CPSC430Computers & Society

Class 6A: Bias, Fairness, and Artificial Intelligence

Dr. Firas Moosvi | 2024_S2 Slides courtesy of Dr. Kevin Leyton-Brown

Class Outline

- 1. Announcements (5 mins)
- 2. Al Journey So far and Current Trends (20 mins)
- 3. Spot the Fakes (20 mins)
- 4. Student Experience of Instruction (5 mins)
- 5. Break (10 mins)
- 6. Bias and Fairness (50 mins)
- 7. Break (10 mins)
- 8. Peering into the crystal ball of AI (50 mins)

Announcements

- Essay O-7 scores are released
- We will handle Appeals as they come in...
- Last Participation scores will be released after class today
- Final Course grades will be available at some point next week

August 2024

	Sun 4	Mon 5	Tue	6	Wed	7	Thu 8	Fri 9	
all-day	E10 Window								
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The (AI) Journey So Far...

What is AI and what can it do today? How much is real and how much is hype?

Microsoft, Go





Why is it happening?

Scientific/mathematical breakthroughs, especially in machine learning

2. Growth in raw computing power

1965.



Data source: Karl Rupp, Microprocessor Trend Data (2022)

For comparison:

Species	# Neur in Bra
Fruit Fly	105
Cat	10 ⁹
Chimpanzee	10 ¹⁰
Human	10 ¹

OurWorldInData.org/technological-change | CC BY



What short term impacts should we expect? What kinds of social impacts are they having?

CURRENT TRENDS

Machine Learning

- Narrow: building predictive models from data
- learn from experience rather than being told what to do
- Where's it **headed**?
 - More and more data collection
 - sensors
 - behavior tracking
 - Image, text, speech understanding
 - Data mining/personalization/profiling _
 - Self programming/optimization

Broad: a new approach to computer programming, where computers





Virtual and Physical Worlds Collide

- Smart interfaces
 - remote controls; microwaves; clocks; …
- Augmented reality
- More intuitively "programmable" systems
- Much better context awareness
- Assistance
 - elderly; children; disabled; education
- Social agents/games







Growing Military Use

- Increasing use of AI in military applications
- Already quite **commonplace** in some applications
 - smart bombs
 - surveillance systems
 - missile defence (Patriot, Iron Dome, etc)
- Autonomous weapons are becoming practical
 - drones are widely used; becoming more autonomous
 - land-based robotic systems are improving quickly
 - swarms of drones could revolutionize urban warfare
- The main barrier to adoption is public opinion







LLMs in the workplace

OpenAl report:

- How "exposed" are different occupations to automation with large language models (LLMs)?
- ~80% of the US workforce could have at least 10% of their work tasks affected by LLMs
- ~19% may see at least 50% of their tasks impacted
- Most affected tasks: writing and programming.
- Higher-income jobs (such as translators, tax consultants, and web designers) potentially face greater exposure



GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models

Tyna Eloundou, Sam Manning, Pamela Mishkin, Daniel Rock

We investigate the potential implications of large language models (LLMs), such as Generative Pre-trained Transformers (GPTs), on the U.S. labor market, focusing on the increased capabilities arising from LLM-powered software compared to LLMs on their own. Using a new rubric, we assess occupations based on their alignment with LLM capabilities, integrating both human expertise and GPT-4 classifications. Our findings reveal that around 80% of the U.S. workforce could have at least 10% of their work tasks affected by the introduction of LLMs, while approximately 19% of workers may see at least 50% of their tasks impacted. We do not make predictions about the development or adoption timeline of such LLMs. The projected effects span all wage levels, with higher-income jobs potentially facing greater exposure to LLM capabilities and LLM-powered software. Significantly, these impacts are not restricted to industries with higher recent productivity growth. Our analysis suggests that, with access to an LLM, about 15% of all worker tasks in the US could be completed significantly faster at the same level of quality. When incorporating software and tooling built on top of LLMs, this share increases to between 47 and 56% of all tasks. This finding implies that LLM-powered software will have a substantial effect on scaling the economic impacts of the underlying models. We conclude that LLMs such as GPTs exhibit traits of generalpurpose technologies, indicating that they could have considerable economic, social, and policy implications.

