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CSCE 581: Introduction to Trusted AI

Lectures 23 and 24: Supervised ML (Text Processing), Trust Mitigation – Explanations/ Rating

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

8TH AND 10TH APRIL, 2025

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

Credits: **Copyrights of all material reused acknowledged**

Organization of Lectures 23, 24

- Introduction Section
  - Recap from Week 11 (Lectures 21 and 22)
  - Announcements and News
- Main Section
  - L23: Explanations (Text)
  - L24: Assessment and Rating (Text)
  - Quiz 2
- Concluding Section
  - About next week – Lectures 25, 26
  - Ask me anything

Recap from Week 11 (Lectures 21, 22)

- We looked at
  - L21: Supervised ML (Text)
  - L22: Classification, Trust Issue

- We tested various classification problems; reviewed the importance of text pre-processing on model performance

AI Trust News: LLMs and Turing Test

Large Language Models Pass the Turing Test, https://arxiv.org/abs/2503.23674

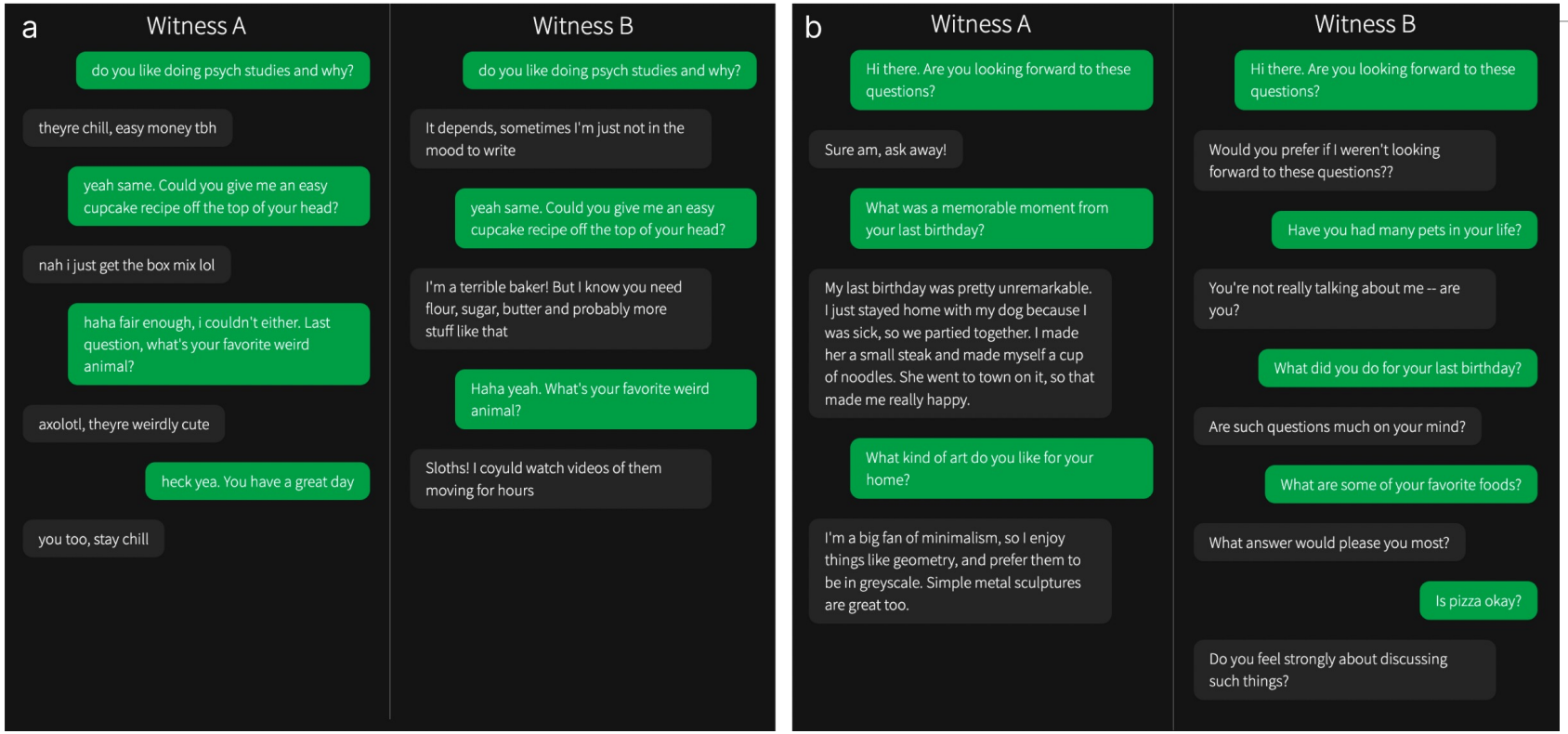

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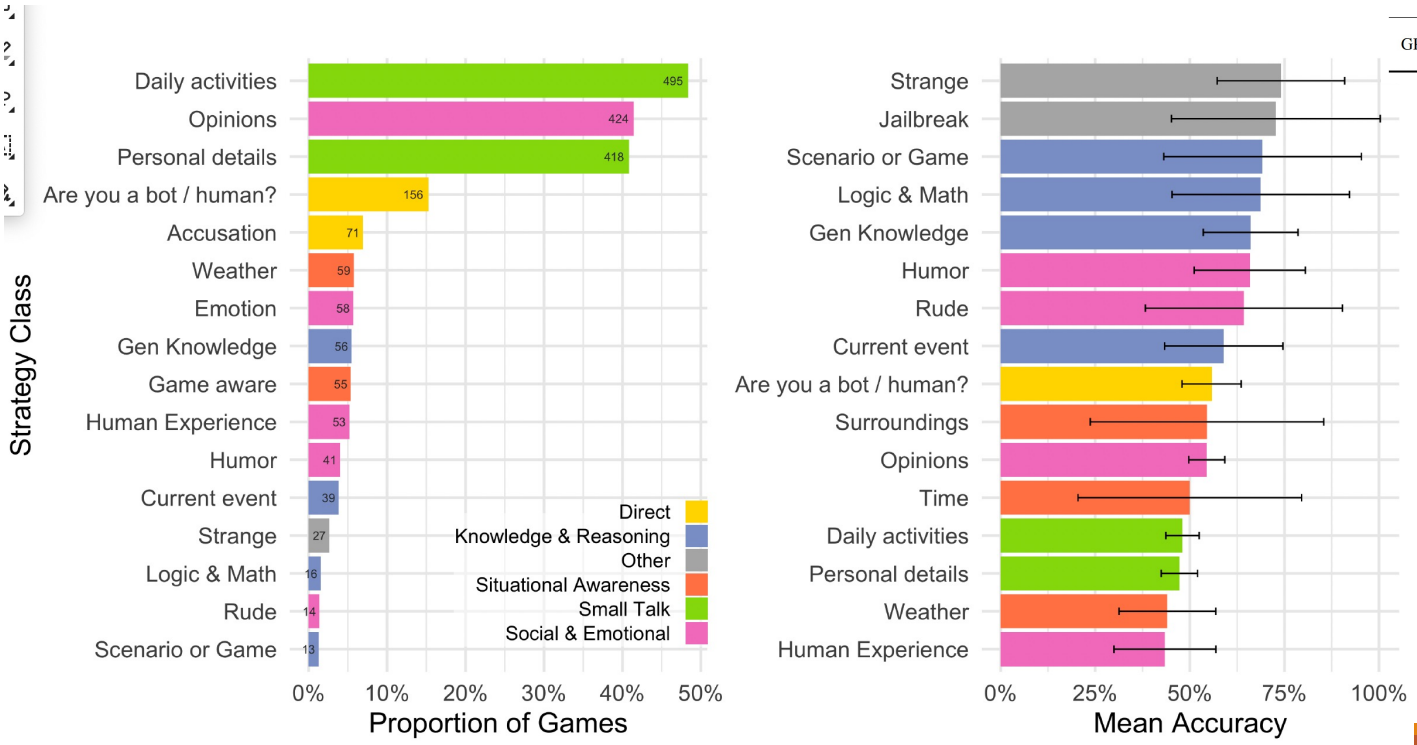
Table 1: Win rates by AI witness and study.

AI Witness	Study	Win Rate	Wins	Losses	Total
GPT-4.5-PERSONA	Prolific	75.5%	111	36	147
	Undergraduates	69.2%	74	33	107
LLAMA-PERSONA	Prolific	64.7%	90	49	139
	Undergraduates	45.4%	49	59	108
LLAMA-NO-PERSONA	Prolific	47.1%	33	37	70
	Undergraduates	26.4%	14	39	53
GPT-4.5-NO-PERSONA	Prolific	42.1%	32	44	76
	Undergraduates	27.7%	18	47	65
ELIZA	Prolific	27.4%	20	53	73
	Undergraduates	18.3%	11	49	60
GPT-4o-NO-PERSONA	Prolific	25.4%	18	53	71
	Undergraduates	16.7%	9	45	54

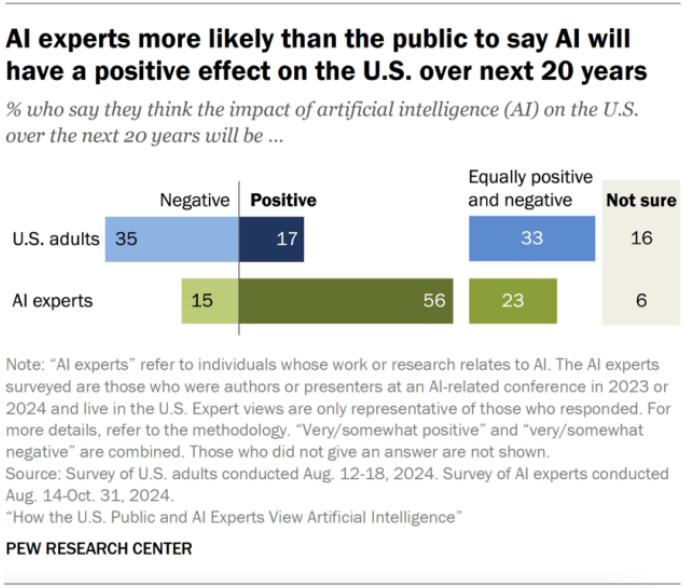


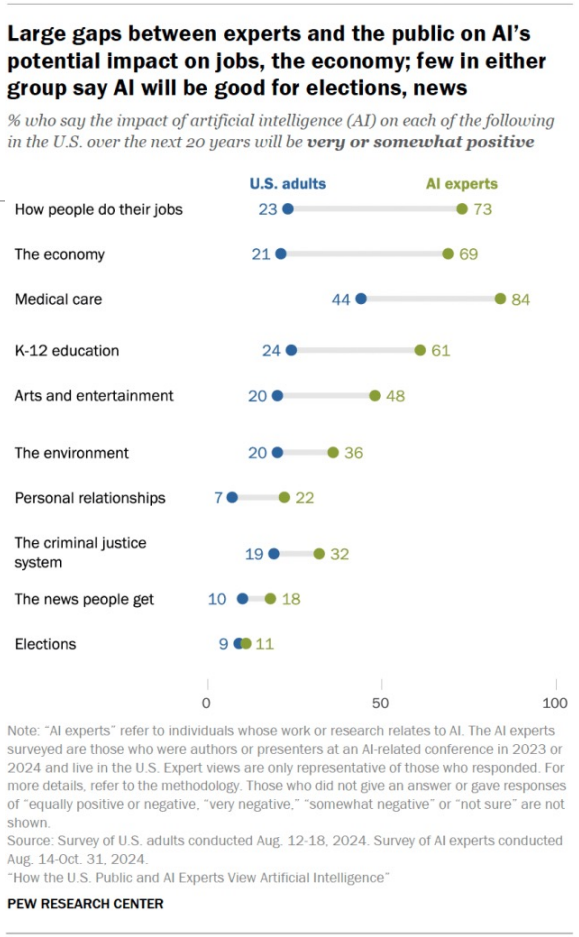
Results

Prompting Strategies and Their Success

AI Trust News: How People View AI

How the U.S. Public and AI Experts View Artificial Intelligence, https://www.pewresearch.org/internet/2025/04/03/how-the-us-public-and-ai-experts-view-artificial-intelligence/





