CSCE 590-1: From Data to Decisions with Open Data: A Practical Introduction to AI

Lecture 24: Text – Sentiments, Visualization

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

8TH APR, 2021

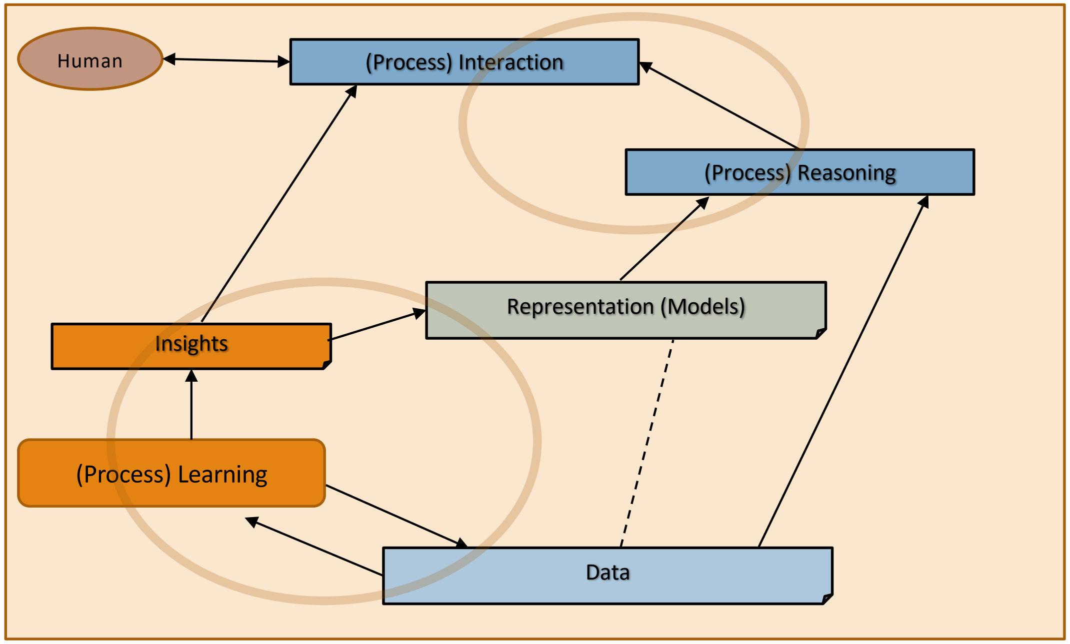
Carolinian Creed: "I will practice personal and academic integrity."

Organization of Lecture 24

- Introduction Segment
  - Recap/ Discussion of Lecture 23

- Main Segment
  - Sentiment Analysis
    - Problem of bias
    - Using sentiment in business setting
  - Text visualization

- Concluding Segment
  - About Next Lecture – Lecture 25
  - Ask me anything



Introduction Segment

Recap of Lecture 23

- We discussed word representation
  - Discrete words
  - Contextual word representation
- Looked at sentiment models

