CMSC 473/673 Natural Language Processing

Instructor: Lara J. Martin (she/they)

TA: Maitri Mistry

Schedule

Intro to Lara & Maitri

Why are you taking this?

Course logistics

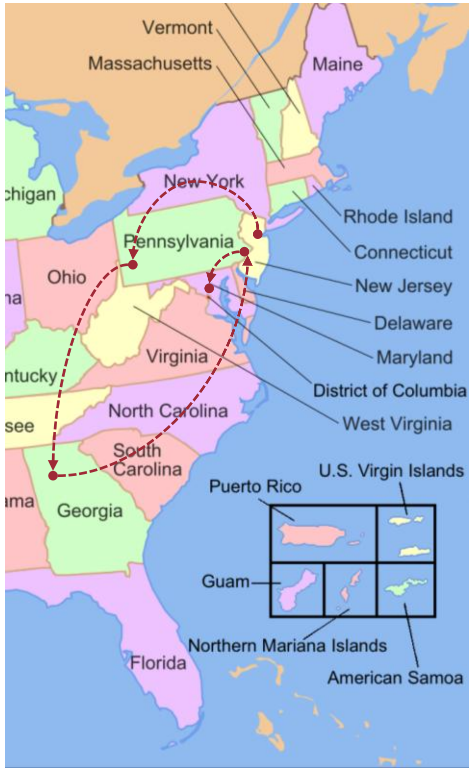
What is NLP?

Who is Lara?

laramar@umbc.edu

laramartin.net

- BS CS & Linguistics @ Rutgers
- MS Language Technologies @ CMU
- PhD Human-Centered Computing @ GT
- CIFellows Postdoc @ UPenn
- Assistant Prof @ UMBC

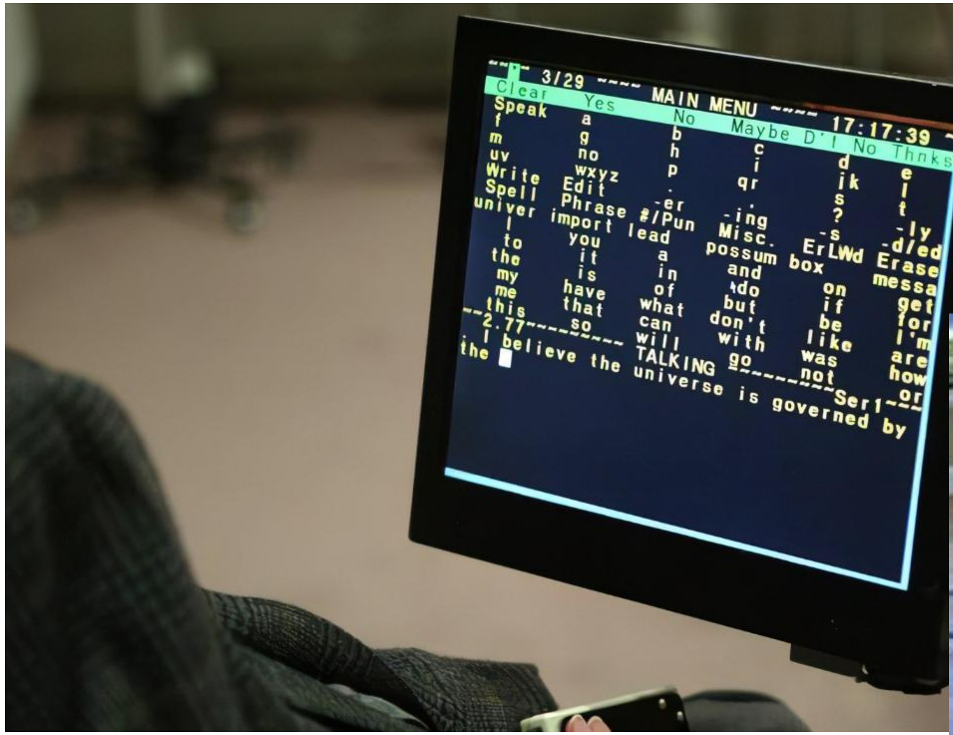


https://upload.wikimedia.org/wikipedia/commons/a/a4/Map_of_USA_with_state_and_territory_names_2.png

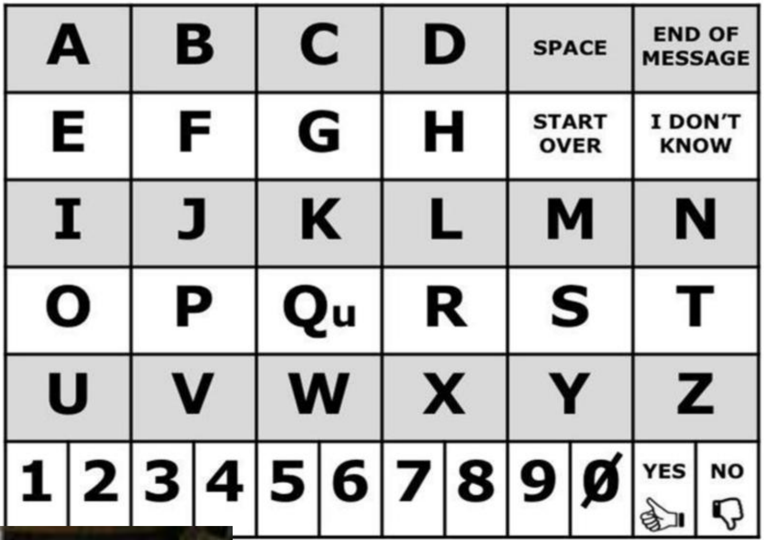
What do I work on?

- Applied NLP
  - human-AI communication
    - Story generation / Dungeons & Dragons AI
    - Chatbots
  - computer-mediated human-human communication
    - Speech processing
    - Augmentative and alternative communication (AAC)

Augmentative & Alternative Communication



https://www.abc.es/media/ciencia/2018/03/15/20576450-kgXH--620x349@abc.jpg



A	B	C	D	SPACE	END OF MESSAGE
E	F	G	H	START OVER	I DON'T KNOW
I	J	K	L	M	N
O	P	Qu	R	S	T
U	V	W	X	Y	Z
1 2	3 4	5 6	7 8	9 Ø	YES NO