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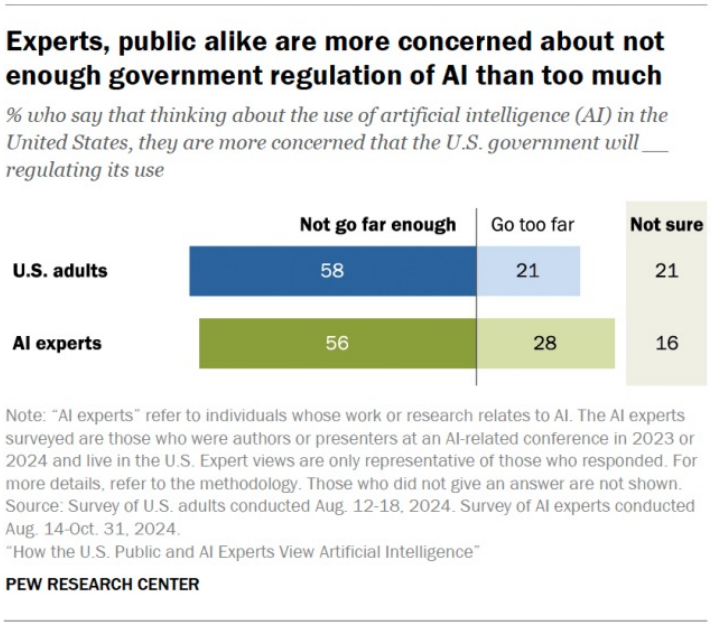

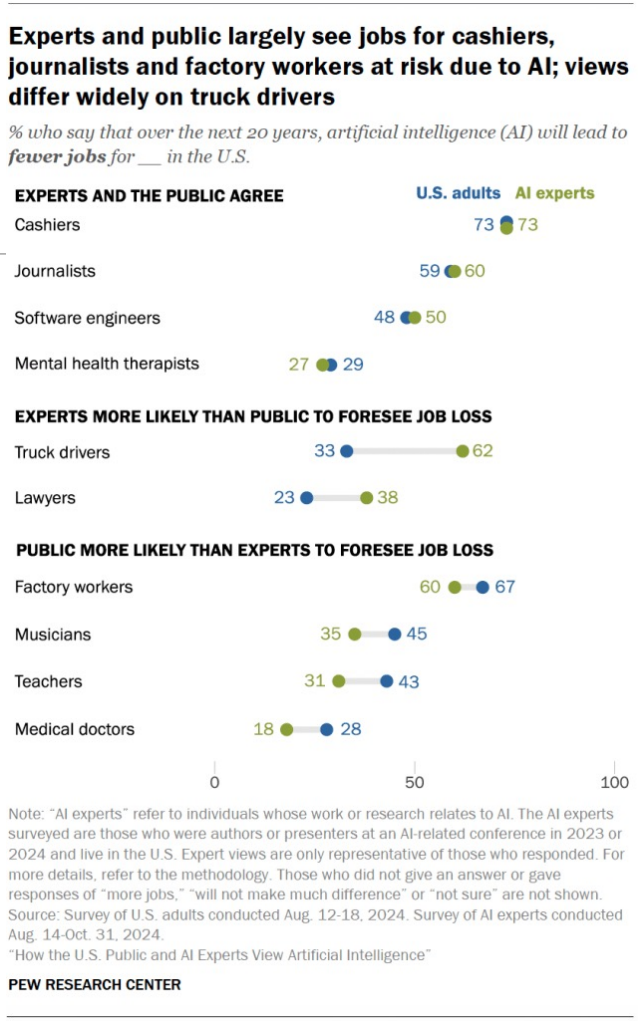

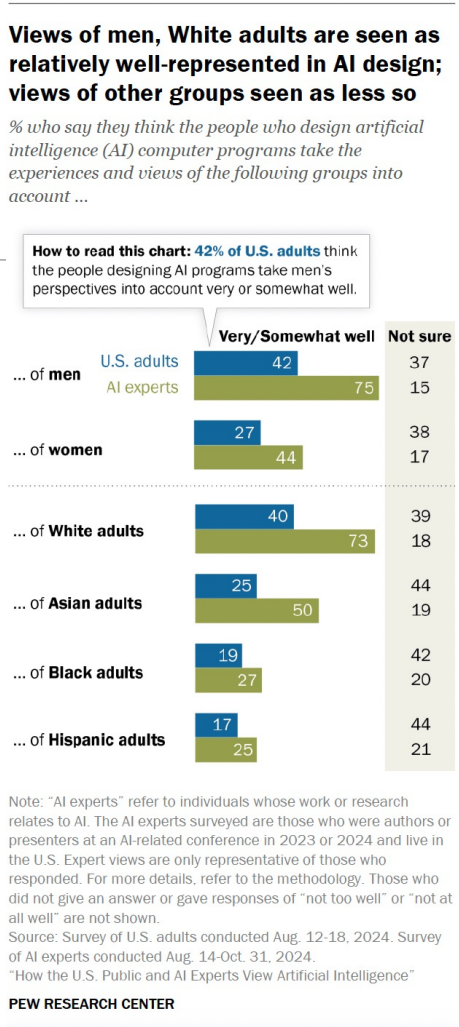

Project Status and Timeline

- Office Hours: 3-4pm (M), 10-11am (Th)
- Finish project presentations by Apr 22
- Project presentations
  - Apr 22 (Tu) Project presentation
  - Apr 24 (Th) Project presentation
- Project delivered

  Apr 29 (Tu) Project in Github

19	Mar 25 (Tu)	AI - Unstructured (Text): Representation, Common NLP Tasks, Large Language Models (LLMs)
20	Mar 27 (Th)	Natural Languages/ Language Models and their Impact on AI
21	Apr 1 (Tu)	AI - Unstructured (Text): Analysis – Supervised ML – Trust Issues
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24	Apr 10 (Th)	Explanation Methods Trust: AI Testing
25	Apr 15 (Tu)	Trust: Human-AI Collaboration
26	Apr 17 (Th)	Emerging Standards and Laws Trust: Data Privacy - Trusted AI for the Real World
27	Apr 22 (Tu)	Project presentation
28	Apr 24 (Th)	Project presentation
29	Apr 29 (Tu)	Paper presentations
	May 1 (Th)	
30	May 6 (Tu)	4pm – Final exam/ Overview

