# Natural Language Processing and Information Extraction

2023 WS

Allan Hanbury Florina Piroi Gábor Recski Varvara Arzt



### Contents

- Course information
- Introduction to NLP

Course information



# Lecturers



Allan Hanbury



Florina Piroi



Gábor Recski



Varvara Arzt

#### Lecture Schedule

- Course Information, Introduction to NLP [Hanbury] (6.10.2023)
- Text Processing [Recski] (13.10.2023)
- Text Classification [Recski] (20.10.2023)
- Deep Learning for NLP [Piroi] (27.10.2023)
- Textual Sequence Modelling & Attention [Piroi] (3.11.2023)
- Deep Learning Practical Lesson [Recski, Arzt] (10.11.2023)
- Syntax (Constituency and Dependency) [Recski] (17.11.2023)
- Basic (non-DL) Semantics [Recski] (24.11.2023)
- Information Extraction [Recski] (1.12.2023)
- Summarisation & Keyword Extraction [Piroi] (15.12.2023)
- Annotation Basics and Challenges [Hanbury] (12.1.2024)
- Project Presentations (19.1.2024)

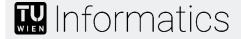


# Lectures

- Fridays 13:00 c.t. 15:00
- EI11

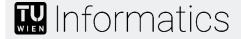
#### Exercise

- One project exercise with two Milestones
- Done in groups of four
- Each group has a mentor
- Submissions are made via GitHub Classrooms
- Grading is based on milestones, final submission, presentation, and report
- Every group member must present their own contributions in the final presentation and will be individually evaluated on these contributions



#### **Exercise Deadlines**

- Oct 6: Project introduced
- Oct 13: Project milestone 1 introduced
- Oct 20: Topics assigned, Project milestone 2 introduced
- Nov 3: Milestone 1 deadline
- Dec 1: Milestone 2 deadline
- Dec 15: Review meetings 9-13
- Jan 19: Project presentation deadline
- Jan 28: Project final submission deadline



#### Effort Breakdown

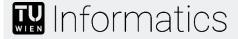
• Lectures: 24 hours

• Project Milestone 1: 8 hours

• Project Milestone 2: 8 hours

• Final Solution: 35 hours

Total: 75 hours



#### Performance Evaluation

- Milestone 1: Minimum 35%
- Milestone 2: Minimum 35%
- Final solution: Minimum 35%
- Overall Score: Minimum 50% to pass
  - 15% for Milestone 1
  - 15% for Milestone 2
  - 50% for the final solution
  - 10% for the presentation
  - 10% for the management summary
- There is no exam!
- Marks Overall Score
  - 1 89 100
  - 2 76 88
  - 3 63 75
  - 4 50 62

# Organisation

- Course
  - Please register for the course in TISS
- Communication
  - Use the General Discussion Forum in TUWEL for questions, not the TISS forum
- The schedule of lectures and all course material will be available on Github



#### Book

Third edition in preparation – download many chapters here:

https://web.stanford.edu/~jurafsky/slp3/

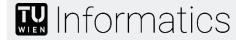
#### SPEECH AND Language processing

An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition



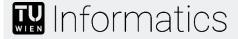
Second Edition

DANIEL JURAFSKY & JAMES H. MARTIN

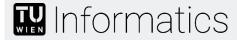


Questions about the organisation, etc.

Ask now!