The report answers the question "which jobs do people think LLMs will automate" and not "which jobs will LLMs automate".





LLMs in the workplace

- work-related ones
- Some people compare it to the advent of Google
- Some issues (ownership of training data, allucinations...)
- Have you used LLMs before?
- professionals in the workforce? How?
- Do you think LLMs should be used in the classroom? How? Do you think that AI will increase the expectations from



Adoption of Large Language Models for various tasks, including

Current State of the Art

- Predictive modeling limited mostly by quality of training data
- Image recognition, face recognition becoming extremely reliable
- Image generation almost there
- Language understanding & generation maturing extremely quickly. Watch this space
- Fueling scientific breakthroughs from protein folding to astronomy
- **Robotics** remains a hard problem, but it's working well in some niche applications



Prompt: Here's a short rhyming poem by Dr. Seuss about Elon Musk's company, Neuralink which is building brain implants to achieve symbiosis with Al. Neuralink's mission statement is "If you Can't Beat'em, join'em". The poem has a structure typical of Dr. Seuss stories with simple alternate line rhymes. In the poem Elon explains why we need to merge with the AI to save humanity.

Neuralink, by Dr. Seuss

Response: I have a friend, Elon Musk, Who wants to join our brains to Al. He thinks that humans can't compete So he's gonna use AI to cheat. They want to build a neural-link. To link us to the Als And save humanity from its demise. They want to put an AI in your brain. They want to use your neurons as a frame. They want to save humanity, If you can't beat'em, join'em





Spot The Fakes

AI can draw hands now. That's bad news for deep-fakes.

Improved AI image-making software churned out believable yet fictional images of former president Donald Trump being arrested

ဂြာ 7 min



INNOVATIONS

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Activity: Spot the Fakes

- How'd you do?



• Do the quiz once individually (3 minutes)

Do the quiz together in a group of 3-5



The growing quality in AI images makes them harder to spot. Can you tell if this image is real or AI generated?

Start Game

Student Experience of Instruction (SEI)







Reminder: Please fill out the Student Experience of Instruction surveys!

Bias and Fairness

Human bias

Bias in people refers to our tendency to take quick decisions based on little information

Published online 11 April 2011 | Nature | doi:10.1038/news.2011.227

News

Hungry judges dispense rough justice

When they need a break, decision-makers gravitate towards the easy option.

Zoë Corbyn

Journal of Economic Perspectives—Volume 12, Number 2—Spring 1998—Pages 41-62

Evidence on Discrimination in Mortgage Lending

Helen F. Ladd

Science faculty's subtle gender biases favor male students

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Edited* by Shirley Tilghman, Princeton University, Princeton, NJ, and approved August 21, 2012 (received for review July 2, 2012)



Why worry about bias in algorithms

Decisions made by a ML algorithm are:

- Cheap
- Scalable
- Automated
- Self-reinforcing
- Seemingly objective
- Often lacking appeals processes
- Not just predicting but also causing the future

Sources of bias in ML algorithms





Representation bias

Representation bias arises while defining and sampling a development population. It occurs when the development population under-represents, and subsequently fails to generalize well, for some part of the use population.

1. The sampling methods only reach a portion of the pop-2. The population of interest has changed or is distinct from the population used during model training. Data ulation. For example, datasets collected through smartphone apps can under-represent lower-income or older that is representative of Boston, for example, may not be groups, who are less likely to own smartphones. Similarly, representative if used to analyze the population of Indianapolis. Similarly, data representative of Boston 30 years medical data for a particular condition may be available ago will likely not reflect today's population. only for the population of patients who were considered serious enough to bring in for further screening.