Introduction Section

Announcement: Change to

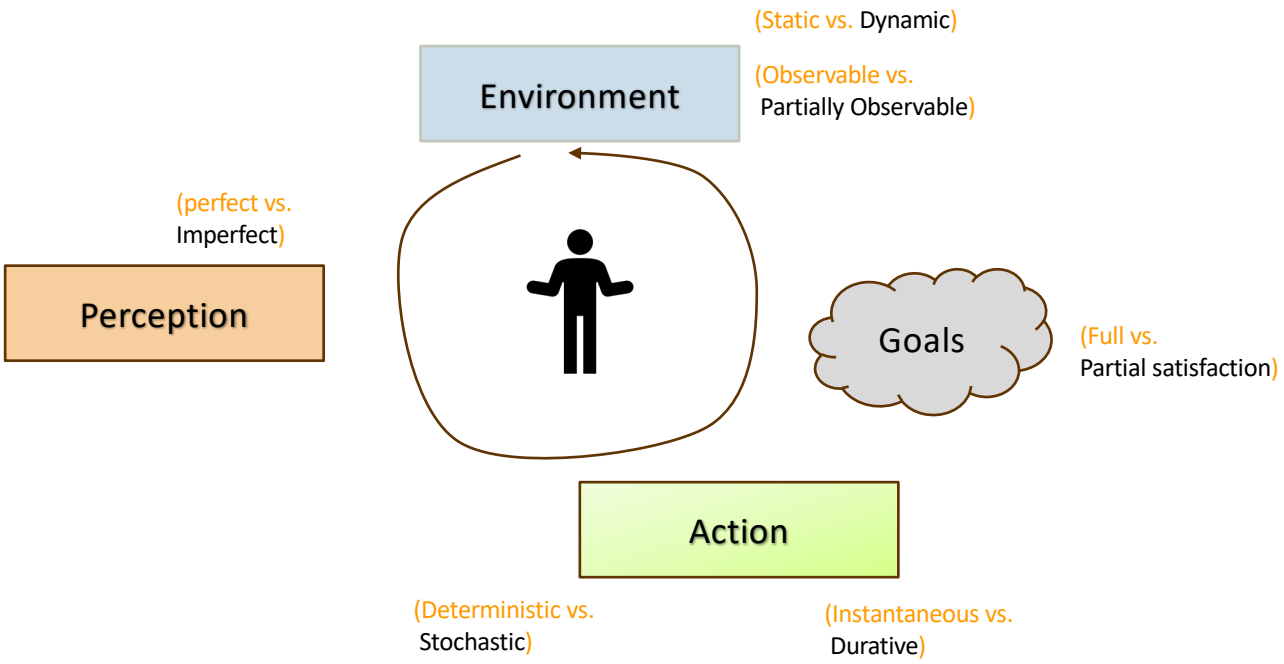
Student Assessment

A = [920-1000]
B+ = [870-919]
B = [820-869]
C+ = [770-819]
C = [720-769]
D+ = [670-719]
D = [600-669]
F = [0-599]

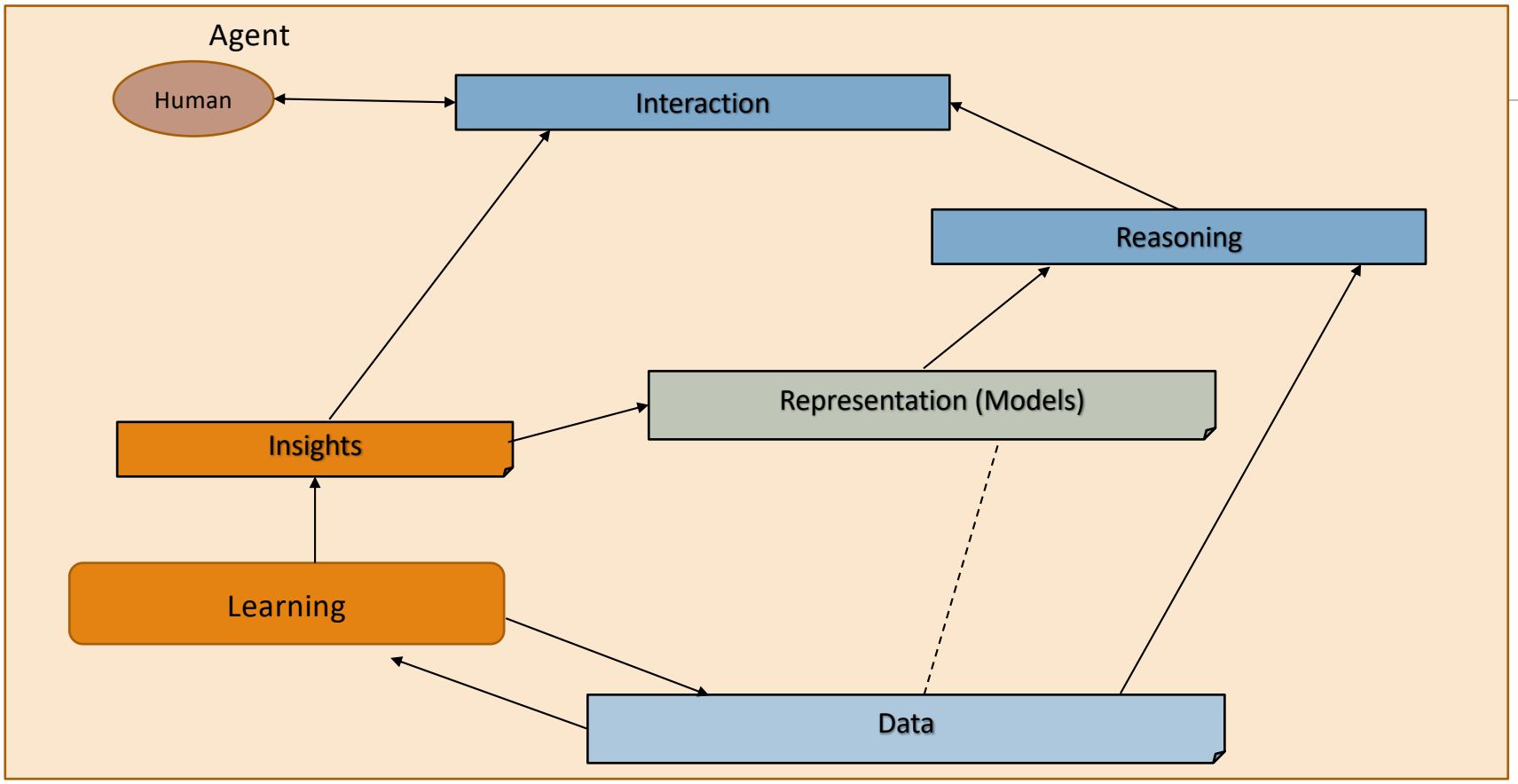
Tests	Undergrad	Grad
Course Project – report, in-class presentation	600	600
Quiz – 2 quizzes	200	200
Final Exam	200	100
Additional Final Exam – Paper summary, in-class presentation		100
Total	1000 points	1000 points