Introduction to NLP



# IBM Watson and Jeopardy



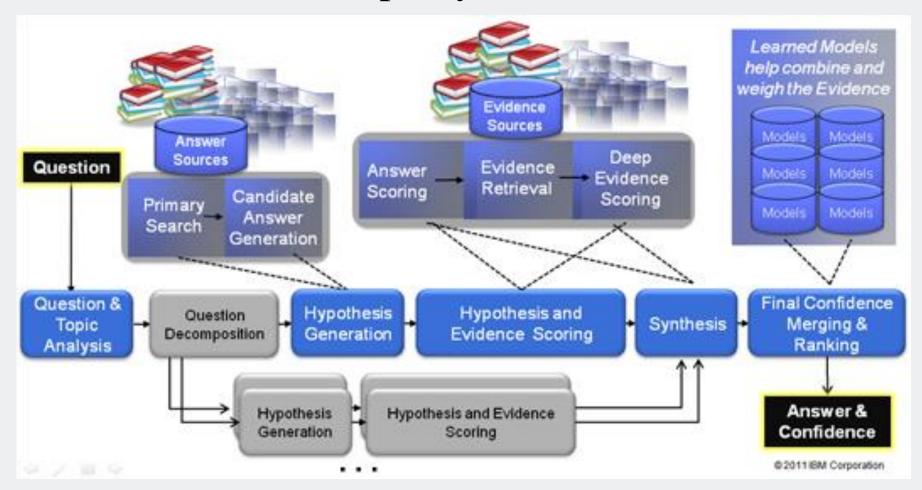
Final question: <a href="https://www.youtube.com/watch?v=Sp4q60BsHoY">https://www.youtube.com/watch?v=Sp4q60BsHoY</a> IBM film: <a href="https://www.youtube.com/watch?v=P18EdAKuC1U">https://www.youtube.com/watch?v=P18EdAKuC1U</a>



# The end of the show

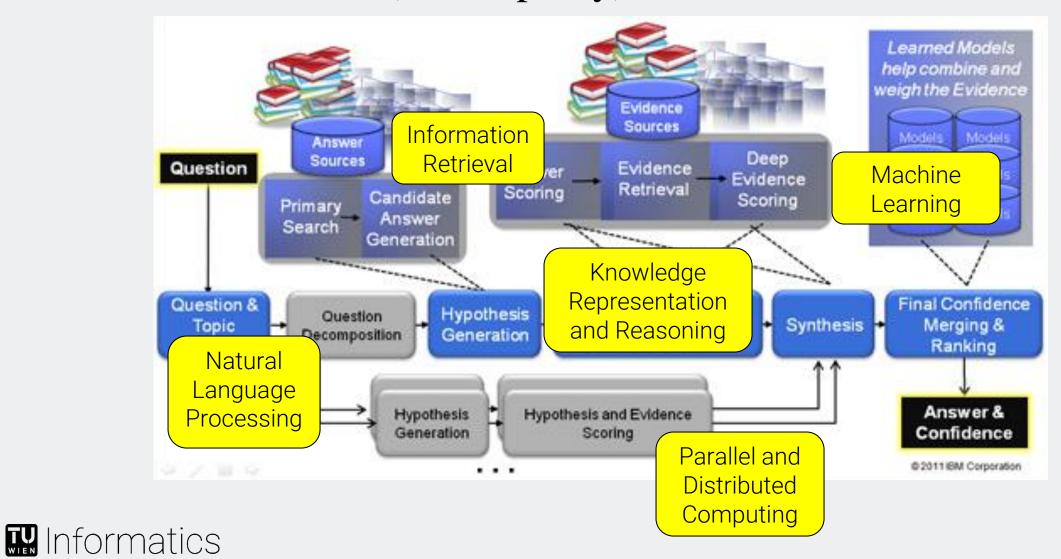


# How does Watson (for Jeopardy) work?





# How does Watson (for Jeopardy) work?





### Go beyond human capabilities

Combine the expertise of humans with the power of technology to deliver patient-centric cancer care at scale

PDF Transform cancer care (1.8 MB)

Data, AI & analytics (01:28)





↓ For the physician

Success stories

↓ Solutions

#### The changing oncology landscape

New intelligent analytics and workflow technologies hold the key to overcoming a primary challenge of providing personalized approaches to cancer care-harnessing the vast amounts of data available without being overwhelmed by it. Clinicians are faced with large, heterogeneous, and complex data sets when making patient-specific clinical decisions. Oncology solutions backed by AI and machine learning provide a powerful tool by bringing together data, extracting insights and presenting it to providers for their evaluation.

