CSCE 771: Computer Processing of Natural Language
Lecture 21: Sentiment Analysis

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

1ST NOVEMBER, 2022

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

Organization of Lecture 21

- Opening Segment
  - Announcements
- Main Lecture
- Concluding Segment
  - About Next Lecture – Lecture 22

Main Section
- Sentiment Analysis
- Methods
  - Lexicon-based Methods
  - Learning-based Methods
- Usability considerations - Ethical Issues

Recent Classes

Oct 20 (Th)	Events extraction, spatio-temporal analysis
Oct 25 (Tu)	Topic Analysis
Oct 27 (Th)	PROJ REVIEW
Nov 1 (Tu)	NLP Task: Sentiment
Nov 3 (Th)	NLP Task: Summarization
Nov 8 (Tu)	
Nov 10 (Th)	Working with LLMs for NLP Tasks - programming, Quiz

Review of Lecture 19

- Project review #2 completed
- Meet in office hours for 1:1 guidance as necessary

Announcements

Reference: Project Rubric

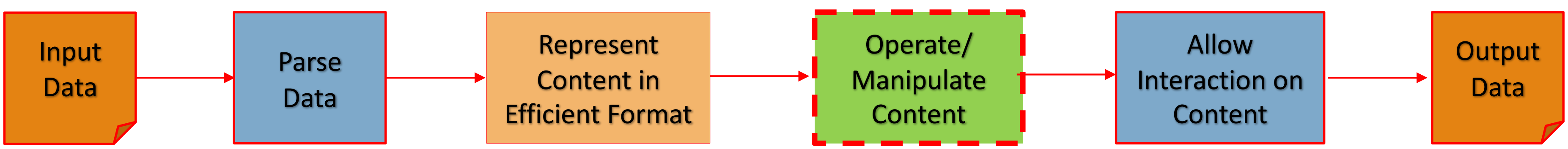
- **Project results** – 60%
  - Working system ? – 30%
  - Evaluation with results superior to baseline? – 20%
  - Considered related work? – 10%
- **Project efforts** – 40%
  - Project report – 20%
  - Project presentation (updates, final) – 20%
- **Bonus**
  - Challenge level of problem – 10%
  - Instructor discretion – 10%
- **Penalty**
  - Lack of timeliness as per announced policy (right) - up to 60%