Letter Board - AEIOU format

.unl.edu/documents/secd/forms/Letter-Boards.png

https://bdnews24.com/lifestyle/2021/05/30/the-talking-dog-of-tiktok

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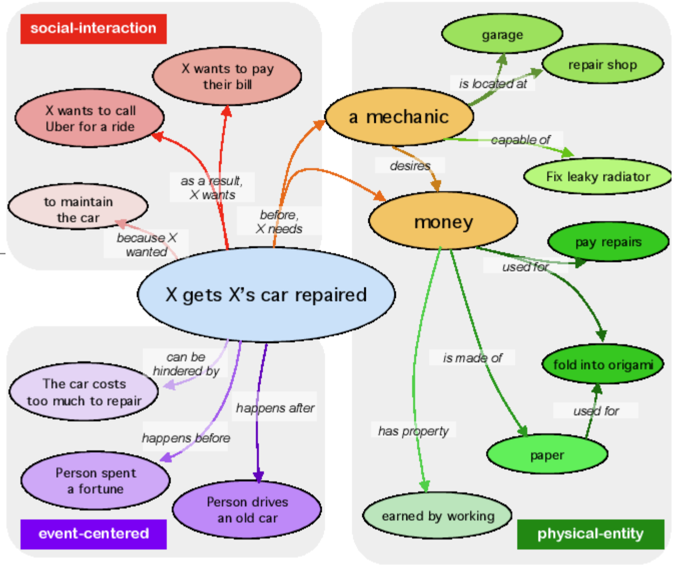
- Using neurosymbolic methods

Neural networks
Neural language models

Old-school AI methods
Discrete, interpretable representations that can help LMs

Knowledge graphs



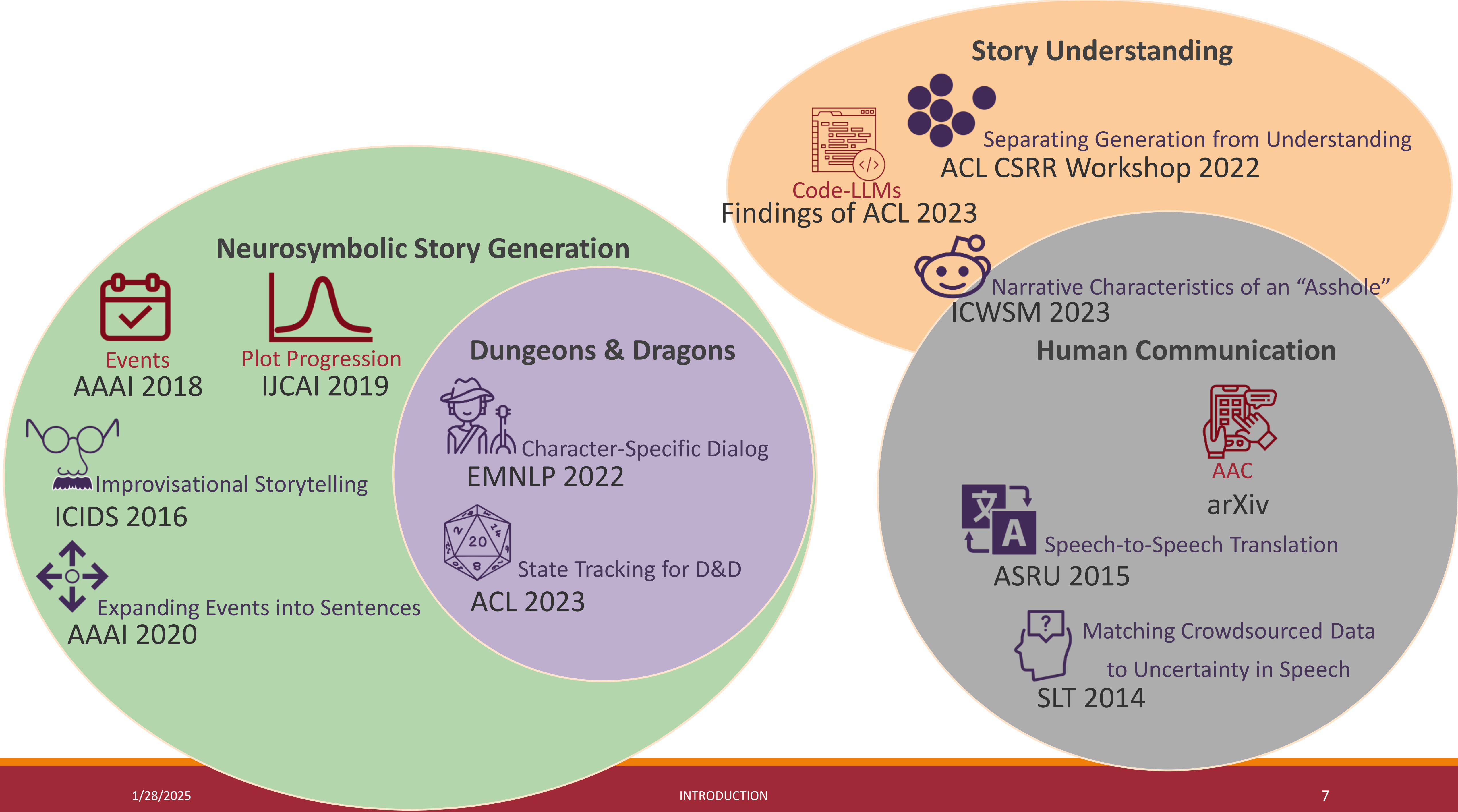
J. D. Hwang *et al.*, "(COMET-)ATOMIC2020: On Symbolic and Neural Commonsense Knowledge Graphs," *AAAI Conference on Artificial Intelligence (AAAI)*, vol. 35, no. 7, pp. 6384–6392, 2021. https://ojs.aaai.org/index.php/AAAI/article/view/16792

Creating structure from sentences

(subject, verb, direct object, modifier)

Original sentence: yoda uses the force to take apart the platform
Event: yoda use force Ø
Generalized Event: <PERSON>0 use-105.1 causal_agent.n.01 Ø

L. J. Martin *et al.*, "Event Representations for Automated Story Generation with Deep Neural Nets," *AAAI*, vol. 32, no. 1, pp. 868–875, Apr. 2018, doi: 10.1609/aaai.v32i1.11430.