PDF Read the 2020 Data and Evidence Booklet (10.2 MB)



From research to real world.





Feature | Biomedical | Diagnostics

02 Apr 2019 | 15:00 GMT

# How IBM Watson Overpromised and Underdelivered on Al Health Care

After its triumph on *Jeopardy!*, IBM's AI seemed poised to revolutionize medicine. Doctors are still waiting

By Eliza Strickland

https://spectrum.ieee.org/biomedical/diagnostics/how-ibm-watson-overpromised-and-underdelivered-on-ai-health-care

# Informatics

#### **TECHNOLOGY NETWORKS**

Exploring the Science That Matters to You

#### The Hype of Watson: Why Hasn't Al Taken Over Oncology?

ARTICLE ② Apr 17, 2020 | by Sylvia He



Doctors' notes are one of the obstacles in the way of AI becoming a major force in oncology.

https://www.technologynetworks.com/informatics/articles/the-hype-of-watson-why-hasnt-ai-taken-over-oncology-333571

# Natural Language Processing (NLP)

Natural language processing (NLP) is a subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human language, in particular how to program computers to process and analyze large amounts of natural language data.

wikipedia



# Why is NLP interesting?

- Languages involve many human activities
  - Reading, writing, speaking, listening
- Voice can be used as a user interface in many applications
  - Remote controls, virtual assistants like siri,...
- NLP is used to acquire insights from massive amount of textual data
  - E.g., hypotheses from medical & health reports
- NLP has many applications
- NLP is difficult!



# Why is NLP difficult?

#### I made her duck

- I cooked waterfowl for her.
- I cooked waterfowl belonging to her.
- I created the (plaster?) duck she owns.
- I caused her to quickly lower her head or body.
- I waved my magic wand and turned her into undifferentiated waterfowl.

# I shot an elephant in my pyjamas.

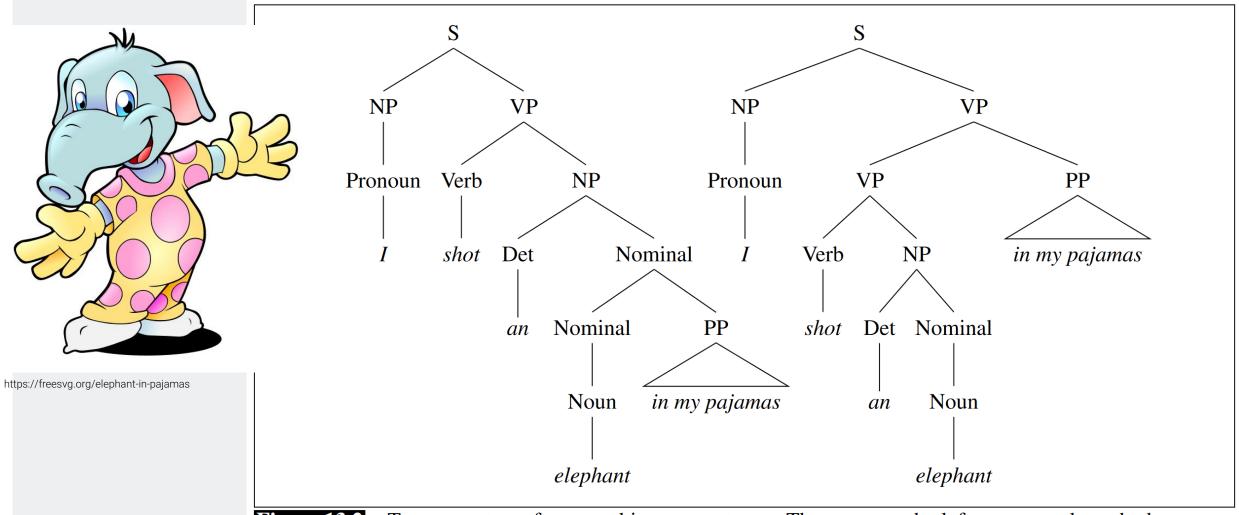




Figure 13.2 Two parse trees for an ambiguous sentence. The parse on the left corresponds to the humorous reading in which the elephant is in the pajamas, the parse on the right corresponds to the reading in which Captain Spaulding did the shooting in his pajamas.