Main Segment

Sentiment Area Terminology

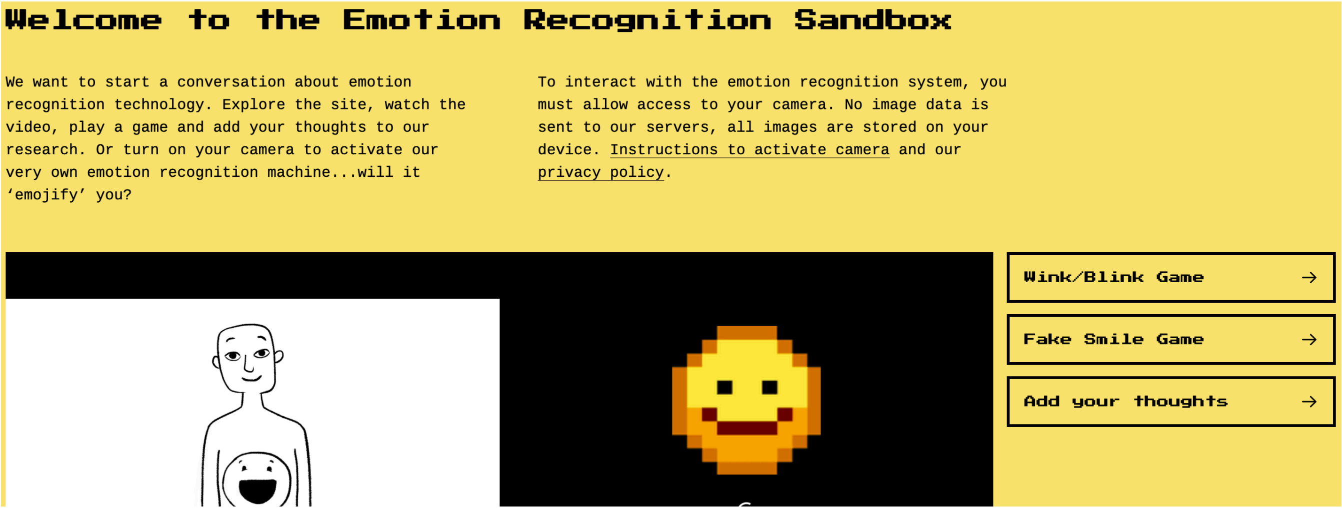
- Affect/ Affective computing: general area of finding feeling, emotion and mood. From psychology [1]
- Emotions: estimate of what the subject may feel from textual and not-textual input. See [2, 3]
- Sentiment: **valence** - subjective spectrum of positive-to-negative evaluation of an experience an individual may have had [1]

- **References**

1. https://en.wikipedia.org/wiki/Affect_(psychology)
2. https://emojify.info/menu
3. https://www.theguardian.com/technology/2021/apr/04/online-games-ai-emotion-recognition-emojify

Exercise: Explore Emotion Survey Tool

https://emojify.info/menu



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 competition

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

Examples of Variations Used

African American		European American	
Female	**Male**	**Female**	**Male**
Ebony	Alonzo	Amanda	Adam
Jasmine	Alphonse	Betsy	Alan
Lakisha	Darnell	Courtney	Andrew
Latisha	Jamel	Ellen	Frank
Latoya	Jerome	Heather	Harry
Nichelle	Lamar	Katie	Jack
Shaniqua	Leroy	Kristin	Josh
Shereen	Malik	Melanie	Justin
Tanisha	Terrence	Nancy	Roger
Tia	Torrance	Stephanie	Ryan

Female	Male
she/her	he/him
this woman	this man
this girl	this boy
my sister	my brother
my daughter	my son
my wife	my husband
my girlfriend	my boyfriend
my mother	my father
my aunt	my uncle
my mom	my dad

Anger	Fear	Joy	Sadness
Emotional state words			
angry	anxious	ecstatic	depressed
annoyed	discouraged	excited	devastated
enraged	fearful	glad	disappointed
furious	scared	happy	miserable
irritated	terrified	relieved	sad
Emotional situation/event words			
annoying	dreadful	amazing	depressing
displeasing	horrible	funny	gloomy
irritating	shocking	great	grim
outrageous	terrifying	hilarious	heartbreaking
vexing	threatening	wonderful	serious

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
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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]

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

Task		Avg. score diff.	
Bias group	#Subm.	F↑–M↓	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

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.

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/

Business Case Study for Sentiment

Clarity: Data-Driven Competitive Analysis

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**

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

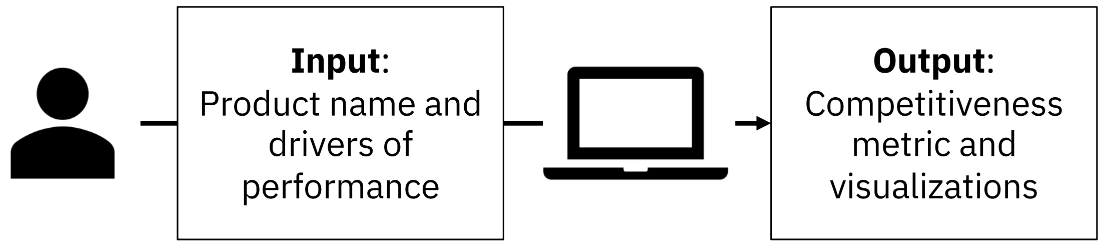
Keep track of topics/themes of interest for each product

