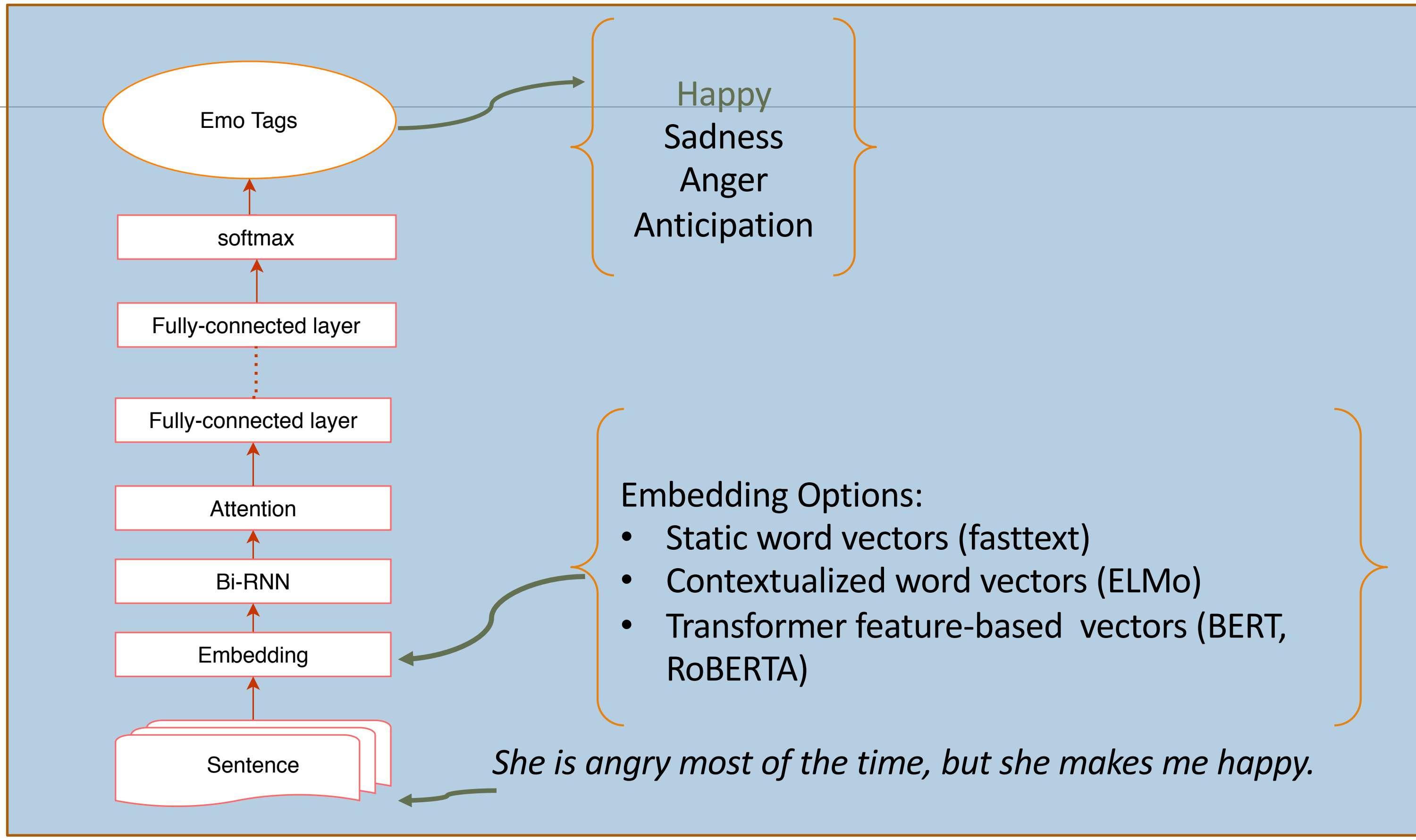
nervous, anxious, reckless, morose, hostile, envious, jealous