Neurosymbolic Story Generation

Events
AAAI 2018

Plot Progression
IJCAI 2019

Improvisational Storytelling
ICIDS 2016

Expanding Events into Sentences
AAAI 2020

Dungeons & Dragons

Character-Specific Dialog
EMNLP 2022

State Tracking for D&D
ACL 2023

Story Understanding

Separating Generation from Understanding
ACL CSRR Workshop 2022

Code-LLMs
Findings of ACL 2023

Narrative Characteristics of an “Asshole”
ICWSM 2023

Human Communication

AAC
arXiv

Speech-to-Speech Translation
ASRU 2015

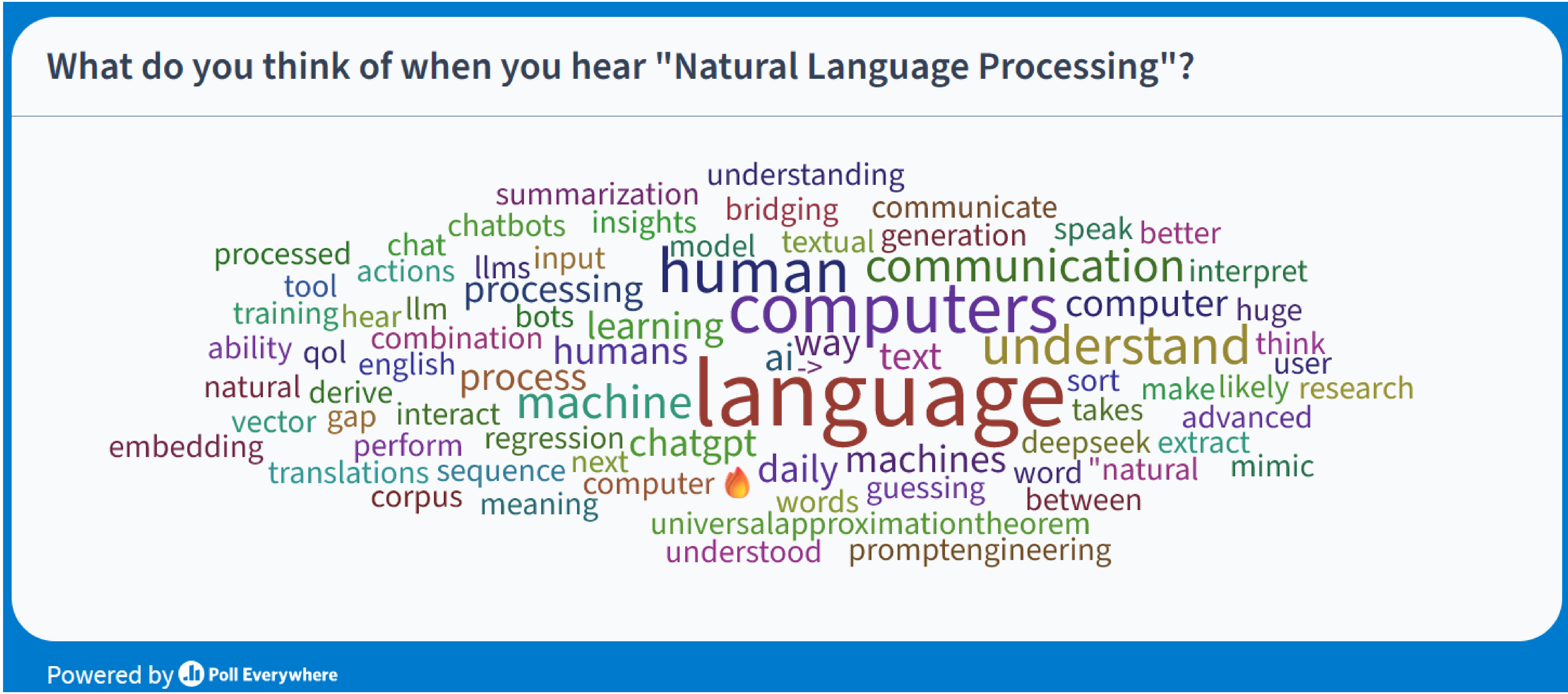
Matching Crowdsourced Data
to Uncertainty in Speech
SLT 2014

Who is Maitri?