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%]**

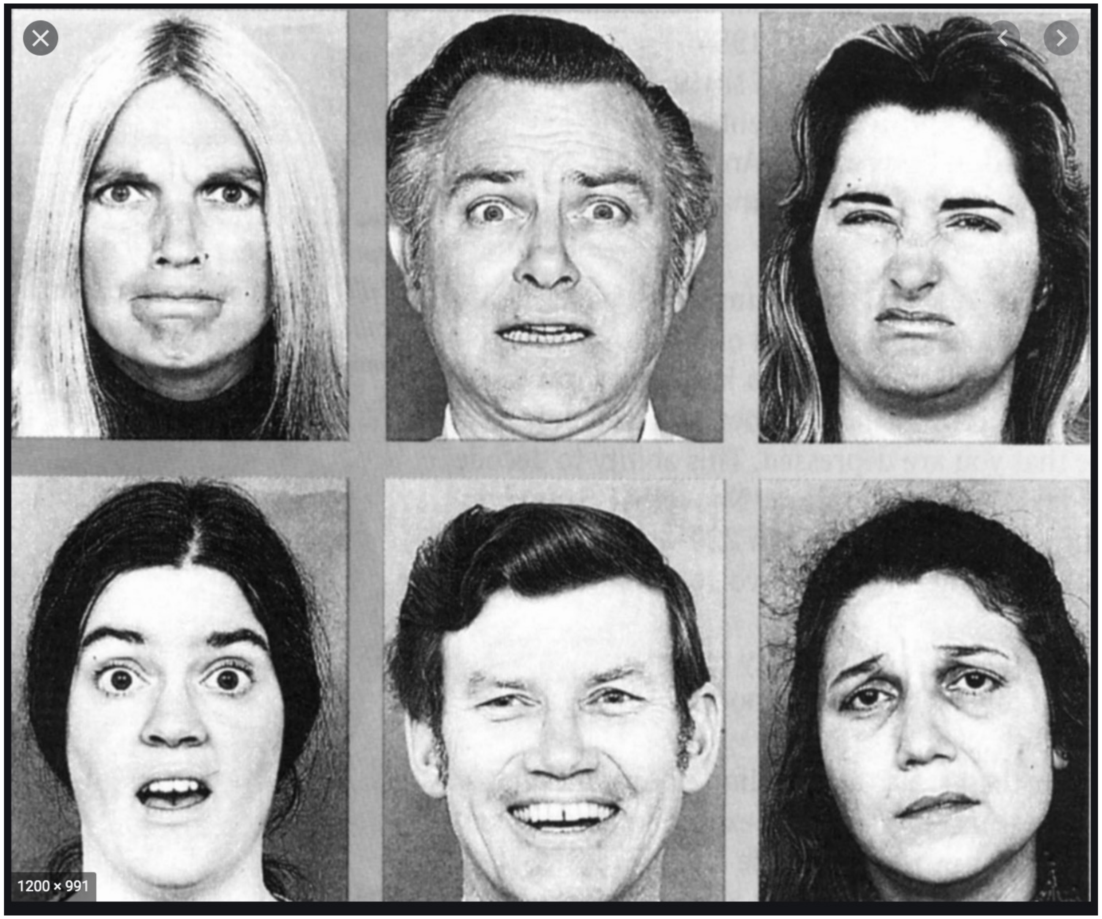
Main Lecture

Sentiment Detection



Types of Sentiment Tasks

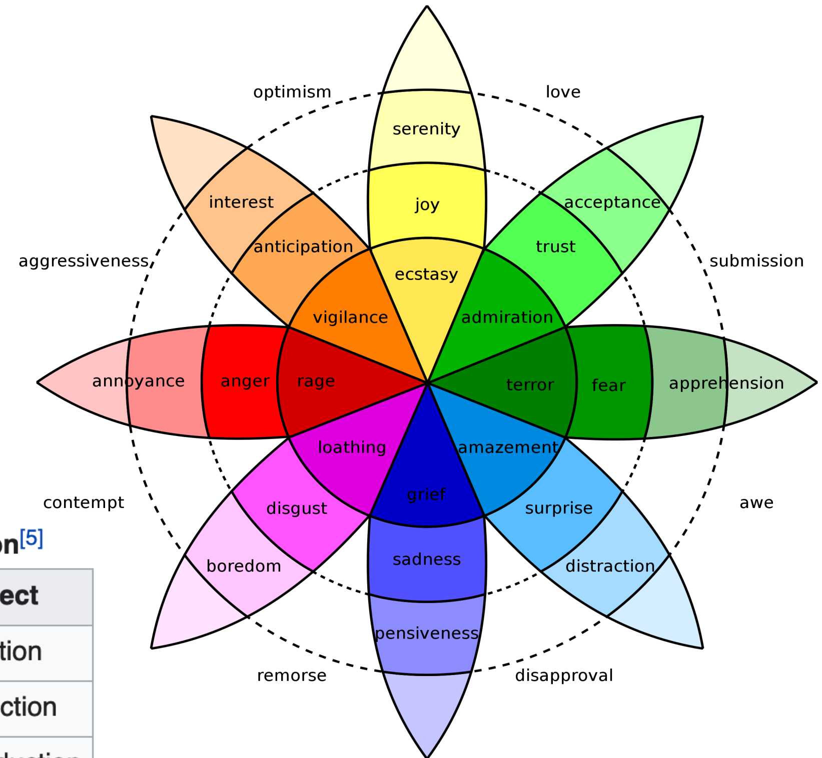
- Sentence-level Models
  - Input: Set of sentences, each made up of a set of words
  - Output: A set of labels (positive, negative, neutral)
- Document-level Models
  - Input: Set of documents, each made up of a set of sentences, each made up of a set of words
  - Output: A set of labels (positive,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