Source: Jurafsky & Martin

A Simple Rule-Based Sentiment Engine

- Process input to get tokens
  - Perform: Stemming, tokenization, part-of-speech tagging and semantic parsing.
- Use lexicons to find polarity of words
- Use a method to aggregate over polarity of words

Learning Based Emotion Classification



Sentiment is Easy (to Explain) and Hard (to Get Right)

- Easy
  - Many business applications
  - Basic methods easy to use
- Hard
  - Language specific subtilties (e.g., sarcasm), code switching
  - Issue of bias: output may vary based on gender and race of subject

Basic Sentiment Analysis

Sample code for TextBlob, Vader:
https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l23-textrepresent/Basic%20Sentiment.ipynb

Bias issues:
ROSE:
- Demo: https://ai4society.github.io/sentiment-rating/
- Video: https://www.youtube.com/watch?v=QsL3nWkRGXU

More References

- EMNLP 2016, **Neural Networks for Sentiment Analysis**
  - Yue Zhang and Duy Tin Vo
  - https://mirror.aclweb.org/emnlp2016/tutorials/zhang-vo-t4.pdf

- MonkeyLearn blog: https://monkeylearn.com/sentiment-analysis/

Question Answering

Types of Question Answering

- Many Types:
  - open world: any domain or changing information
  - closed world: specific domain or fixed information

Most complex will be: any domain and changing information

- Solution
  - Parse query
  - Convert it to internal form
    - Matching based approach OR
    - Reasoning based approach
  - Ranking results

Match based example:
- Vector representation
- cosine similarity

Logic based example:
- Entailment
- Ontology-based reformulation

Illustration with TF-IDF

Sample code:
https://github.com/biplav-s/course-tai/blob/main/sample-code/l13-l16-supervised-text/l14-contextual-representation.ipynb

Text Summarization

Motivation for Summarization

- We have a variety of data around
  - Volume: Single document, Multiple documents
  - Variety: Text, numbers/ tables, figures, …
  - Languages
- Can one get a quick insight about the data ? Meaning ?
  - Choice 1: **Important** ideas in the input
  - Choice 2: **Representative** ideas in the input
  - Choice 3: **Example** ideas in the input
    - Random selection is sufficient?

A Few Ways to Generate Insights

- Word tag cloud (textual data; based on frequency)
  - Important
- Topic analysis (textual data, based on learned patterns)
  - Important
- **Summary generation** – formal study
  - Representative
  - Important
  - Example

Summarization Type and Methods

- **Extractive**: extract summary **with** content in the input
  - Should be able to trace output back to the input
  - Interpretability is easy to show

- **Abstractive**: create summary **from ideas** in the content in the input
  - but using at least some different words
  - Useful in creative task – digital journalism

- **Compressive**: remove redundant from input
  - shorter sentence by removing redundant information
  - Preserve grammar and important content in the input

Evaluation of Text Summarization

- **Intrinsic** – How good is the output ?
- Considerations
  - Quality of output - readability
  - Coherence of information – out of context sentences ?
  - Compression of information

Comparison against a reference summary

- Is this the only summary possible?
- A scale of what summary should contain
- Constraints on summary characteristics. E.g., number of words

Where is the refence summary?

- Experts do not agree on summaries
  - Variance between experts
  - Not even their when separated 8-weeks apart nearly 50% times
- But experts often agree on important sentences that make up into a summary

Summarization Evaluation: An Overview, Inderjeet Mani, http://research.nii.ac.jp/ntcir/workshop/OnlineProceedings2/sum-mani.pdf 2019

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Automatic Evaluation

- Against a set of criteria
- Criteria can be task independent or task-dependent
- Can also be about sentences to include and their rank
- Can also be about topics in content and in summary

Metrics

- ROUGE (Recall Oriented Understudy for Gisting Evaluation) score
- METEOR (Metric for Evaluation of Translation with Explicit Ordering) score
- BLEU (bilingual evaluation understudy) score
- SUMMAC summary automatic scoring