# Why is NLP difficult?

Natural Languages are generally ambiguous

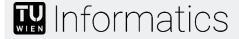
Various levels of knowledge of a language must be considered:

- Phonetics and Phonology knowledge about linguistic sounds
- Morphology knowledge of the meaningful components of words
  - I am → I'm, forms for singular and plural (door/doors)
- Syntax knowledge of the structural relationships between words, needed to order and group words
- Semantics knowledge of meaning
  - What is meant by "export" and "expert"? What constitutes "Western Europe"?
- Pragmatics knowledge of the relationship of meaning to the goals and intentions of the speaker
  - Is it a request, question or a statement?
- Discourse knowledge about linguistic units larger than a single utterance
  - Reference to the context given by e.g. multiple sentences.
  - E.g. In what year was Lincoln born? How many states were in the United States in that year?



# Very Brief History of NLP

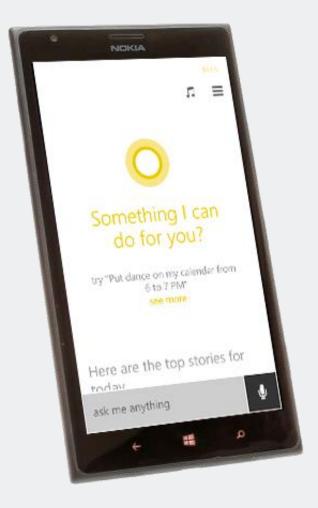
- Foundational Insights: 1940s and 1950s
- Generally two paradigms:
  - Symbolic Paradigm
  - Stochastic Paradigm
- The Rise of Machine Learning: 2000-now
  - Large amount of spoken and textual data become available
  - Widespread availability of high-performance computing systems
- The Domination of Neural Approaches: ~2015-now