Measurement bias

Measurement Bias arises when choosing and measuring features and labels to use; these are often proxies for the desired quantities. The chosen set of features and labels may leave out important factors or introduce groupor input-dependent noise that leads to differential performance.

The defined classification task is an oversimplification. In order to build a supervised ML model, some label to predict must be chosen. Reducing a decision to a single attribute can create a biased proxy label because it only captures a particular aspect of what we really want to measure. Consider the prediction problem of deciding whether a student will be successful (e.g., in a college admissions context). Fully capturing the outcome of 'successful student' in terms of a single measurable attribute is impossible because of its complexity. In cases such as these, algorithm designers resort to some available label such as 'GPA' (Kleinberg et al. 2018), which ignores different indicators of success achieved by parts of the population.

- 1. The measurement process varies across groups. For example, if a group of factory workers is more stringently or frequently monitored, more errors will be observed in that group. This can also lead to a feedback loop wherein the group is subject to further monitoring because of the apparent higher rate of mistakes (Barocas and Selbst 2016)
- 2. The quality of data varies across groups. Structural discrimination can lead to systematically higher error rates in a certain group. For example, women are more likely to be misdiagnosed or not diagnosed for conditions where self-reported pain is a symptom (Calderone, 1990). In this case, "diagnosed with condition X" is a biased proxy for "has condition X."





Historical bias

Historical bias arises when there is a misalignment between world as it is and the values or objectives to be encoded and propagated in a model. It is a normative concern with the state of the world, and exists even given perfect sampling and feature selection.

Example: image search In 2018, 5% of Fortune 500 CEOs were women (Zarya, 2018). Should image search results for "CEO" reflect that number? Ultimately, a variety of stakeholders, including affected members of society, should evaluate the particular harms that this result could cause and make a judgment. This decision may be at odds with the available data even if that data is a perfect reflection of the world. Indeed, Google has recently changed their Image Search results for "CEO" to display a higher proportion of women.



Fairness in algorithms

- Increasing attention on algorithms being fair, not just accurate
- Fairness can be measured as:
 - demographic (or statistical) parity: population percentage should be reflected in the output classes
 - Equality of false negatives or equalized odds: constant false-negative (or both false-negative and true-negative) rates across groups.
 - Equal opportunity: equal True Positive Rate for all groups
 - Other metrics...
- Accuracy and fairness tend to be at odds with each other.
- Algorithms can be audited to test their fairness.
- Are we ethically required to sacrifice accuracy for fairness? To what extent?





When the metric becomes the target (Goodhart's Law)

"When a measure becomes a target it ceases to be a good measure"

- caused people to game it:
 - Cancelled scheduled operations to draft extra staff to ER
 - Required patients to wait outside the ER, e.g. in ambulances
 - Put stretchers in hallways and classified them as "beds"
 - Hospital and patients reported different wait times
- Big Data is significantly changing college applications
 - _ and having more students accept their offers (while tuition is not considered)
 - _ good students who they think will not accept. Can affect applications to "safety schools"
- Can you think of more examples?
- Can you think of ways to avoid this trap?

Metrics introduced in the **British public healthcare system** (e.g. waiting time in ER)

Universities are given higher ranking for things such as receiving more applications, being more selective,

This even pushed some mid-tier universities to reduce the number of offer letter sent out, especially to





Ethics of pricing algorithms

- Algorithms are currently used to adjust prices based on:
 - Willingness of buyer
 - Availability
- Uber surge pricing:
 - In 2014, terrorists attacked a café in Sidney, holding 10 customers and 8 employees hostage for 16 hours
 - During this time, people from the surrounding areas were evacuated. Transportation was disrupted.
 - Uber prices adapted by increasing the rate to a minimum of 100\$
 - In general, underserved (poorer) areas get worse rates under current pricing policy
 - Drivers are also subjected to different pricing/waiting times —
 - https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4331080
- Is Uber morally obliged to avoid such pricing disparities?