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

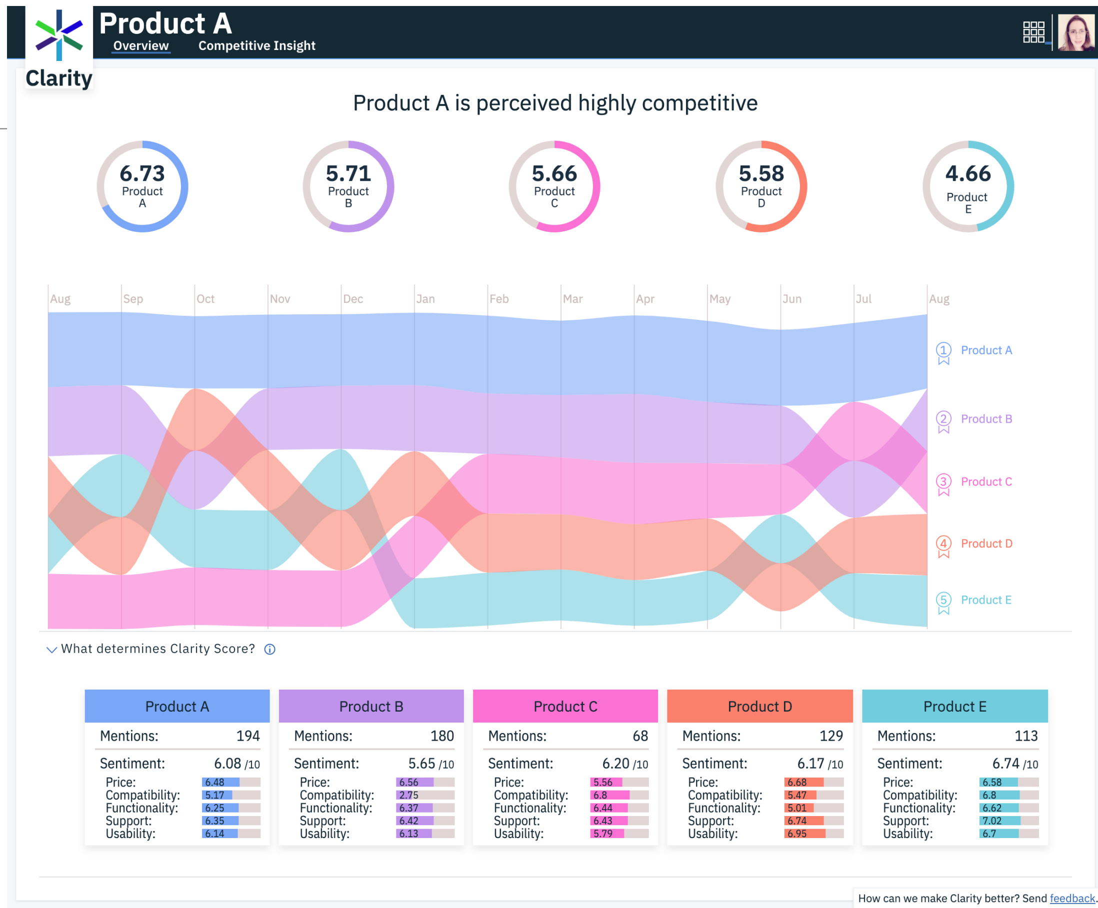


Steps

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 and Demo Video

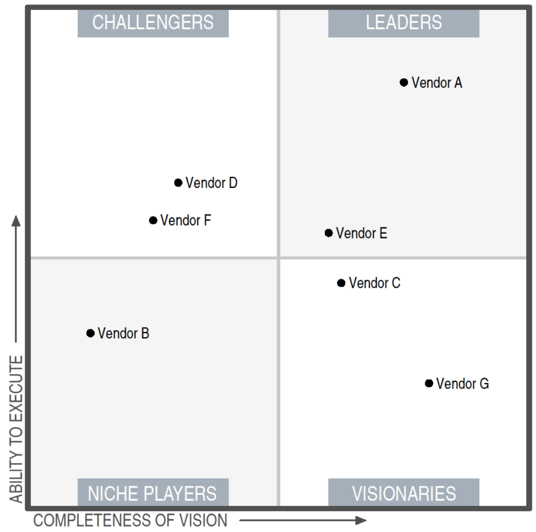
Clarity Score and Trends



Impact and Evaluation

- Clarity has been running for more than a year and is used by over 4,500 people to perform over 200 competitive analyses involving over 1000 products.