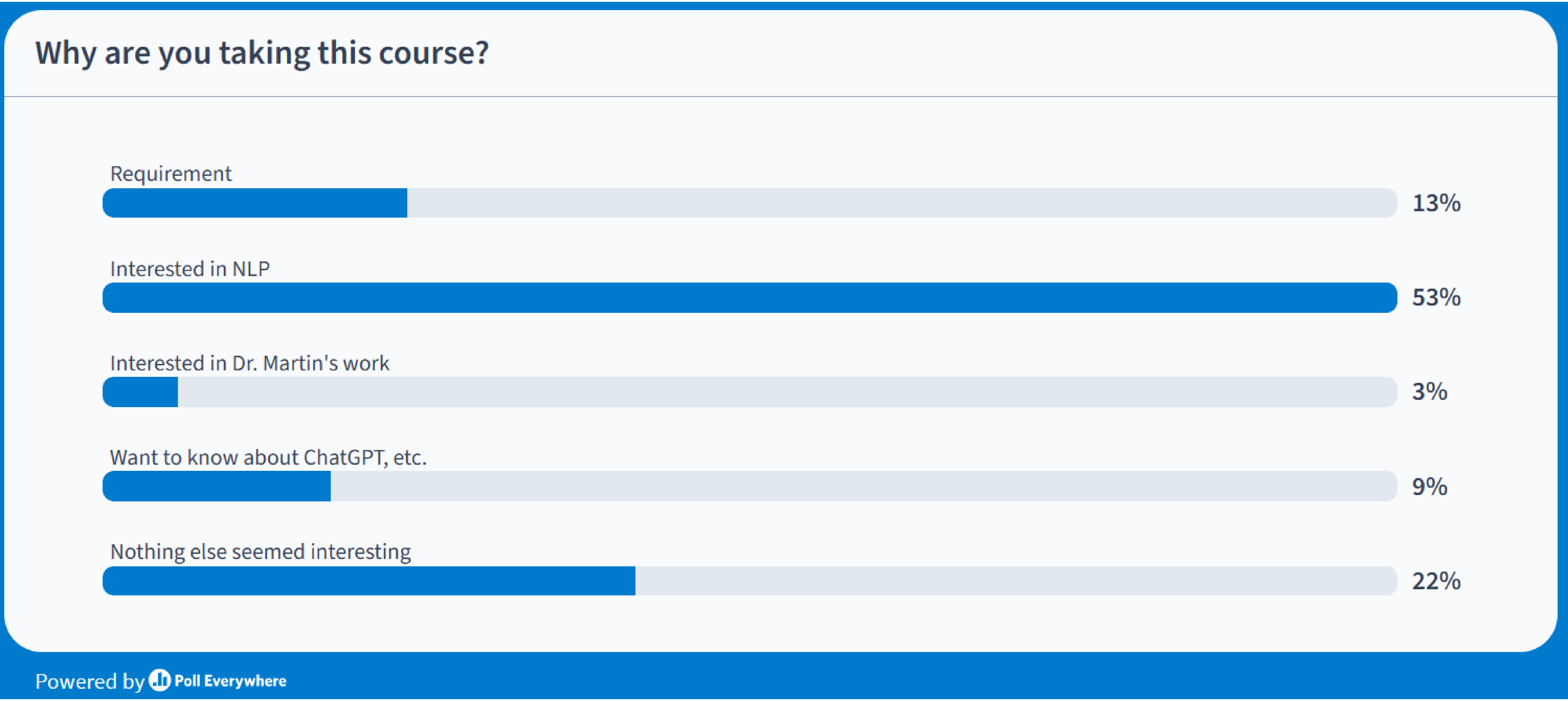
mmistry3@umbc.edu

MS student

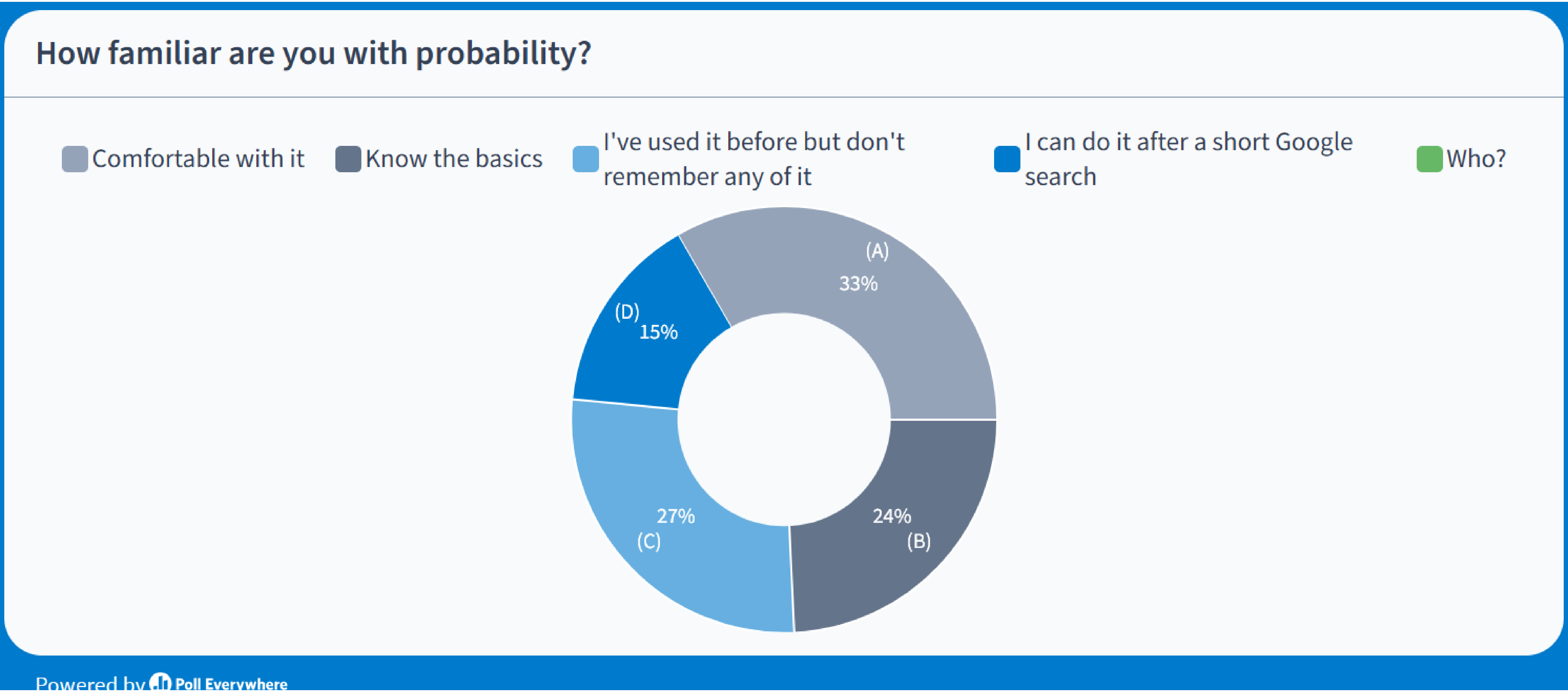
Has TAed this class with Dr. Frank Ferraro before



What do you think of when you hear "Natural Language Processing"?



Why are you taking this course?



How familiar are you with probability?

Comfortable with it
Know the basics
I've used it before but don't remember any of it
I can do it after a short Google search
Who?
(A)
33%
(D)
15%
27%
(C)
24%
(B)
Powered by Poll Everywhere

Logistics

Materials

Course Website: https://laramartin.net/NLP-class

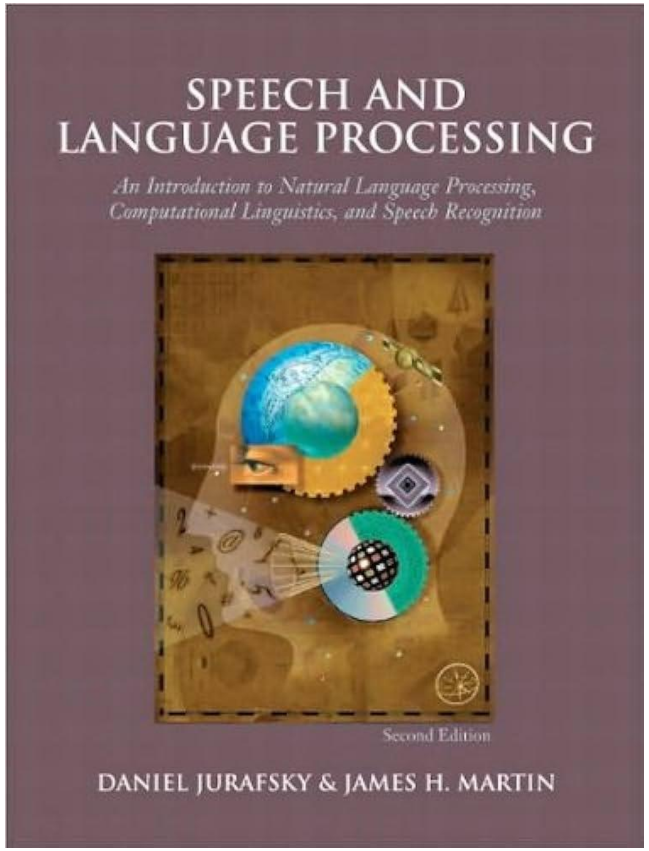
- Schedule
- Assignment descriptions
- Policies

Blackboard

- Assignment submission
- Grades

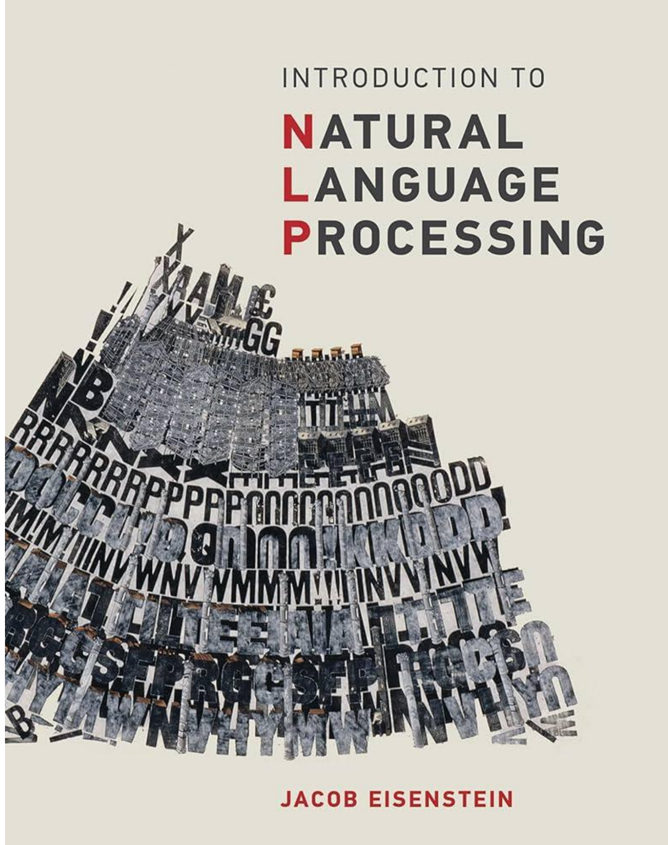
Textbooks

See links for both books on the course website


SPEECH AND LANGUAGE PROCESSING
An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition
Second Edition
DANIEL JURAFSKY & JAMES H. MARTIN