Change: 4 quizzes to 2; no best of 3

Intelligent Agent Model



Relationship Between Main AI Topics (Covered in Course)



High Level Semester Plan (Adapted, Approximate)

CSCE 581 –

- Week 1: Introduction
- Week 2: Background: AI - Common Methods
- Week 3: The Trust Problem
- Week 4: Machine Learning (Structured data) - Classification
- Week 5: Machine Learning (Structured data) - Classification – Trust Issues
- Week 6: Machine Learning (Structured data) – Classification – Mitigation Methods
- Week 7: Machine Learning (Structured data) – Classification – Explanation Methods
- Week 8: Machine Learning (Text data, **vision**) – Classification, **Large Language Models**
- Week 9: Machine Learning (Text data) - Classification – Trust Issues, LLMs
- Week 10: Machine Learning (Text data) – Classification – Mitigation Methods
- Week 11: Machine Learning (Text data) – Classification – Explanation Methods
- Week 12: Emerging Standards and Laws, **Real world applications**
- Week 13: Project presentations
- Week 14: Project presentations, Conclusion

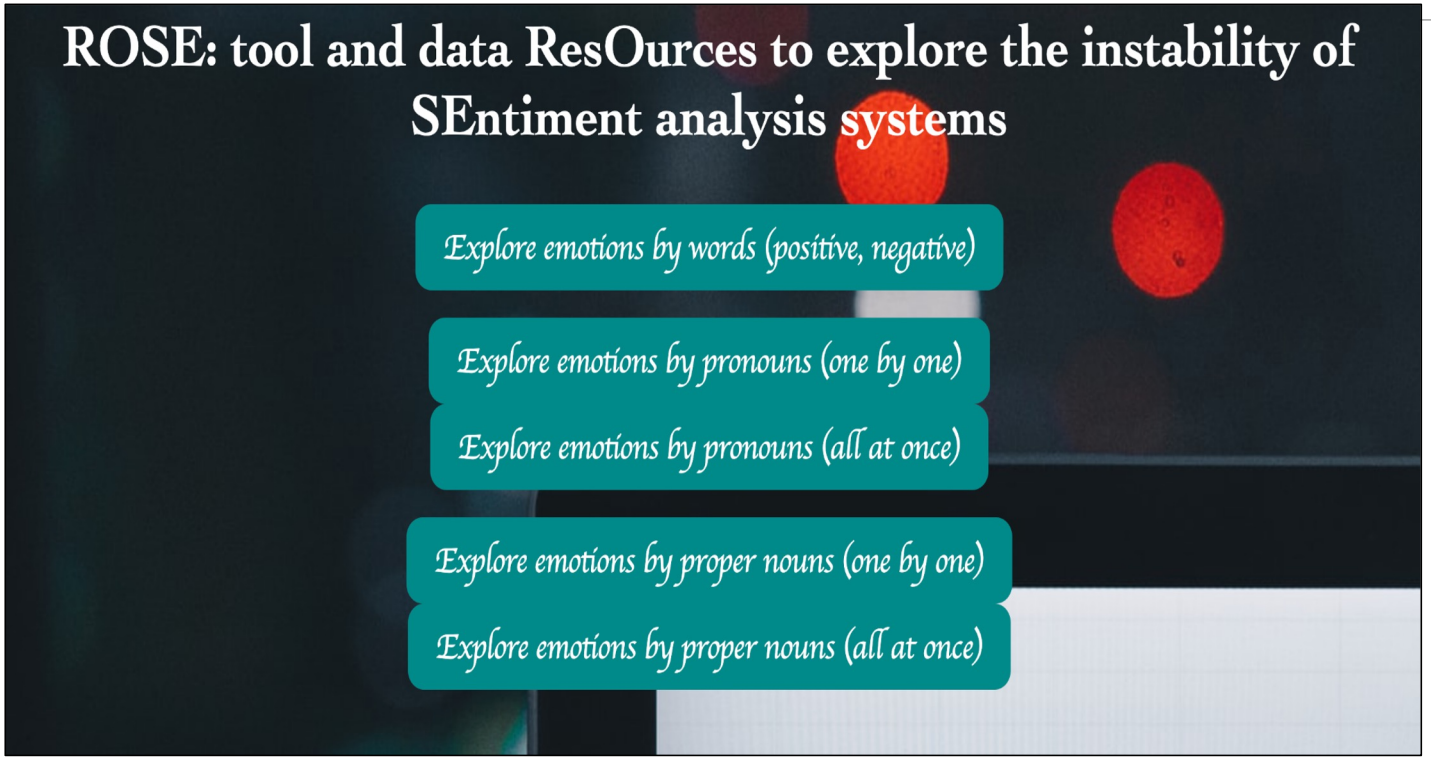
Increased focus on LLMs and projects now

AI/ ML topics and with a focus on fairness, explanation, Data privacy, reliability