From trading to gambling addiction?

- Case study: Robinhood Trading app
- Designed to make trading more accessible and equitable. Robinhood's mission statement is "To democratize finance for all"
- Concerns around the most "dopamine-inducing" features (<u>source</u>):
 Green confetti to celebrate transactions.
 - A constant update of stock related articles.
 - A colorful, eye-catching interface.
 - Emoji phone notifications.
 - One-click trading for instant gratification.
 - Free stocks in the shape of lottery tickets.



cation. tickets.









Reminder: Please fill out the Student Experience of Instruction surveys!

Peering into the Crystal Ball

PEERING INTO THE CRYSTAL BALL

Bold predictions about where AI is headed in the longer term

Technology that will be in widespread use

- Tailored solutions for specific tasks, not general intelligence
- Prototypes that work today in labs & narrow deployments
- Some examples:
 - Non-text input modalities (vision; speech)
 - Consumer modeling (recommendation; marketing)
 - Cloud services (translation; question answering; Al-mediated outsourcing)
 - Transportation (automated trucking; some self-driving cars)
 - Industrial robotics (factories; some drone applications)
 - Al knowledge work (logistics planning; radiology; legal research; call centers)
 - Policing & security (electronic fraud; cameras; predictive policing)



Technologies that won't take off as quickly

- Overall, areas in which
 - major entrenched regulatory regimes need to be navigated
 - there exist social/cultural barriers to adoption
 - the human touch is crucial
 - substantial new hardware would need to be developed
- Some examples:
 - childcare, healthcare, eldercare
 - education
 - coaching, counselling
 - consumer robots beyond niche applications
 - semantically rich language understanding





Superhuman Intelligence

- Al systems will increasingly be capable of reaching human-level performance
- Superhuman intelligence isn't such a foreign, scary thing
 - governments, corporations, NGOs exhibit behavior much more sophisticated and complex than that of any individual
- Many important problems need superhuman intelligence; AI can help
 - improved collective decision making
 - more efficient use of scarce resources
 - addressing underserved communities
 - climate change; other societal challenges

SUPERHUMAN

The Invisible Made Visible



Ethics of AI

Will a new technology:

- disempower individuals vs corporations?
 - \Rightarrow user modeling; data mining; fostering addictive behaviors; developmental effects on children

disempower individuals vs governments?

⇒ facilitate disinformation (deep fakes; bots masquerading as people; filter bubbles); enable qualitatively new military or security tactics

take autonomous actions in a way that obscures responsibility

 \Rightarrow autonomous weapons; self-driving cars; loan approval systems

disproportionately affect vulnerable/marginalized groups

⇒ automated decision making tools trained in ways that may encode existing biases









Social Impact

- How will AI technologies transform society?
- Will there be a **social backlash** against AI?
 - If so, what will be considered AI?
- This generation of children will grow up taking for granted many technologies that strike us as magical
- How will human relationships change in the presence of alwaysavailable social agents?
- As we are increasingly augmented by Al, what are our inherent cognitive/emotional/motivational limitations, beyond which augmentation won't help?



Ethical consideration of advances in Al

- Is it wrong to create machines capable of making human labor obsolete? Will humans become demoralized by the presence of vastly more intelligent robots?
- How can we ensure that intelligent robots will not be put to an evil purpose by a malevolent human? How can we ensure they do not adopt malevolent purposes themselves?
- Is it morally acceptable to create "personal" (selfconscious) AI?



Retrospective

huge range of topics and subjects!

Congratulations !

 Over 80% of you made it over the 1.0 dependability score threshold !

• You've written a LOT of essays this term, and made a lot of arguments for a



Retrospective

- Last prompt of the term!
- In this course...
 - Green: "What was the most surprising thing you learned?"

 - read?"

• Blue: "What was the most upsetting thing thing you heard/read?"

Yellow: "What was the most inspiring/optimistic thing you heard/



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