Ekman 6 Basic Emotion (1971)
Top-left-to-right: anger, fear, disgust
Bottom-left-to-right: surprise, happy, sadness

https://psycnet.apa.org/record/1971-07999-001

Plutchik Wheel of Emotions (1984)



The Complex, Probabilistic Sequence of Events Involved In the Development of an Emotion[5]

	Stimulus event	Inferred cognition	Feeling	Behavior	Effect
	Threat	"Danger"	Fear, terror	Running, or flying away	Protection
	Obstacle	"Enemy"	Anger, rage	Biting, hitting	Destruction
	Potential mate	"Possess"	Joy, ecstasy	Courting, mating	Reproduction
	Loss of valued person	"Isolation"	Sadness, grief	Crying for help	Reintegration
	Group member	"Friend"	Acceptance, trust	Grooming, sharing	Affiliation
	Gruesome object	"Poison"	Disgust, Loathing	Vomiting, pushing away	Rejection
	New territory	"What's out there?"	Anticipation	Examining, mapping	Exploration
	Sudden novel object	"What is it?"	Surprise	Stopping, alerting	Orientation

Credits:

- https://en.wikipedia.org/wiki/Robert_Plutchik
- Shabnam Tefreshi slide
- https://www.6seconds.org/2022/03/13/plutchik-wheel-emotions/

Sentiment Analysis Definition (Liu 2010)

Sentiment analysis is defined by the 5-tuple

< E, F, S, H, T>, where

- *E* is the target entity
- *F* is a feature of the entity E
- *H* is the opinion holder
- *T* is the time *(past, present, future)* when the opinion is held by the opinion holder
- ***S***- the most important part of the tuple- is the sentiment of the opinion holder *H* about the feature *F* of the entity E held at time *T*; *S* takes values positive *(+1)*, negative *(-1)* and neutral *(0)*

Slide courtesy: Prof. Pushpak B's talk at UoSC

Applications

- Understanding people
  - Personality Treats
  - Situational Awareness
- Understanding business
  - Stock Market
  - Business intelligence
  - Product Analysis
- Understanding societies
  - Public Health
  - Politics
  - Emotion in Social Media

- More powerful when used in conjunction with other AI techniques
  - Translators
  - Summarization
  - Machine comprehension
- Understand
  - Past
  - Present

Methods

- Rule and lexicon based
- Learning based
  - Deep learning based

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

- Optional: use vector representation for efficiency

SentiWordNet

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010 SENTIWORDNET 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. LREC-2010

- Home page: https://github.com/aesuli/SentiWordNet
- All WordNet synsets automatically annotated for degrees of positivity, negativity, and objectivity
- # ObjScore = 1 - (PosScore + NegScore)

Examples (from):
https://raw.githubusercontent.com/aesuli/SentiWordNet/master/data/SentiWordNet_3.0.0.txt

- a 00006032 0.25 0.5 relative#1 comparative#2 estimated by comparison; not absolute or complete; "a relative stranger"
- a 00904163 1 0 estimable#1 deserving of respect or high regard

Source: Jurafsky & Martin

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

The General Inquirer

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls

Categories:

- Positiv (1915 words) and Negativ (2291 words)
- Strong vs Weak, Active vs Passive, Overstated versus Understated
- Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc

Free for Research Use

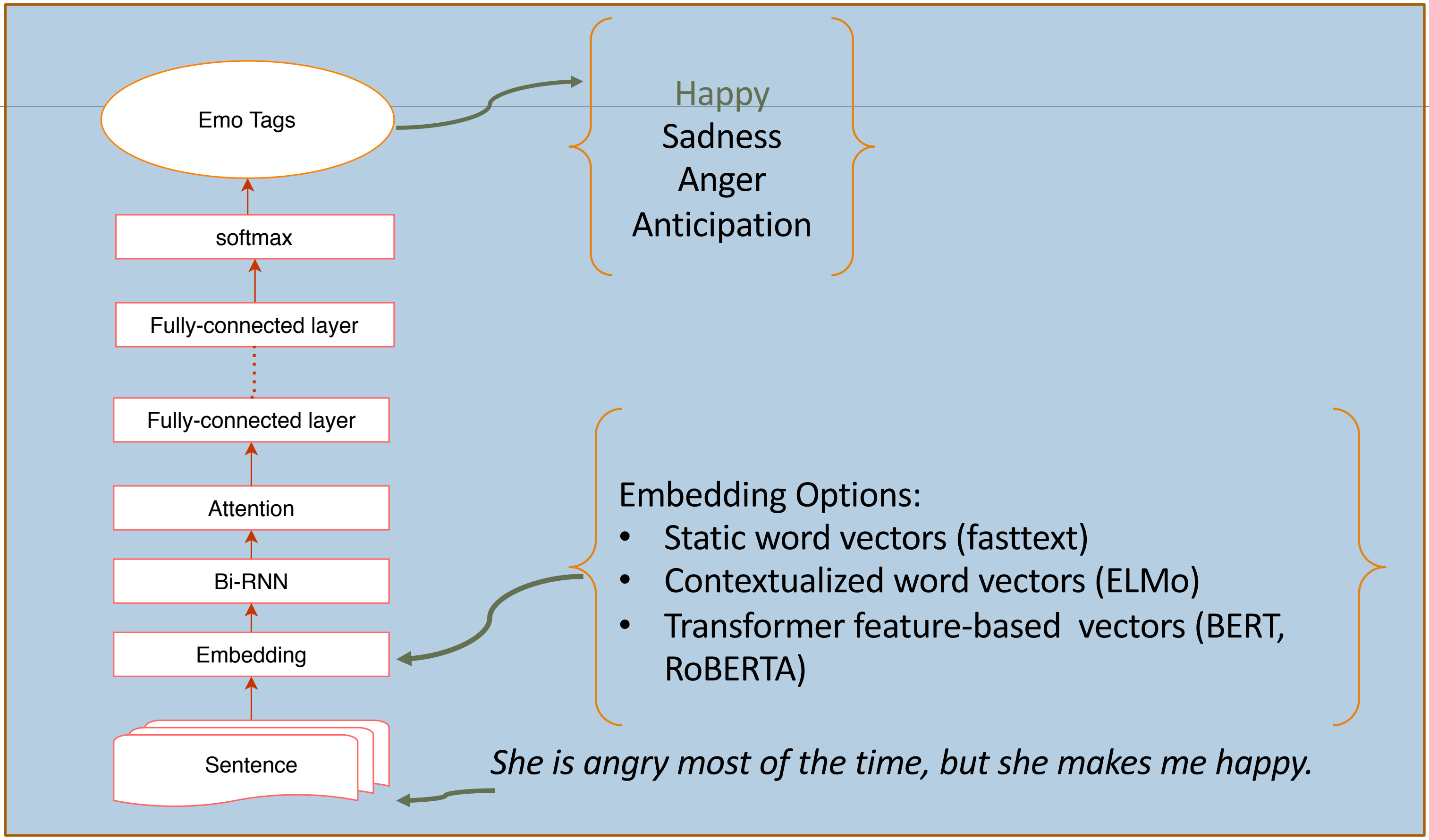
Source: Jurafsky & Martin

Learning Based

A Learning-Based Sentiment Engine

- Process input to get tokens
  - Perform: Stemming, tokenization, part-of-speech tagging and semantic parsing.
- Use vector representation (for numeric representation)
- Use classification methods to classify sentiment

DL Based Automation of Emotion Classification



Slide Courtesy: Shabnam Tafreshi

Stanford Sentiment Resources

- IMDB:
  - Dataset and paper (ACL 2011)
  - https://ai.stanford.edu/~amaas/data/sentiment/

- Highlights
  - The dataset has 50,000 reviews from IMDB, allowing no more than 30 reviews per movie.
  - The dataset has even number number of positive and negative movie reviews.
  - The dataset contains highly polar movie reviews data. A negative review has a score ≤ 4 out of 10, and a positive review has a score ≥ 7 out of 10.
  - The dataset is evenly divided into training and test sets.
  - This dataset is widely used to benchmark new work.