Summarization Evaluation: An Overview, Inderjeet Mani,
http://research.nii.ac.jp/ntcir/workshop/OnlineProceedings2/sum-mani.pdf 2019

Evaluation of Text Summarization

- **Extrinsic** – What is the impact of the output ?
- Overall idea
  - Describe a task that a person wants to do with a summary
  - Given the generated summary, how well can a person do that job
- Comments
  - Extrinsic useful for business sponsor but not directly to technical developer

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Coding Illustration - Extractive

https://github.com/biplav-s/course-nl/tree/master/l20-textsumm

Pretrained embedding and NLP Tasks

Contextual Word Embeddings - Recap

	Name	Description	URL, References
1.	Elmo (embeddings from language models)	Contextual, deep, character-based	https://allennlp.org/elmo; Deep contextualized word representations, Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, Luke Zettlemoyer. NAACL 2018.
2	Word2Vec	Word-based, prediction focus	*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.*
3	Glove	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]
4	Fasttext	Variation of word2vec, works with N-gram, words not in vocabulary	
5	Transformers		https://arxiv.org/abs/1706.03762, http://www.columbia.edu/~jsl2239/transformers.html , Huggingface tutorial: https://huggingface.co/course/chapter0

Commentaries/ Tutorials:
- https://jalammar.github.io/illustrated-bert/ , https://cai.tools.sap/blog/glove-and-fasttext-two-popular-word-vector-models-in-nlp/
- Neural Machine Translation and Sequence-to-sequence Models: A Tutorial, Graham Neubig, https://arxiv.org/abs/1703.01619

Code Example

Pretrained models and Common Tasks - Sample code:
https://github.com/biplav-s/course-tai/blob/main/sample-code/l13-l16-supervised-text/l15-langmodel-commontasks.ipynb

Concluding Segment

Lecture 15: Concluding Comments

- Looked at more common NLP Tasks
  - Sentiment Detection
  - Question Answering
  - Summarization
- Saw working of pretrained embedding on some NLP Tasks
  - Using transformers

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Lecture 16: Unstructured Text - Classification

- Classification with Unstructured Text
- Examples:
  - spam v/s non-spam
  - positive v/s negative
  - toxic v/s non-toxic

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About Speaker - 1

- **Diptikalan Saha**, IBM Research
  - https://researcher.watson.ibm.com/researcher/view.php?person=in-diptsaha

Dr. Diptikalan Saha (Dipti) is a Senior Technical Staff Member and manager of Reliable AI team in Data&AI department of IBM Research at Bangalore. His research interest includes Artificial Intelligence, Natural Language Processing, Knowledge representation, Program Analysis, Security, Software Debugging, Testing, Verification, and Programming Languages. received my Ph.D. degree in Computer Science from the State University of New York at Stony Brook. My advisors were Prof. C. R. Ramakrishnan and Prof. Scott A. Smolka. I received my B.E. degree in Computer Science and Engineering from Jadavpur University. His group's work on Bias in AI Systems is available through AI OpenScale in IBM Cloud as well as through open-source AI Fairness 360.

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About Speaker - 2

- **Vijay Arya**, IBM Research
  - https://researcher.watson.ibm.com/researcher/view.php?person=in-vijay.arya

Vijay Arya is a senior researcher in IBM Research AI at the IBM India Research Lab where he works on problems related to Trusted AI. Vijay has 15 years of combined experience in research and software development. His research work spans Machine learning, Energy & smart grids, network measurements & modeling, wireless networks, algorithms, and optimization. His work has received outstanding technical achievement awards at IBM and has been deployed by power utilities in USA. Before joining IBM, Vijay worked as a researcher at National ICT Australia (NICTA) and received his PhD in Computer Science from INRIA, France, and a Masters from Indian Institute of Technology (IIT) Delhi. He has served on the program committees of IEEE, ACM, and IFIP conferences, he is a senior member of IEEE & ACM, and has more than 60 conference & journal publications and patents.