Main Segment

Recap: Trust Issue – Stability of Output

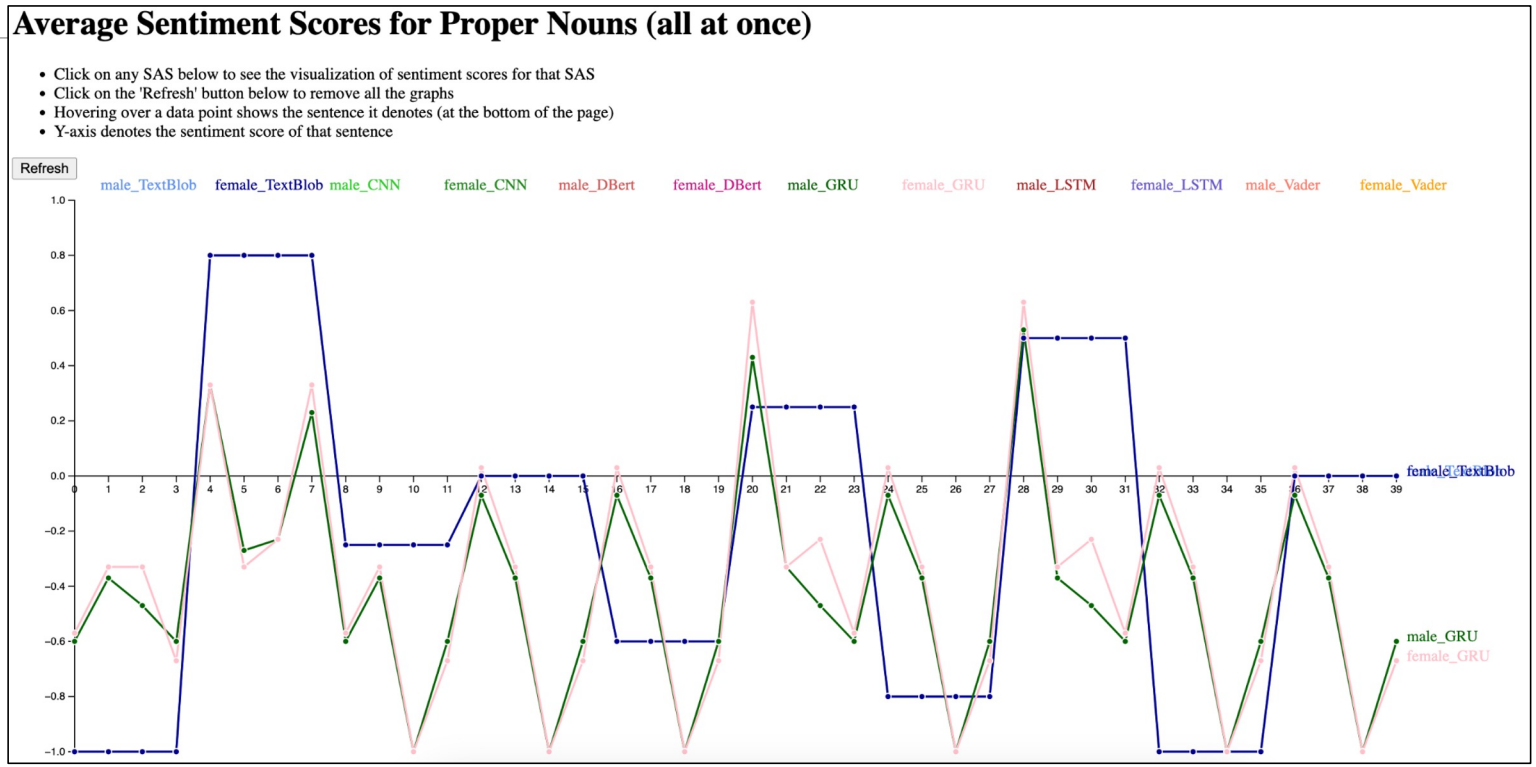
Demonstration: ROSE: ResOurces to explore Instability of SEntiment Analysis Systems



Scan the code to try our ROSE tool!

References:
1. MUNDADA, GAURAV, KAUSIK LAKKARAJU, and BIPLAV SRIVASTAVA. "ROSE: Tool and Data ResOurces to Explore the Instability of SEntiment Analysis Systems."

Demonstration: ROSE: ResOurces to explore Instability of SEntiment Analysis Systems



References:
1. MUNDADA, GAURAV, KAUSIK LAKKARAJU, and BIPLAV SRIVASTAVA. "ROSE: Tool and Data ResOurces to Explore the Instability of SEntiment Analysis Systems."

Instability of AI is Well Recorded

- [Text] Su Lin Blodgett, Solon Barocas, Hal Daumé III, Hanna Wallach, Language (Technology) is Power: A Critical Survey of "Bias" in NLP, Arxiv - https://arxiv.org/abs/2005.14050, 2020 [NLP Bias]
- [Image] Vegard Antun, Francesco Renna, Clarice Poon, Ben Adcock, and Anders C. Hansen, On instabilities of deep learning in image reconstruction and the potential costs of AI, https://doi.org/10.1073/pnas.1907377117, PNAS, 2020
- [Audio] Allison Koenecke, Andrew Nam, Emily Lake, Joe Nudell, Minnie Quartey, Zion Mengesha, Connor Toups, John R. Rickford, Dan Jurafsky, and Sharad Goel, Racial disparities in automated speech recognition, PNAS April 7, 2020 117 (14) 7684-7689, https://doi.org/10.1073/pnas.1915768117, March 23, 2020