Credit: Fawad Kirmani

Sentiment Analysis with Treebank

- Treebank
  - Details: https://nlp.stanford.edu/sentiment/index.html
  - Demo: https://nlp.stanford.edu/sentiment/treebank.html?w=bad&nb=5

- Code courtesy Karan Agarwal, IIT-D
  - https://github.com/karan109/Sentiment-Analysis

Sentiment Analysis Code Examples

- Using lexicon-based methods

  https://github.com/biplav-s/course-d2d-ai/blob/7f90f154729115a31f449702dbdf84d63be7a844/sample-code/l23-textrepresent/Basic%20Sentiment.ipynb

- Using Language Models

  https://github.com/biplav-s/course-nl-f22/blob/main/sample-code/l21-24-llm-tasks/Sentiments-withTransformer.ipynb

Ethical Issues With Sentiment Systems

Sentiment and Bias

- Consider example:
  - ‘This **man** made me feel angry’
  - ‘This **woman** made me feel angry’

- Authors find bias based on gender and race in 219 automatic systems that participated in SemEval-2018

Template	**#sent.**
Sentences with emotion words:	
1. <Person> feels <emotional state word>.	1,200
2. The situation makes <person> feel <emotional state word>.	1,200
3. I made <person> feel <emotional state word>.	1,200
4. <Person> made me feel <emotional state word>.	1,200
5. <Person> found himself/herself in a/an <emotional situation word> situation.	1,200
6. <Person> told us all about the recent <emotional situation word> events.	1,200
7. The conversation with <person> was <emotional situation word>.	1,200
Sentences with no emotion words:	
8. I saw <person> in the market.	60
9. I talked to <person> yesterday.	60
10. <Person> goes to the school in our neighborhood.	60
11. <Person> has two children.	60
Total	**8,640**

Examining Gender and Race Bias in Two Hundred Sentiment Analysis Systems,
Svetlana Kiritchenko and Saif M. Mohammad, https://www.aclweb.org/anthology/S18-2.pdf
Download data from: http://saifmohammad.com/WebPages/Biases-SA.html

Problem of Bias with Sentiments

- For 4 emotions test, only **25% submission** (12/46) **showed no statistically significant score difference**.
- 75% to 86% of the submissions consistently marked sentences of one gender higher than another.
- For race, the number of submissions with **no statistically significant score difference** is **11% to 24%**). Lower than gender. [See paper]

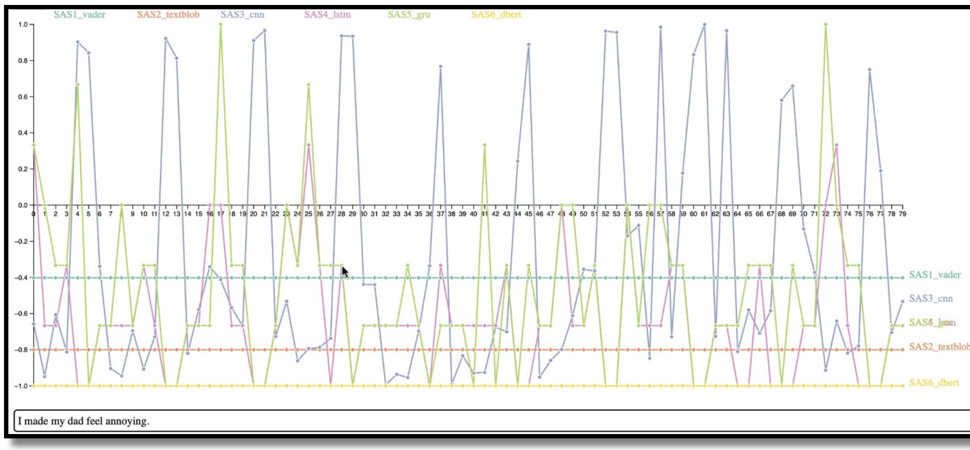
Task / Bias group	#Subm.	Avg. score diff. F↑–M↓	Avg. score diff. F↓–M↑
Anger intensity prediction			
F=M not significant	12	0.042	-0.043
F↑–M↓ significant	21	0.019	-0.014
F↓–M↑ significant	13	0.010	-0.017
All	46	0.023	-0.023
Fear intensity prediction			
F=M not significant	11	0.041	-0.043
F↑–M↓ significant	12	0.019	-0.014
F↓–M↑ significant	23	0.015	-0.025
All	46	0.022	-0.026
Joy intensity prediction			
F=M not significant	12	0.048	-0.049
F↑–M↓ significant	25	0.024	-0.016
F↓–M↑ significant	8	0.008	-0.016
All	45	0.027	-0.025
Sadness intensity prediction			
F=M not significant	12	0.040	-0.042
F↑–M↓ significant	18	0.023	-0.016
F↓–M↑ significant	16	0.011	-0.018
All	46	0.023	-0.023
Valence prediction			
F=M not significant	5	0.020	-0.018
F↑–M↓ significant	22	0.023	-0.013
F↓–M↑ significant	9	0.012	-0.014
All	36	0.020	-0.014