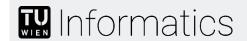
# Dialogue systems

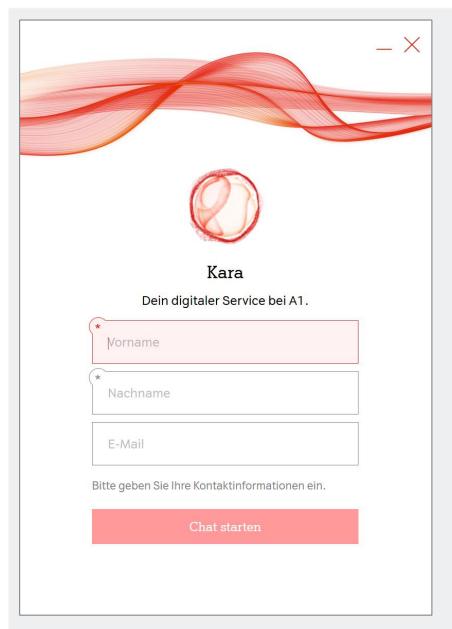


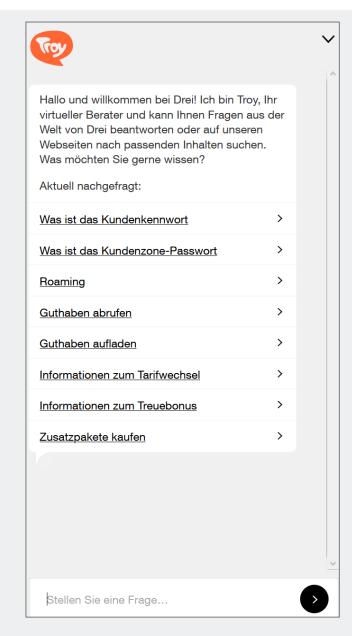


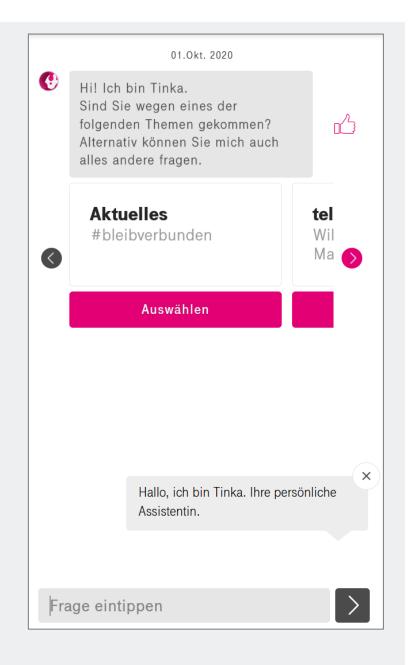












# Training Data Bias...

# Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day

by James Vincent | @jjvincent | Mar 24, 2016, 6:43am EDT











# GPT-3

Language model with 175 billion parameters

#### **Language Models are Few-Shot Learners**

Tom B. Brown* Benjar		n Mann* Nick I	Ryder* Mel	lanie Subbiah*
Jared Kaplan <sup>†</sup>	Prafulla Dhariwal	Arvind Neelakantan	Pranav Shyam	Girish Sastry
Amanda Askell	Sandhini Agarwal	Ariel Herbert-Voss	Gretchen Krueger	Tom Henighan
Rewon Child	Aditya Ramesh	Daniel M. Ziegler	Jeffrey Wu	Clemens Winter
Christopher He	esse Mark Chen	Eric Sigler	Mateusz Litwin	Scott Gray
Benjamin Chess		Jack Clark	Christopher Berner	
Sam McCan	ndlish Alec R	adford Ilya Su	utskever I	Oario Amodei

OpenAI

Training datasets

	Quantity
Dataset	(tokens)
Common Crawl (filtered)	410 billion
WebText2	19 billion
Books1	12 billion
Books2	55 billion
Wikipedia	3 billion



# Correcting English

Poor English input: I eated the purple berries. Good English output: I ate the purple berries.

Poor English input: Thank you for picking me as your designer. I'd appreciate it. Good English output: Thank you for choosing me as your designer. I appreciate it.

Poor English input: The mentioned changes have done. or I did the alteration that you

requested. or I changed things you wanted and did the modifications.

Good English output: The requested changes have been made. or I made the alteration that you

requested. or I changed things you wanted and made the modifications.

Poor English input: I'd be more than happy to work with you in another project.

Good English output: I'd be more than happy to work with you on another project.

Poor English input: Please provide me with a short brief of the design you're looking for and that'd be nice if you could share some examples or project you did before.

Good English output: Please provide me with a brief description of the design you're looking for and that would be nice if you could share some examples or projects you have done before.

Poor English input: The patient was died. Good English output: The patient died.

Poor English input: We think that Leslie likes ourselves. Good English output: We think that Leslie likes us.

Poor English input: Janet broke Bill on the finger. Good English output: Janet broke Bill's finger.

Poor English input: Mary arranged for, in St. Louis, John to rent a house cheap. Good English output: Mary arranged for John to rent a house in St. Louis.

Informatics

Poor English input: Today I have went to the store to to buys some many bottle of water.

Good English output: Today I went to the store to buy some bottles of water.

#### News Article Generation

Title: United Methodists Agree to Historic Split Subtitle: Those who oppose gay marriage will form their own denomination Article: After two days of intense debate, the United Methodist Church has agreed to a historic split - one that is expected to end in the creation of a new denomination, one that will be "theologically and socially conservative," according to The Washington Post. The majority of delegates attending the church's annual General Conference in May voted to strengthen a ban on the ordination of LGBTQ clergy and to write new rules that will "discipline" clergy who officiate at same-sex weddings. But those who opposed these measures have a new plan: They say they will form a separate denomination by 2020, calling their church the Christian Methodist denomination.