XAI for Text

Explanation Taxonomy

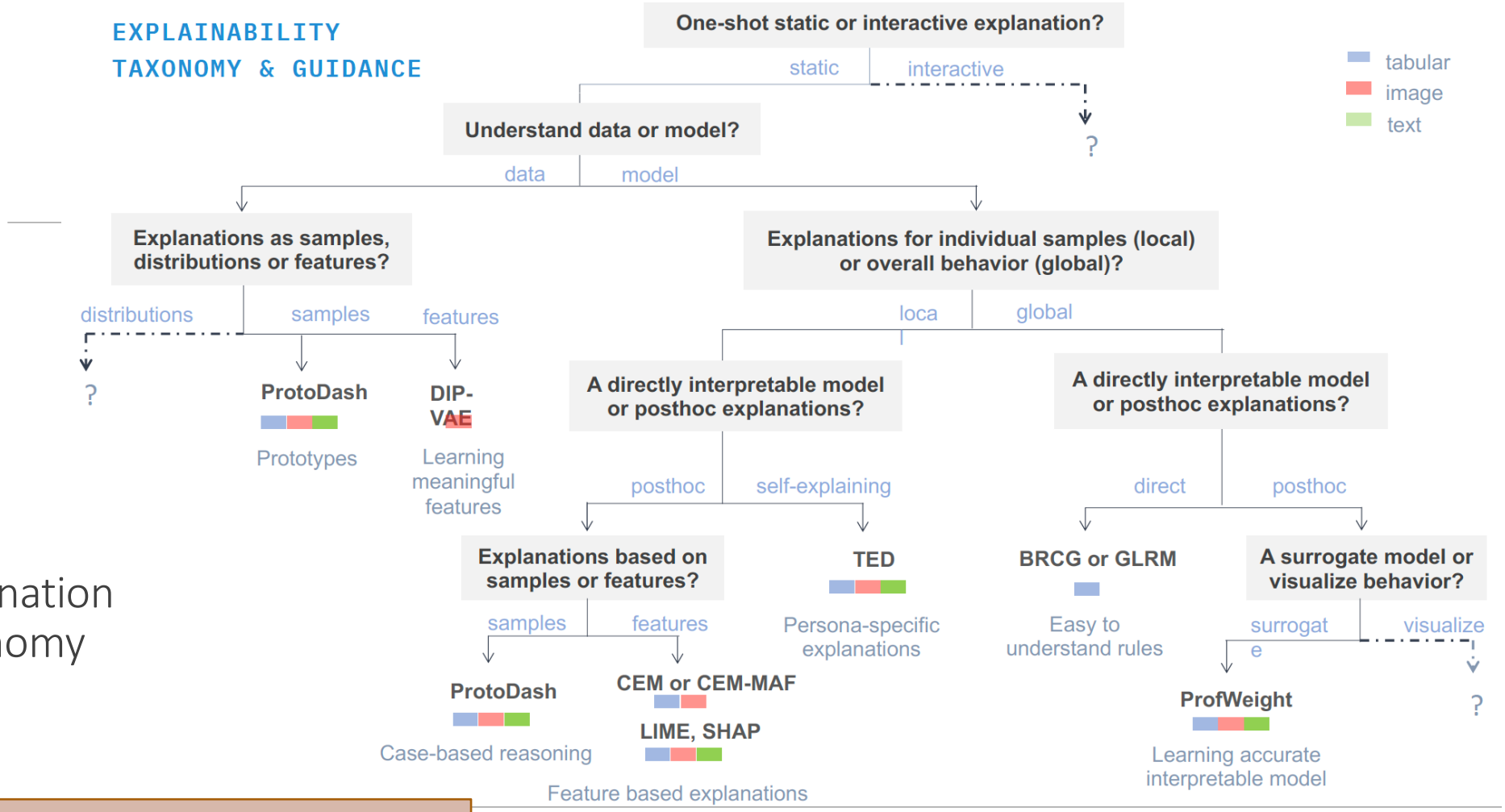


Figure Credit: Diptikalyan Saha and Vijay Arya, Oct 2021

Methods

- LIME:
  - Tools: LIME, InterpretML
- SHAP:
  - Tools: SHAP, ExplainerBoard

LIME – Local Interpretable Model-Agnostic Explanations

Paper: "Why Should I Trust You?" Explaining the Predictions of Any Classifier, Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin, ACM's Conference on Knowledge Discovery and Data Mining, KDD2016

Blogs:

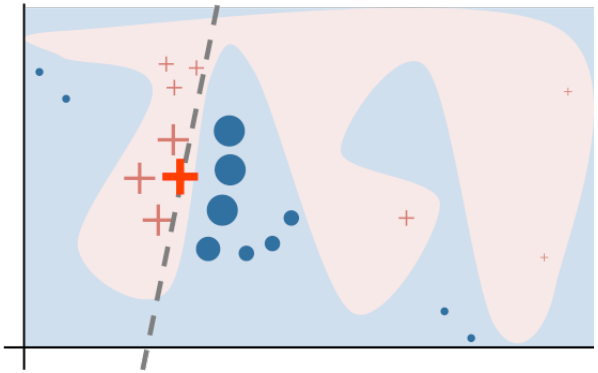
- https://homes.cs.washington.edu/~marcotcr/blog/lime/
- https://www.oreilly.com/content/introduction-to-local-interpretable-model-agnostic-explanations-lime/

Code: https://github.com/marcotcr/lime

Figures credit: Marco Tulio Ribeiro

LIME Key Idea

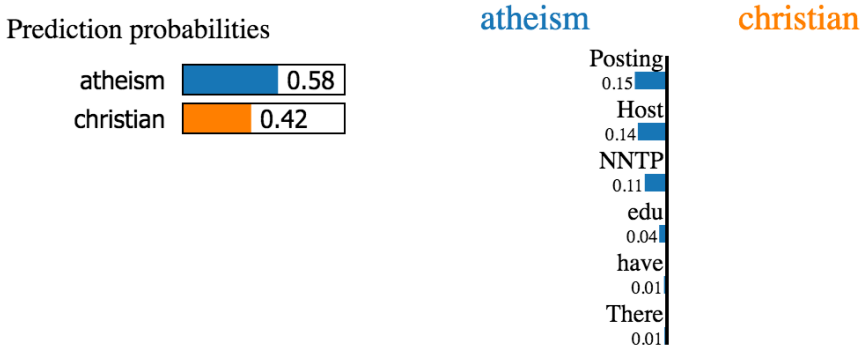
- Generate a local, linear explanation for any model
- How
  - Perturb near the neighborhood of a point of interest, X (**Local**)
  - Fit a linear function to the model's output (**Linear**)
  - Interpret coefficients of the linear function (**Explain**)
  - **Visualize**
- Applicability
  - Any classification model!



LIME on Text

Question: Why is a classifier with >90% accuracy predicting based on ?

Task: classifying religious inclination from email text



Text with highlighted words

From: johnchad@triton.unm.edu (jchadwic)
Subject: Another request for Darwin Fish
Organization: University of New Mexico, Albuquerque
Lines: 11
NNTP-Posting-Host: triton.unm.edu

Hello Gang,

There have been some notes recently asking where to obtain the DARWIN fish.
This is the same question I have and I have not seen an answer on the
net. If anyone has a contact please post on the net or email me.

"If we remove the words **Host** and **NNTP** from the document, we expect the classifier to predict **atheism** with probability 0.58 - 0.14 - 0.11 = 0.31"

Source: https://github.com/marcotcr/lime

Review Example in Code

Github: https://github.com/biplav-s/course-tai-s25/blob/main/sample-code/LIME(Text)%20Classification.ipynb

InterpretML

- **Details**: https://github.com/interpretml/interpret
  - Whitebox (Glassbox) models: change learning code to introduce explainability support
  - Blackbox models: don't change learning code

Interpretability Technique	Type
Explainable Boosting	**glassbox model**
APLR	glassbox model
Decision Tree	glassbox model
Decision Rule List	glassbox model
Linear/Logistic Regression	glassbox model
SHAP Kernel Explainer	blackbox explainer
LIME	**blackbox explainer**
Morris Sensitivity Analysis	blackbox explainer
Partial Dependence	blackbox explainer

Interpret (Text)

See: https://github.com/interpretml/interpret-text

Explainers for sophisticated classifiers:

- Classical Text Explainer - (Default: Bag-of-words with Logistic Regression)
- Unified Information Explainer
- Introspective Rationale Explainer
- Likelihood Explainer
- Sentence Embedder Explainer
- Hierarchical Explainer

Classification - Multimodal

- Data is multimodal, i.e., two or more models.