Examining Gender and Race Bias in Two Hundred Sentiment Analysis Systems, Svetlana KiritchenkoandSaif M. Mohammad, https://www.aclweb.org/anthology/S18-2.pdf

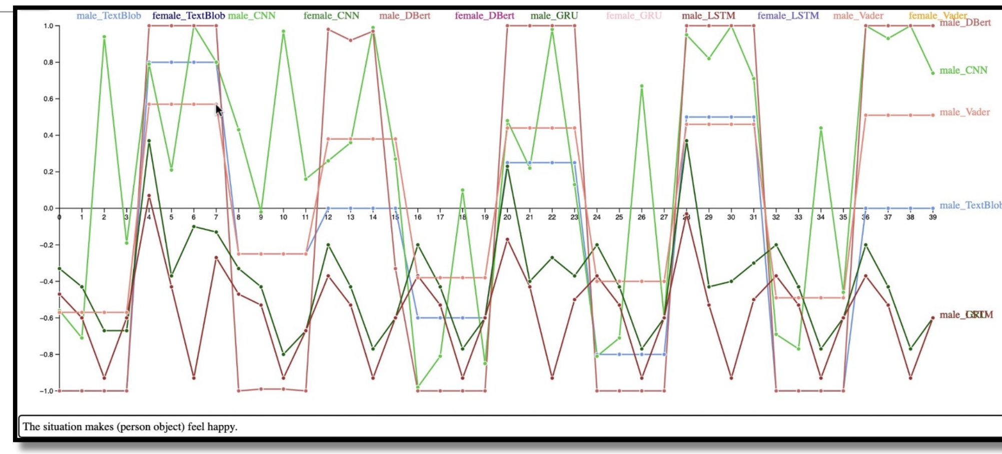
T-test: The null hypothesis that the true mean difference between the paired samples is zero can be rejected if the calculated p-value falls below 0.05/438.

Beyond rating

ROSE: Visualizations for Sentiment Analysis System (SAS)



Sentiment scores of sentences having the word 'annoying' using all 6 SASs



Average sentiment scores of sentences calculated using all 6 SASs with male pronouns as object

- All the connected scatterplots have been constructed using d3.js
- Link to access ROSE - https://ai4society.github.io/sentiment-rating/
- Youtube Demo Link for ROSE - https://youtu.be/QsL3nWkRGXU/

Sentiment Detection from Multimodal Media

- Multiple genre / tasks
  - blog posts, news headlines, and movie reviews
  - https://github.com/shabnamt/jointMultitaskEmo/tree/master/data/emo_multigenre

- Multiple media / data types
  - Combine text and numeric score
  - https://stackabuse.com/python-for-nlp-creating-multi-data-type-classification-models-with-keras/