"Speech and Language Processing"
by Dan Jurafsky and James Martin
3rd Edition (Draft) online

"Introduction to Natural Language Processing"
by Jacob Eisenstein
Notes PDF on GitHub
(I also have a physical copy)



Images from Amazon

Office Hours

Lara: Tuesdays & Thursdays 1:45 - 2:30PM

- ITE 216 (or online if you tell me)
- Also by appointment: https://calendly.com/laramar/schedule

Maitri: In-person Mondays 2 - 3 pm and online Thursdays 2:30 - 3:30 pm

- Online link: https://us04web.zoom.us/j/71390545038?pwd=crYbcQcb0sYBCH3ebobB6fpNJb1RNU.1
- Also by appointment: mmistry3@umbc.edu

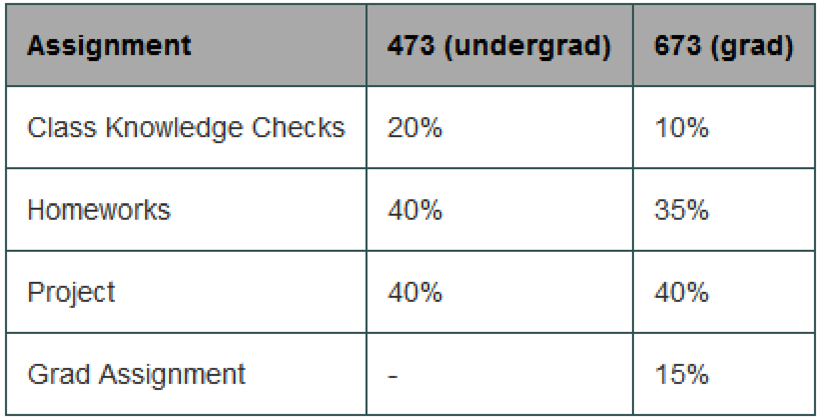
Learning Objectives

By the end of the course, you will be able to…

1. Recall common tasks in NLP and formulate problems for them. (HW1)
2. Diagnose and setup appropriate evaluation metrics for a given problem, including determining what an appropriate baseline might be. (HW2)
3. Compare and contrast language models and other NLP methods. (HW3)

Knowledge Checks

4. Implement AI systems that use popular NLP toolkits and libraries. (Grad Assignment)
5. Construct a literature review from state-of-the-art research. (Grad Assignment)
6. Plan and create an NLP system for a particular task. (Project)



Assignment	473 (undergrad)	673 (grad)
Class Knowledge Checks	20%	10%
Homeworks	40%	35%
Project	40%	40%
Grad Assignment	-	15%

Policies

Everyone has 5 free late days (3 max per homework)

- No excuse needed/no need to tell me you’re using them

You can collaborate on knowledge checks (in pairs) and the project (3-5 person groups), **not** the homeworks or the grad assignment

Academic Integrity

- If you feel the need to cheat on the assignment to do well on it, please talk to me or Maitri first. We can work it out ahead of time, but once you cheat it’s hard to do anything.

If you cheat or plagiarize, you…

- aren’t learning anything
- wasting money paying for tuition
- will get an F on the assignment (at the very least)

More details on course website

Disclaimer about POTS

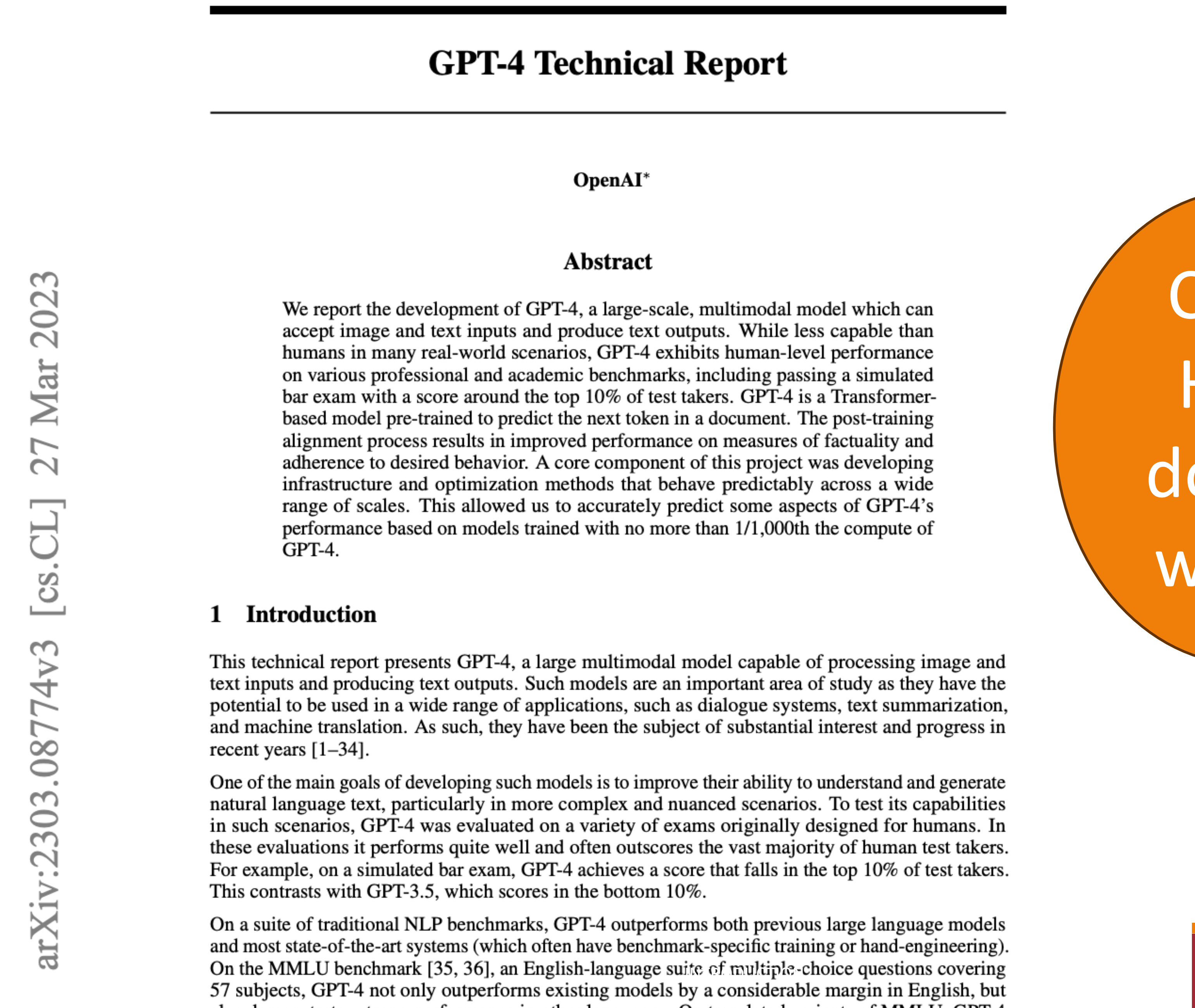
I have a disability called Postural Orthostatic Tachycardia Syndrome (POTS)

- It means that my blood doesn’t always go where I need it to go
- It’s a *dynamic disability*, meaning that it’s worse some days than others

How does it affect this class?