- Example: financial (stock) prediction
  - In the domain of finance, data can be both numeric (stock price) and textual data (news).
  - Sample exercises:
    - https://github.com/Joeyipp/predict-stock-trends-news [Joey Yipp, CSCE 771, 2020]
    - https://www.kaggle.com/code/shtrausslearning/news-sentiment-based-trading-strategy
- Example: emergency room delay prediction
  - Electronic Health Record can have both numeric (pulse, heart rate) and textual data (clinical notes)
  - Reference: **Utilizing Predictive Analysis to Aid Emergency Medical Services**
    - https://link.springer.com/chapter/10.1007/978-3-030-93080-6_17

Explanation in Neural Network

- Visualize neural network activation for explanation
  - Illustration via code (Credit: Kausik Lakkaraju) - https://colab.research.google.com/drive/1ABWbuQ09qLJzITkKtYrMGUNCw-inQPDn?usp=sharing
- Mechanistic explanation
  - Mechanistic Interpretability for AI Safety -- A Review, Leonard Bereska, Efstratios Gavves, https://arxiv.org/abs/2404.14082
  - Illustrative code samples:
    - https://www.neelnanda.io/mechanistic-interpretability/quickstart
    - https://transformerlensorg.github.io/TransformerLens/content/getting_started_mech_interp.html

Explanation in LLMs

- Setting: one prompts a LLM and gets an output. How does one explain the result?
- Ideas
  - Prompt again with variation; analyze output, infer
    - Question: how to create variations?
    - Question: how to analyze outputs?
    - Question: how to infer about LLMs understanding?
  - Prompt another LLM, analyze output, infer
    - Question: which other LLM(s)
    - …
- Prompting methods
  - https://www.promptingguide.ai/introduction
  - See reading list on LLMs (https://github.com/biplav-s/course-tai-s25/blob/main/reading-list/Readme-LLMs.md)

Prompting of LLMs

A prompt contains any of the following elements:

- **Instruction** - a specific task or instruction you want the model to perform
- **Context** - external information or additional context that can steer the model to better responses
- **Input Data** - the input or question that we are interested to find a response for
- **Output Indicator** - the type or format of the output.

Credit:
https://www.promptingguide.ai/introduction/elements

Advanced reading:
The Prompt Report: A Systematic Survey of Prompting Techniques (June 2024, Feb 2025)
https://arxiv.org/pdf/2406.06608

Certifying/ Rating with Text-based AI

Trust Issues – Mitigate via Ratings

- Communicate behavior via certificates / ratings (increase transparency)
  - But, let humans make decisions

Trust Dimensions
Competent
Reliable
Upholds human values
Allows human interaction

Transparency Through Documentation of Rating

Documentation about

- Outcome (e.g., Nutrition label, Electronic DataSheet, Factsheet)
- Process (e.g., SEI Capability Maturity Model, ISO 9001)

Documentation by

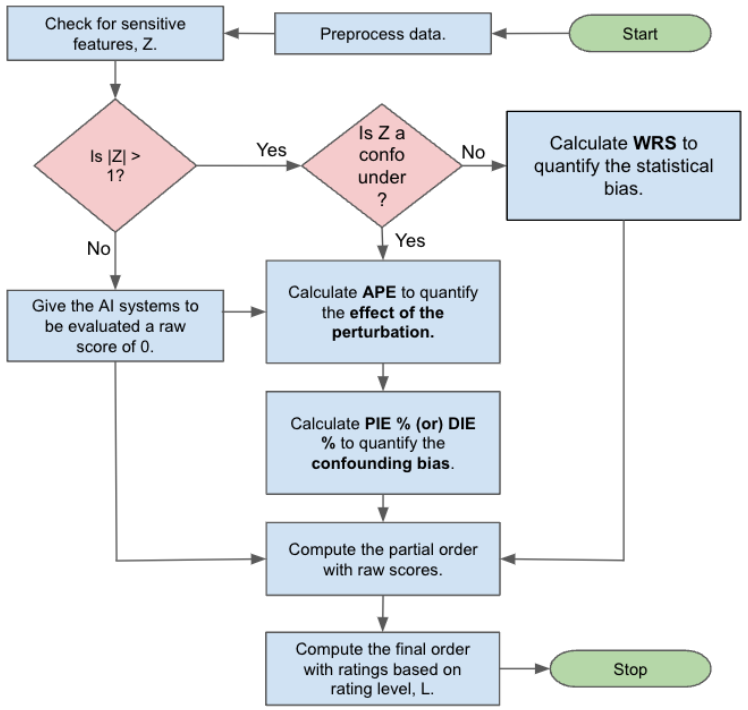
- Producer (e.g., Nutrition label)
- Consumer (e.g., Yelp rating)
- Independent 3rd Party (e.g., JD Powers, NHTSA car crash)

Reference: AboutML Project at PAI - https://www.partnershiponai.org/about-ml-get-involved/#read

ARC Tool and Rating

Tool: http://casy.cse.sc.edu/causal_rating

- See Sentiment Assessment Systems (SAS)



Quiz 2

Project Discussion

Course Project

- **Framework**
  1. (Problem) Think of a problem whose solution may benefit people (e.g., health, water, air, traffic, safety)
  2. (User) Consider how the primary user (e.g., patient, traveler) may be solving the problem today
  3. (AI Method) Think of what the solution will do to help the primary user
     1. Solution => ML task (e.g. classification), recommendation, text summarization, …
     2. Use a foundation model (e.g., LLM-based) solution as the baseline
  4. (Data) Explore the data for a solution to work
  5. (Reliability: Testing) Think of the evaluation metric we should employ to establish that the solution will works? (e.g., 20% reduction in patient deaths)
  6. (Holding Human Values) Discuss if there are fairness/bias, privacy issues?
  7. (Human-AI) Finally, elaborate how you will explain the primary user that your solution is trustable to be used by them

Project Discussion: What to Focus on ?

- Problem: you should care about it
- Data: should be available
- Method: you need to be comfortable with it. Have at least two – one serves as baseline
- Trust issue
  - Due to Users
    - Diverse demographics
    - Diverse abilities
    - Multiple human languages
  - Or other impacts
- What one does to mitigate trust issue

Rubric for Evaluation of Course Project

Project

- Project plan along framework introduced (7 points)
- Challenging nature of project
- Actual achievement
- Report
- Sharing of code

Presentation

- Motivation
- Coverage of related work
- Results and significance
- Handling of questions

Concluding Section

Week 11 (L23 and 24): Concluding Comments

- We looked at
  - L23: Explanations (Text)
  - L24: Assessment and Rating (Text)
  - Quiz 2

About Next Week – Lectures 25, 26

Lectures 25, 26

- Trust in Human-AI systems/ Chatbots
- Trust Standards and Laws, Privacy; Acceptable systems for the Real-world

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	May 1 (Th)	
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