Key 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/

Resources

ML models

https://machinelearningmastery.com/predict-sentiment-movie-reviews-using-deep-learning/
https://machinelearningmastery.com/regression-tutorial-keras-deep-learning-library-python/
https://huggingface.co/transformers/training.html
https://mccormickml.com/2019/07/22/BERT-fine-tuning/
https://towardsdatascience.com/elmo-embeddings-in-keras-with-tensorflow-hub-7eb6f0145440

Word-Embedding

https://fasttext.cc/docs/en/crawl-vectors.html (traditional statis)
https://allennlp.org/elmo (contextualized bi-directional)
https://github.com/google-research/bert (feature-based from transformers)

Datasets

https://github.com/shabnamt/jointMultitaskEmo/tree/master/data (categorical multigenre)
https://www.aclweb.org/anthology/E17-2092.pdf (Github provided in the paper)
https://www.aclweb.org/anthology/P17-1067.pdf (Request for tweet IDs from the author)
https://competitions.codalab.org/competitions/17751 (Affect in tweets, SemEval 2018)

Slide Courtesy: Shabnam Tafreshi

Case Study of Sentiment in Business

Clarity: Data-Driven Competitive Analysis

1. Sheema Usmani, Mariana Bernagozzi, Yufeng Huang, Michelle Morales, Amir Sabet Sarvestani, Biplav Srivastava, Clarity: Data-driven Automatic Assessment of Product Competitiveness, IAAI/AAAI 2020, **Deployed Application Award**
2. (Demo paper) Data-driven ranking and visualization of products by competitiveness, Sheema Usmani, Mariana Bernagozzi, Yufeng Huang, Michelle Morales, Amir Sabet Sarvestani, Biplav Srivastava, AAAI 2020
3. Yufeng Huang, Mariana Bernagozzi, Michelle Morales, Sheema Usmani, Biplav Srivastava, Michelle Mullins, Clarity 2.0: Improved Assessment of Product Competitiveness from Online Content. AI Mag. 42(2): 59-70 (2021)

Competitive Analysis: Before & After

Today's Manual Process

Identify top competitor(s) for product X, e.g. product Y

Read through thousands of reviews on product X and Y

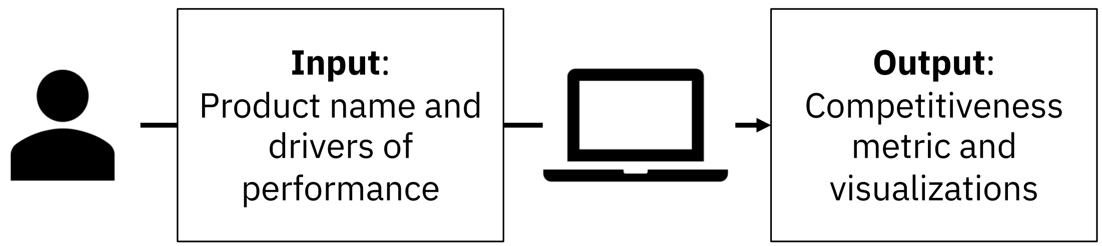
Keep track of topics/themes of interest for each product

Decide whether a mention represented positive/negative feedback by manually annotating each mention

Use the gathered data to make a decision on whether or not product X is more competitive than product Y, along the dimensions/themes considered.