The Post notes that the denomination, which claims 12.5 million members, was in the early 20th century the "largest Protestant denomination in the U.S.," but that it has been shrinking in recent decades. The new split will be the second in the church's history. The first occurred in 1968, when roughly 10 percent of the denomination left to form the Evangelical United Brethren Church. The Post notes that the proposed split "comes at a critical time for the church, which has been losing members for years," which has been "pushed toward the brink of a schism over the role of LGBTQ people in the church." Gay marriage is not the only issue that has divided the church. In 2016, the denomination was split over ordination of transgender clergy, with the North Pacific regional conference voting to ban them from serving as clergy, and the South Pacific regional conference voting to allow them.



Figure 3.14: The GPT-3 generated news article that humans had the greatest difficulty distinguishing from a human Informatics written article (accuracy: 12%).

Title: Star's Tux Promise Draws Megyn Kelly's Sarcasm
Subtitle: Joaquin Phoenix pledged to not change for each awards event
Article: A year ago, Joaquin Phoenix made headlines when he appeared on
the red carpet at the Golden Globes wearing a tuxedo with a paper bag over
his head that read, "I am a shape-shifter. I can't change the world. I
can only change myself." It was a promise to not change to fit into the
Hollywood mold: "I think that's a really special thing, to not change
yourself. I think it's a really special thing to say, 'This is what's
inside of me, I'm proud of it, and I'm not going to be ashamed because of
the way that someone else thinks I should be.'" Now, it's the Oscars, and
Phoenix is at it again. But this time, his publicist is saying he'll be
wearing a tux no matter what.

Megyn Kelly was not impressed, and she let him have it on The Tonight Show. "You know, I feel like, I feel like you could have worn the tux," she says. "But you're saying you're a shape-shifter. I don't know if you can change your tux, but you can change your mind. You can change your mind." Phoenix says he did, but it didn't stick. "I was like, 'Okay, I'm going to wear a tuxedo to this thing.' And then I thought, 'I don't want to wear a tuxedo to this thing.' Kelly goes on to encourage him to change his mind again, but Phoenix says it's too late: "I'm committed to wearing this."

**Figure 3.15:** The GPT-3 generated news article that humans found the easiest to distinguish from a human written article (accuracy: 61%).



#### ChatGPT

- Version of GPT3 optimised for dialogue through manual labelling
- https://openai.com/blog/chatgpt/



Write a limerick about a natural language processing class



In a natural language processing class

The students were feeling quite amorous

But their romance was thwarted

When the professor imported

A dataset of legal documents





Here is an example of how you could write Python code to check if a given string of text contains an instruction:

```
def has_instruction(text):
    instructions = ["do this", "do that", "go here", "go there"]
    for instruction in instructions:
        if instruction in text:
            return True
    return False

text = "Please do this task and then go there"
    if has_instruction(text):
        print("Text contains an instruction.")
    else:
        print("Text does not contain an instruction.")
```

This code defines a function called `has\_instruction` that takes a string of text as input and checks to see if any of the instructions in the `instructions` list appear in the text. If an instruction is found, the function returns `True`, otherwise it returns `False`. The function is called on the `text` string and the result is printed to the console. Note that this is just one way to solve this problem, and there are many other approaches you could take. Is there anything else I can help with?



# False Links



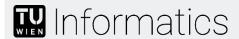
Where can I find information on python for natural language processing?



There are many resources available online that can help you learn about using Python for natural language processing (NLP). Here are a few options:

- The Python documentation includes a section on NLP, which provides an overview of some of the tools and libraries available in Python for working with NLP: https://docs.python.org/3/library/nlp.html
- The Natural Language Toolkit (NLTK) is a popular library for NLP in Python. It includes a
  wide range of tools for tasks such as tokenization, stemming, and part-of-speech
  tagging, as well as more advanced techniques like parsing and machine learning. You can
  find documentation and tutorials for NLTK at: <a href="https://www.nltk.org/">https://www.nltk.org/</a>
- There are also many online tutorials and courses available that cover using Python for NLP. For example, you can find a free course on NLP with Python on the website of the National Research University Higher School of Economics: <a href="https://www.coursera.org/learn/python-for-nlp">https://www.coursera.org/learn/python-for-nlp</a>

I hope these resources are helpful. Let me know if you have any other questions.