- I will be lecturing sitting down
- I might get brain fog and have trouble thinking

What about “Large Language Models”?



arXiv:2303.08774v3 [cs.CL] 27 Mar 2023

GPT-4 Technical Report

OpenAI*

Abstract

We report the development of GPT-4, a large-scale, multimodal model which can accept image and text inputs and produce text outputs. While less capable than humans in many real-world scenarios, GPT-4 exhibits human-level performance on various professional and academic benchmarks, including passing a simulated bar exam with a score around the top 10% of test takers. GPT-4 is a Transformer-based model pre-trained to predict the next token in a document. The post-training alignment process results in improved performance on measures of factuality and adherence to desired behavior. A core component of this project was developing infrastructure and optimization methods that behave predictably across a wide range of scales. This allowed us to accurately predict some aspects of GPT-4's performance based on models trained with no more than 1/1,000th the compute of GPT-4.

1 Introduction

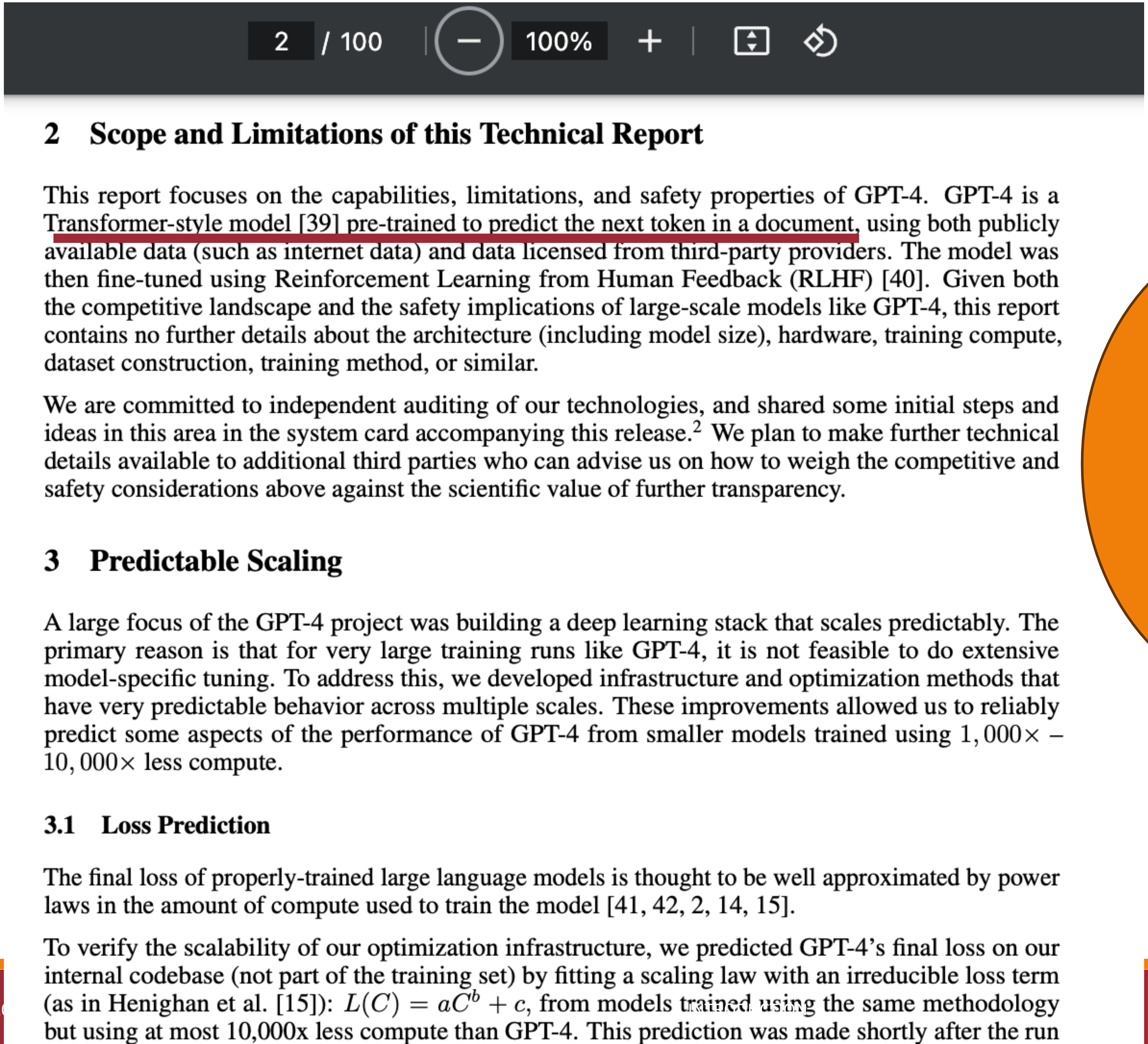
This technical report presents GPT-4, a large multimodal model capable of processing image and text inputs and producing text outputs. Such models are an important area of study as they have the potential to be used in a wide range of applications, such as dialogue systems, text summarization, and machine translation. As such, they have been the subject of substantial interest and progress in recent years [1–34].

One of the main goals of developing such models is to improve their ability to understand and generate natural language text, particularly in more complex and nuanced scenarios. To test its capabilities in such scenarios, GPT-4 was evaluated on a variety of exams originally designed for humans. In these evaluations it performs quite well and often outscores the vast majority of human test takers. For example, on a simulated bar exam, GPT-4 achieves a score that falls in the top 10% of test takers. This contrasts with GPT-3.5, which scores in the bottom 10%.

On a suite of traditional NLP benchmarks, GPT-4 outperforms both previous large language models and most state-of-the-art systems (which often have benchmark-specific training or hand-engineering). On the MMLU benchmark [35, 36], an English-language suite of multiple-choice questions covering 57 subjects, GPT-4 not only outperforms existing models by a considerable margin in English, but

Cool! How does it work?