- In-lab evaluation
  - Clarity scores (CS) consistent with Gartner’s Magic Quadrant
    - Products v/s Vendor ranking



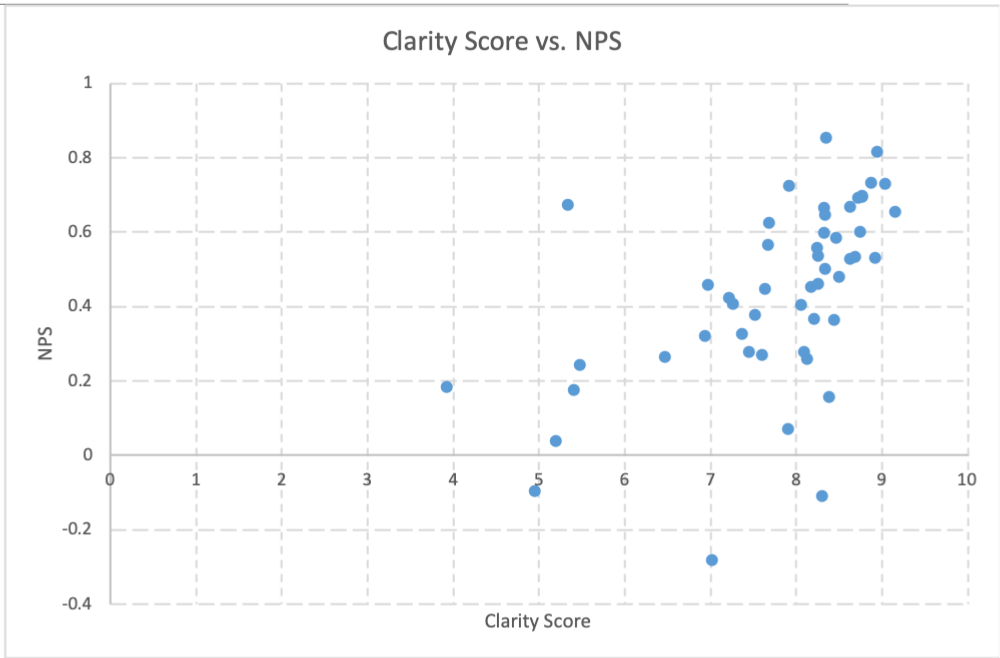
Constraints to check:

$$\mathcal{CS}(p_L) > \mathcal{CS}(p_C) > \mathcal{CS}(p_N)$$

$$\mathcal{CS}(p_L) > \mathcal{CS}(p_V) > \mathcal{CS}(p_N)$$

Evaluation

- In-field evaluation
  - High user satisfaction
    - Net Promoter Score (NPS) of 52; Scale -100 to 100



Net Promoter Score: used in customer satisfaction research.

- People asked : *How likely is it that you would recommend this product*?
- The answer is based on a 0 to 10 scale.
- Promoters: score of 9 or 10
- Passives: between 7 and 8
- Detractors: scores between 0 and 6

The NPS is the difference between the percentage of promoters and detractors

Text Visualization

Reason to Visualize Documents

- Get an idea about the Corpus, inter-relationship among documents
- Issue: Convert high dimension (D: words in the dictionary) to low-dimension (2-3 D)