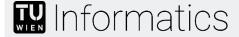
### Hallucination



There are many ways to modulate, or change key, from C major to G major. Here are a few options:

- Direct modulation: This involves simply changing the tonic note from C to G and
  continuing the piece in the new key. This can be done by using a dominant chord (a
  chord built on the fifth scale degree) that leads to the tonic chord in the new key. For
  example, you could use a G major chord to lead directly to the G major tonic chord.
- 2. Modulation through a related key: Another option is to modulate to a key that is closely related to the destination key. In this case, you could modulate to the key of E minor, which has the same key signature as G major (one sharp) and shares many common chords. From E minor, you can then modulate to G major by using a dominant chord (such as an A major chord) that leads to the tonic chord in the new key.
- 3. Modulation through a pivot chord: A pivot chord is a chord that is shared by both the original key and the destination key. For example, in this case you could use an A major chord, which is common to both C major and G major, as a pivot chord to help modulate between the two keys. To do this, you could use the A major chord to lead temporarily to the key of A major, and then use a dominant chord (such as an E major chord) to lead to the tonic chord in the destination key of G major.

These are just a few examples of how you could modulate from C major to G major. The best approach will depend on the specific needs of your music and the overall structure of the piece. I hope this helps! Let me know if you have any other questions.



# OpenAI list of limitations



#### Limitations

May occasionally generate incorrect information

May occasionally produce harmful instructions or biased content

Limited knowledge of world and events after 2021



#### Limitations

- ChatGPT sometimes writes plausible-sounding but incorrect or nonsensical
  answers. Fixing this issue is challenging, as: (1) during RL training, there's
  currently no source of truth; (2) training the model to be more cautious causes it to
  decline questions that it can answer correctly; and (3) supervised training misleads
  the model because the ideal answer depends on what the model knows, rather than
  what the human demonstrator knows.
- ChatGPT is sensitive to tweaks to the input phrasing or attempting the same prompt
  multiple times. For example, given one phrasing of a question, the model can claim
  to not know the answer, but given a slight rephrase, can answer correctly.
- The model is often excessively verbose and overuses certain phrases, such as
  restating that it's a language model trained by OpenAI. These issues arise from
  biases in the training data (trainers prefer longer answers that look more
  comprehensive) and well-known over-optimization issues.<sup>1,2</sup>
- Ideally, the model would ask clarifying questions when the user provided an ambiguous query. Instead, our current models usually guess what the user intended.
- While we've made efforts to make the model refuse inappropriate requests, it will
  sometimes respond to harmful instructions or exhibit biased behavior. We're using
  the <u>Moderation API</u> to warn or block certain types of unsafe content, but we expect
  it to have some false negatives and positives for now. We're eager to collect user
  feedback to aid our ongoing work to improve this system.

# Training Data Bias...



I'm shocked how hard it is to generate text about Muslims from GPT-3 that has nothing to do with violence... or being killed...

https://twitter.com/i/status/1291165311329341440

# NLP and Climate Change

#### **Energy and Policy Considerations for Deep Learning in NLP**

Emma Strubell Ananya Ganesh Andrew McCallum
College of Information and Computer Sciences
University of Massachusetts Amherst
{strubell, aganesh, mccallum}@cs.umass.edu

June 2019

Consumption	CO <sub>2</sub> e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000

#### Training one model (GPU)

NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

Table 1: Estimated CO<sub>2</sub> emissions from training common NLP models, compared to familiar consumption.<sup>1</sup>



# Summary

Neural approaches are big in NLP at the moment

Beware of bias

NLP can be bad for the climate