Slide by Dr. Frank Ferraro



2 Scope and Limitations of this Technical Report

This report focuses on the capabilities, limitations, and safety properties of GPT-4. GPT-4 is a Transformer-style model [39] pre-trained to predict the next token in a document, using both publicly available data (such as internet data) and data licensed from third-party providers. The model was then fine-tuned using Reinforcement Learning from Human Feedback (RLHF) [40]. Given both the competitive landscape and the safety implications of large-scale models like GPT-4, this report contains no further details about the architecture (including model size), hardware, training compute, dataset construction, training method, or similar.

We are committed to independent auditing of our technologies, and shared some initial steps and ideas in this area in the system card accompanying this release.[2] We plan to make further technical details available to additional third parties who can advise us on how to weigh the competitive and safety considerations above against the scientific value of further transparency.

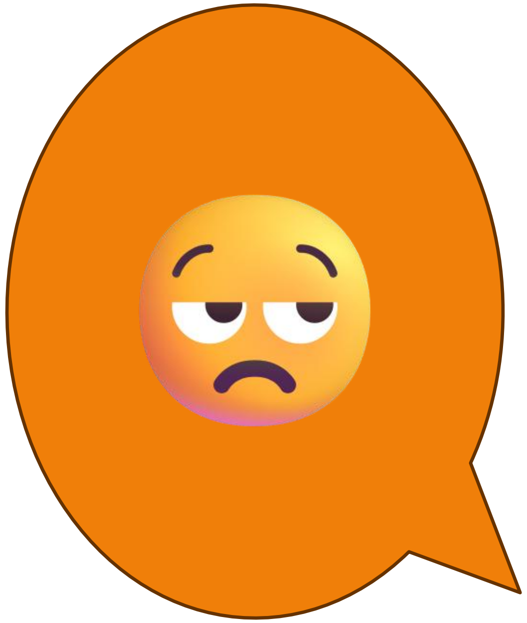
3 Predictable Scaling

A large focus of the GPT-4 project was building a deep learning stack that scales predictably. The primary reason is that for very large training runs like GPT-4, it is not feasible to do extensive model-specific tuning. To address this, we developed infrastructure and optimization methods that have very predictable behavior across multiple scales. These improvements allowed us to reliably predict some aspects of the performance of GPT-4 from smaller models trained using $1,000\times$ – $10,000\times$ less compute.

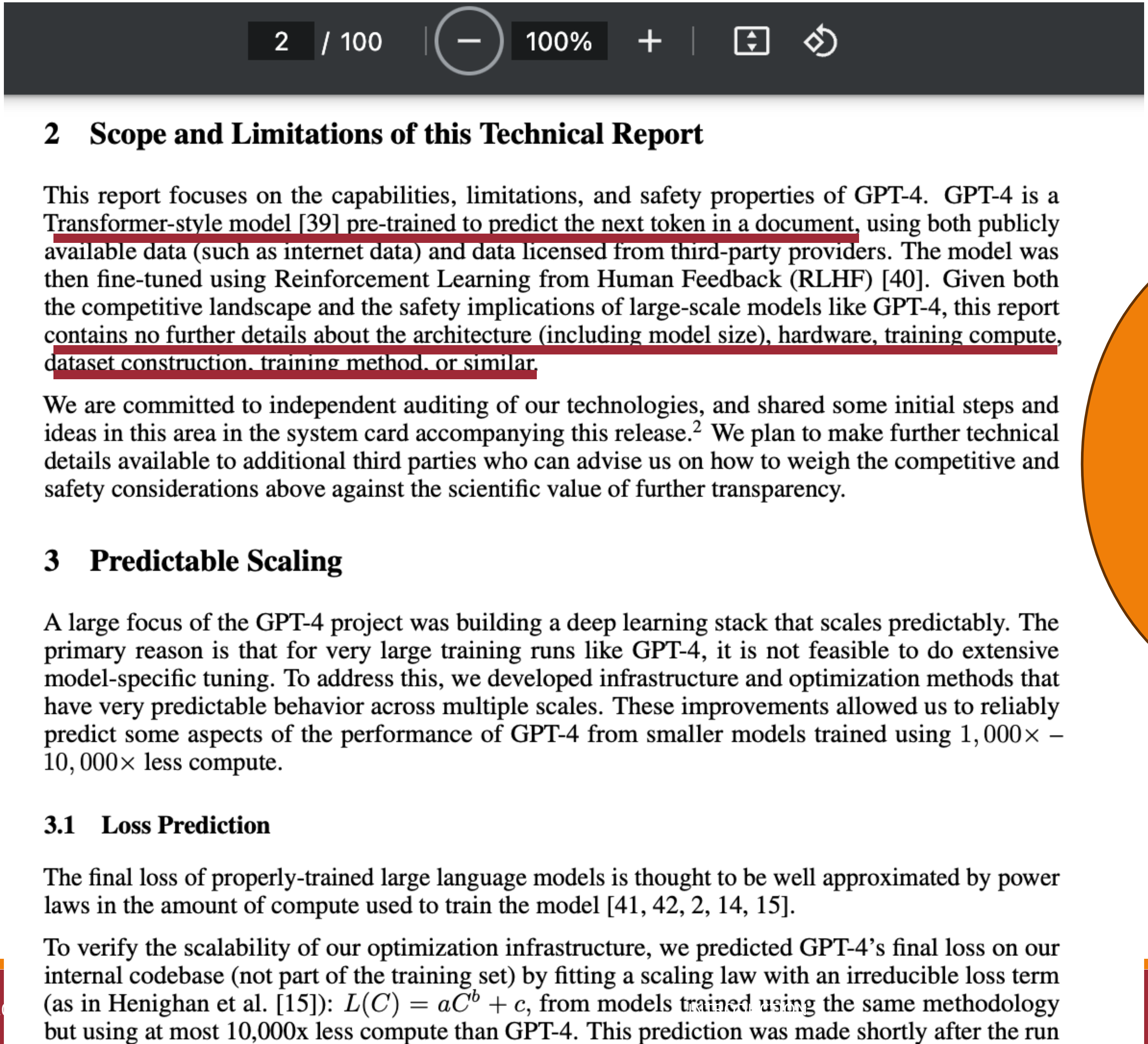
3.1 Loss Prediction

The final loss of properly-trained large language models is thought to be well approximated by power laws in the amount of compute used to train the model [41, 42, 2, 14, 15].