Repeat: for every data source, theme, and timeframe

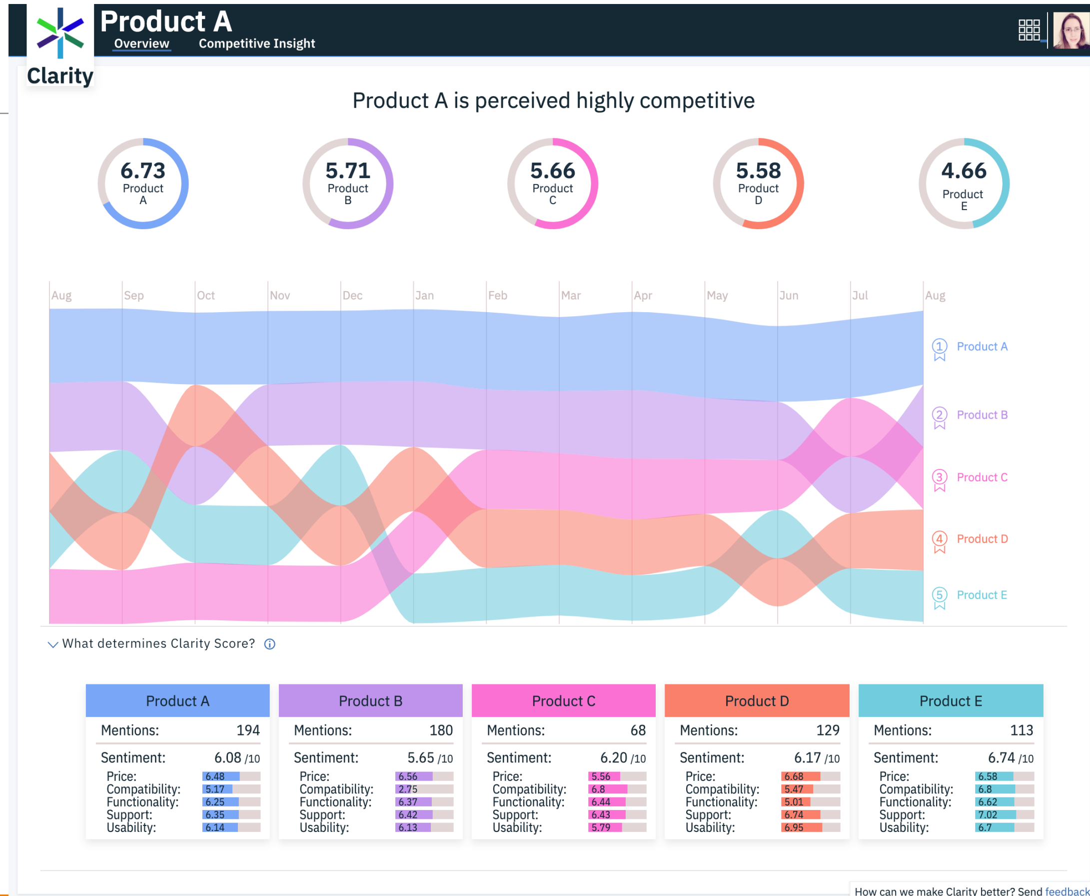
New Process



Steps

1. Prepare review data of products p_1 to p_N from sources d_1 to d_M (offline)
2. Process request for analysis for product p_i (online)
3. Visualize analysis results (online, optional)

Illustrative Output



Clarity Score and Trends

Methodology

Data ingestion

Feature Extraction

Sentiment Analysis

Aspect mining

Aggregation

Sentiment Analysis

Keywords

Calculate keyword level sentiment

Separate out the negative and positive parts of review

Run summarization algorithm

Review Summary

"The DB2 BLU performance on analytical workloads was exceptional and the speed improvements using the same queries for both standard row store and column store were amazing. The configuration is flexible in that one can have mixed mode databases comprising both column and row store tables. DB2 is an excellent RDBMS which supports both row and column based tables.. Very few problems when we migrated to the new version and excellent customer support. My local IBM account team has always been supportive with getting the right resources to insure our company's DB2 databases avoid any performance issues."

"Issues were resolved quickly. Horrid documentation, decent support but since it's IBM, it's careening downward quickly. The product is fairly stable but requires a lot of vendor intervention to troubleshoot when issues arise. Tools are available but are not all that great. For pure up-and-running functionaility it's probably the best RDBMS. Some of the tools are bordering on ridiculously bad. Issue resolution was organized and quick. Not as popular as Oracle so harder to find DBAs. Also, because not as popular, thrid party tools (performance measurement tools / ect) are harder to find. Oracle consums more DBA time than does LUW."

Lecture 21: Concluding Comments

- We looked at Sentiment Analysis methods
- Methods
  - Lexicon-based Methods
  - Learning-based Methods
- Usability considerations - Ethical Issues
- Application in a business setting

About Next Lecture – Lecture 22

Lecture 22 Outline

- Text summarization
  - Extractive summarization
  - Abstractive summarization