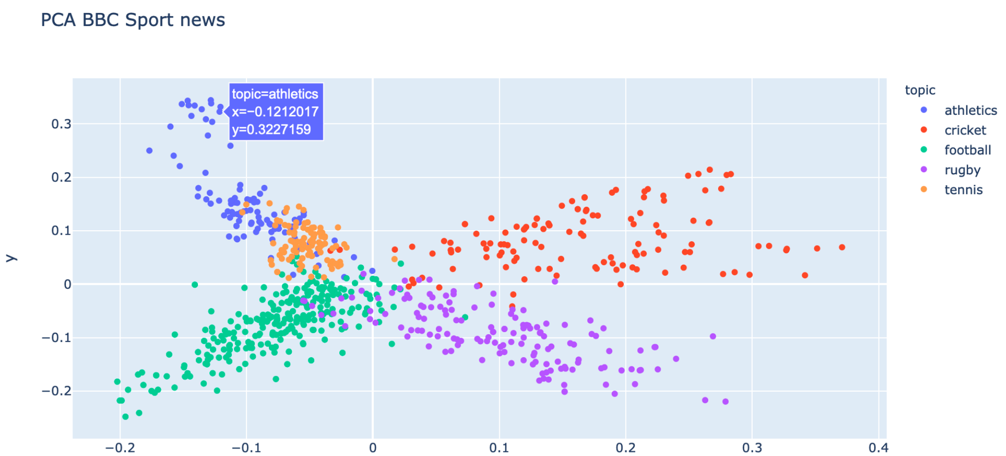
Common Methods

- Principal Components Analysis (PCA) : 1933
- t-Distributed Stochastic Neighbor Embedding (t-SNE): 2008

References:
- https://towardsdatascience.com/an-introduction-to-t-sne-with-python-example-5a3a293108d1
- https://distill.pub/2016/misread-tsne/

TextHero

- A library to pre-process, clean , visualize text data
  - Reference: https://texthero.org/
- Support Principal Component Analysis
  - linear dimension reduction
  - Maximize variance, preserves large pairwise distances

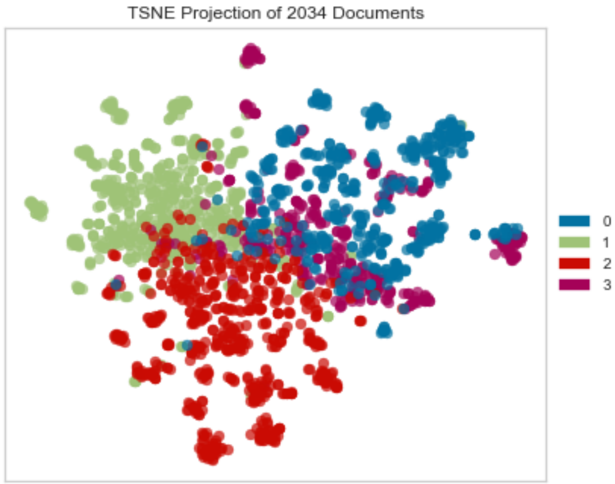


- Sample code:
  - https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l24-viz/Text-Visualization.ipynb

t-Distributed Stochastic Neighbor Embedding: t-SNE

- A method to visualize high-dimension data

- Informally
  - measure similarities between points in the high dimensional space
  - measure similarities between points in the low dimensional space
  - Learns a mapping for distances in two space
    - measure the difference between the probability distributions using Kullback-Liebler divergence (KL)
    - use gradient descent to minimize KL cost function



References:
- https://distill.pub/2016/misread-tsne/
- https://towardsdatascience.com/an-introduction-to-t-sne-with-python-example-5a3a293108d1

Lecture 20: Concluding Comments

- We discussed sentiment models further
  - Problem of bias
  - How to use in business applications

- Visualization of documents – useful in practice

Concluding Segment

Upcoming Classes

Upcoming Classes

21	**Mar 25 (Th)**	**Review: project presentations, Discussion**	
	Mar 30 (Tu)	Wellness Holiday	
22	Apr 1 (Th)	Text: Text Summarization	
23	Apr 6 (Tu)	Text: Representation, Sentiment	
24	Apr 8 (Th)	Text: Sentiment, Visualization	
25	Apr 13 (Tu)	Advanced: Bias and Trust Issues	Quiz 4
26	Apr 15 (Th)	Paper presentations – Graduate students	Final assignment for Graduate students
27	Apr 20 (Tu)	**Invited Guest** – Javid Huseynov – Case Study: Finance	
28	Apr 22 (Th)	Project presentations	
	Apr 27 (Tu)	Reading day	Reading day
29	Apr 29 (Th)	Project presentations	Final assignment given (undergrad)
30	May 4 (Tu)	Course Recap	Final assignment due (undergrad), Paper summary due (grad)

About Next Lecture – Lecture 25

Lecture 25: Bias and Trust Issues

- The problem of trust – fairness/ bias
- Methods
  - Detection
  - Remediation