To verify the scalability of our optimization infrastructure, we predicted GPT-4's final loss on our internal codebase (not part of the training set) by fitting a scaling law with an irreducible loss term (as in Henighan et al. [15]): $L(C) = aC^b + c$, from models trained using the same methodology but using at most 10,000x less compute than GPT-4. This prediction was made shortly after the run



Slide by Dr. Frank Ferraro



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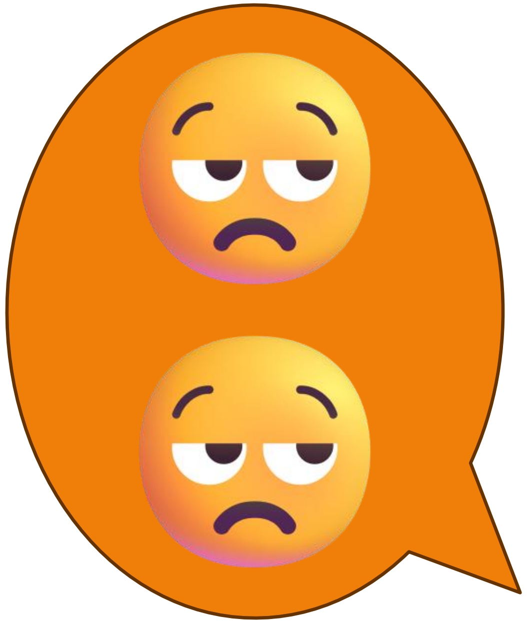
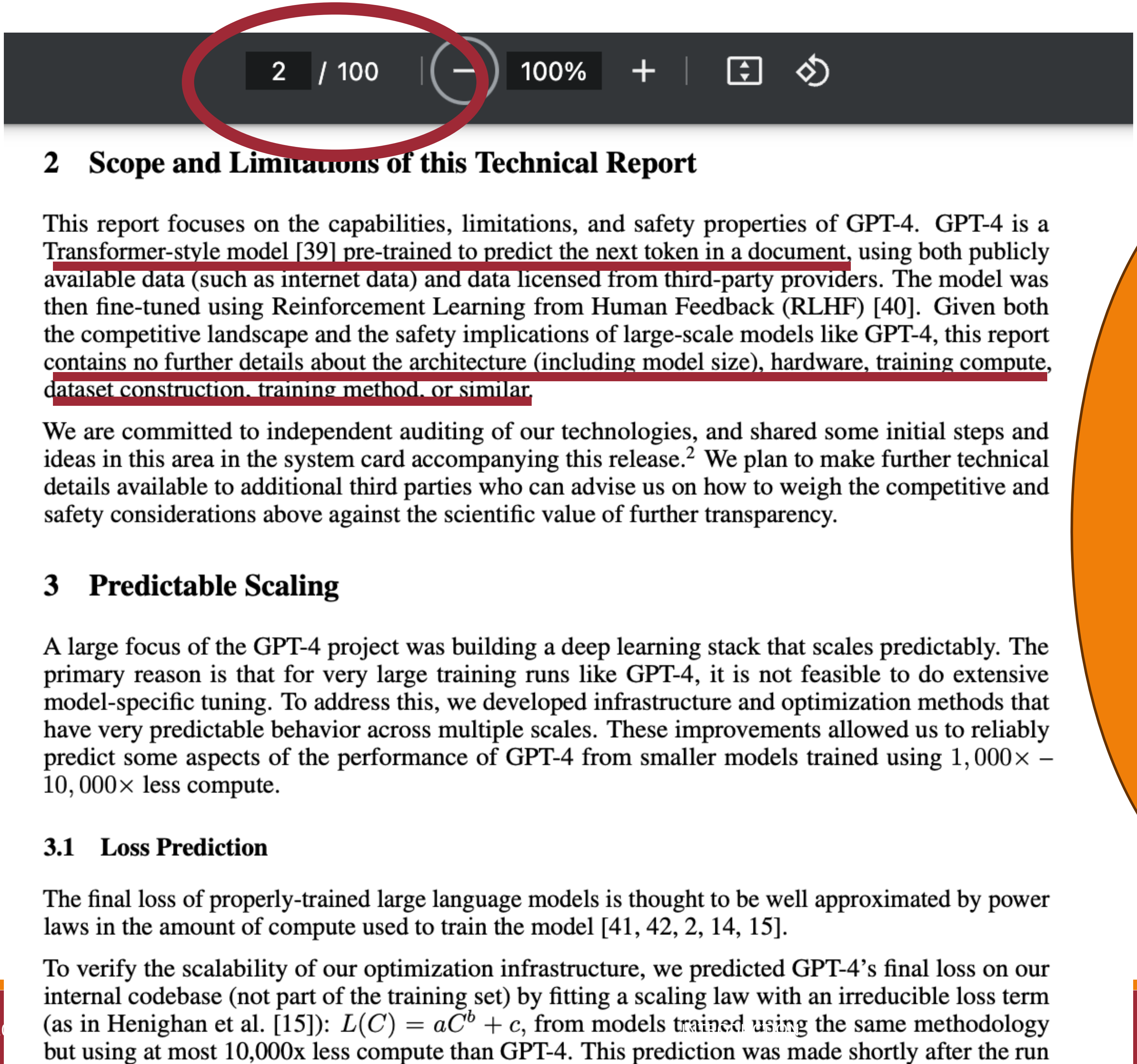


Slide by Dr. Frank Ferraro



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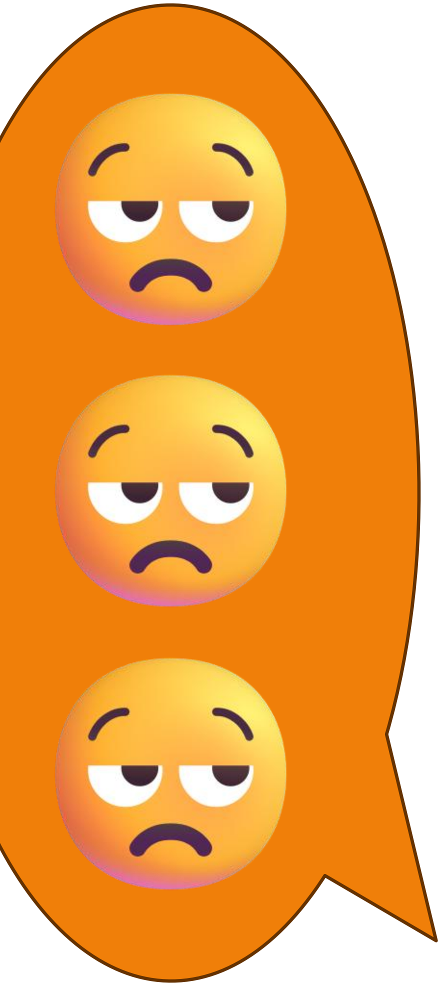

Slide by Dr. Frank Ferraro

Known Issues about LLMs

- Bad reproducibility
- Copyright issues
- Can’t explain what it’s doing
- Can’t remember things long term
- Confident bullshitter

Based on a slide by Dr. Frank Ferraro

If you want to use ChatGPT

- Make sure you're saying that you used it
- Provide your prompt and the original generation (along with how you edited it)
- Make sure that you're not avoiding the learning objectives by using it

- If you do not say you're using it and I notice, that is an academic integrity violation
- It's okay to use grammar tools (e.g., spell check or Grammarly) or small-scale prediction (e.g., next word prediction, tab completion), provided that they don't change the **substance** of your work

What are some NLP applications that you see in your daily life?

- Google search → process search text, AI response
- Retrieving information
- Speech-to-text/Automated speech recognition
- Text prediction/generation
- Translation
- Sentiment analysis
- Reasoning over text (e.g., what box to ship the Amazon product in)
- AI partner