Lecture 7:
Bias, fairness, diversity in data

CS698Y: Human AI Interaction

Prelude

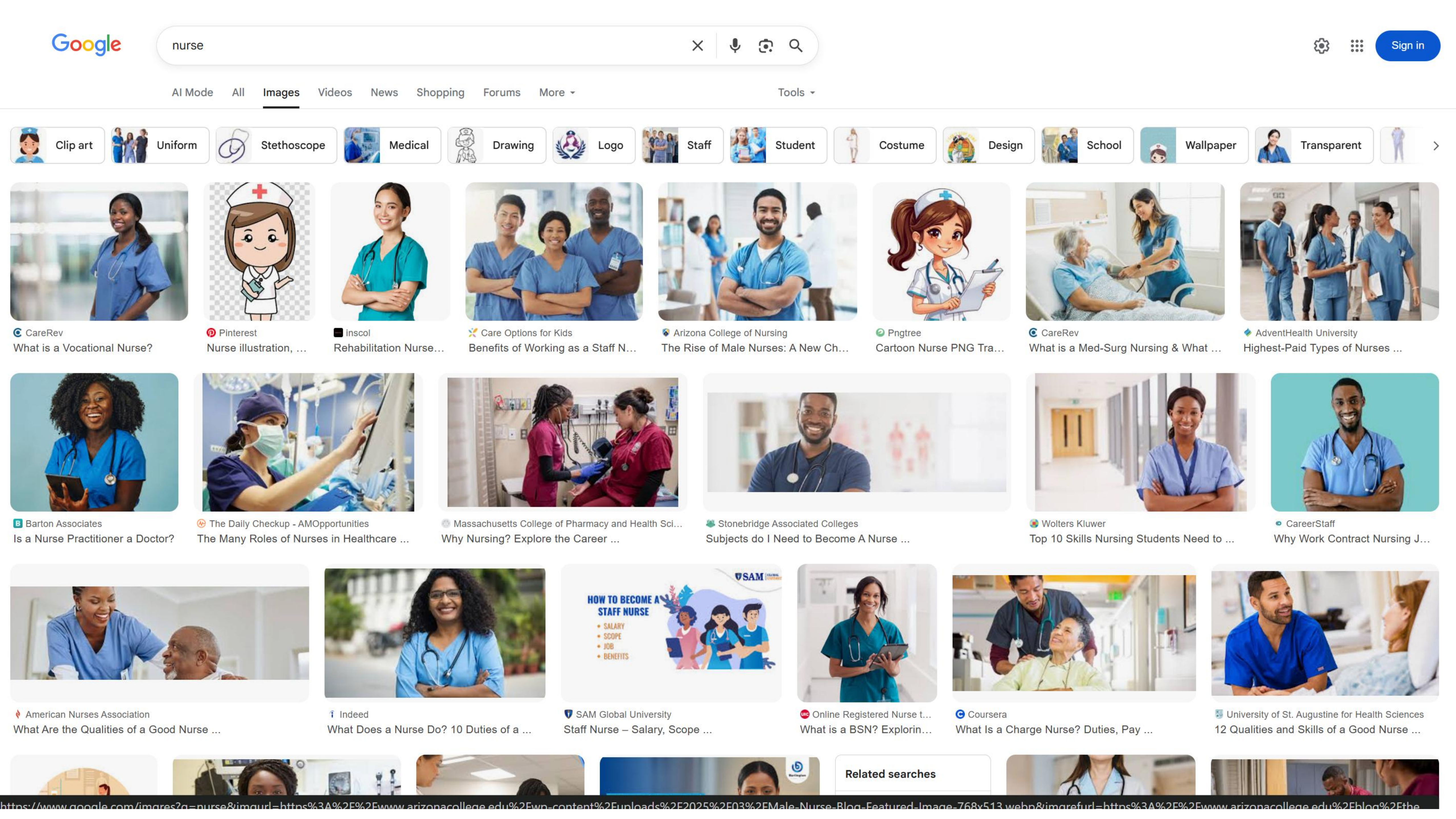
- Principles in Human-AI interaction design
  - HAX guidelines
  - Cognitive principles
  - Sociological principles

- Going forward
  - Designing according to guidelines/principles in practice
  - Hands-on exercises / in-class activities
  - Today → Bias, fairness, diversity in data
  - Why care, details & hands-on explorations

What is Bias?

- Systematic error / skew / preference in data, model, or outcome
- Something is being *over- or under-represented*

- Examples:
  - Speech recognition working poorly for some languages/accents → because data is underrepresented
  - Image classifier mislabels some dog breeds without collar as fox → not enough training data for that kind
  - Model misdiagnoses cardiac diseases in middle aged South Asian women → not enough data on South Asian women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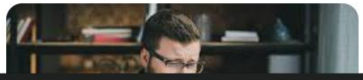


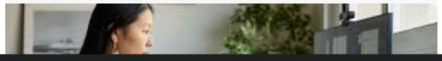

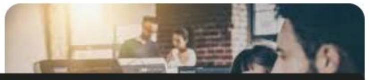

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What is Fairness?

- A *goal/criterion* about equitable treatment and outcomes across groups (doesn't disadvantage one group)
- "Are different groups treated appropriately and justly by the system?"
- Example:
  - Data biased "brown, no collar" = fox
  - Fairness: all dogs are equally accurately recognized as dogs (here, unfair towards brown no-collared ones.
- Goal → ensure fairness even if data is skewed

How to reduce bias & ensure fairness?

- Diversity
  - Training data has many collared dogs, few uncollared dogs.
  - Lack of representation of *uncollared brown dogs* reduces diversity.
  - Broader diversity → more robust AI

- Inclusivity
  - Designing systems so all groups can participate meaningfully
  - Goes beyond representation → asks: who benefits? who is left out?
  - Example → not all pet owners put collars on dogs.

Why bias matters?

- Models reflect, reinforce and amplify these human biases
- Not always intentional — but with real-world effects
  - Lower trust in technology
  - Amplifies biases already existing in society
- Important to guard against these!

- For AI developers / researchers / statisticians → source of interesting problems!

How Bias Enters Data?

- Sampling bias (not enough representation)
  - Data doesn’t have enough collared brown dogs
- Labeling bias (human annotators’ perspectives)
  - Labeler thinks brown uncollared ones in woods are foxes
- Historical bias (reflecting unfair past decisions)
  - Historically, village dogs were collared, some breeds not domesticated
  - Model: dogs =domesticated & collared, fox=in the wild
- Measurement bias (sensors, tools skewed)
  - Camera errors, lighting, blurs, …

How do we mitigate biases?

- Carefully choose subsets of data for training/testing
- Avoid over-representing some groups
- Specific techniques / strategies
  - Resampling
  - Balancing
  - Feature awareness
  - Fairness metrics

Resampling

- Problem: Some groups over- / under- represented in data
- How do you balance?
- Oversampling → Increase minority group data
  - Duplicate minority group data
  - Synthesize training data for minority group
    - Statistical → create distributions and then sample from that
    - Interpolation and extrapolation → based on two or more nearest points
    - Model-based sampling → fit a model (e.g., linear regression) and pick points
    - ML models to generate data → GAN, VAE, LLM, …
- Undersampling → drop data from majority group (rarely!)
  - Cluster and then sample from each cluster

Balancing

- When one group is too small, stratify training set split
  - Instead of random 80%, take appropriate proportions for train/test
  - “Don’t see too many foxes when training, and too many dogs when training”
- Weight loss functions
  - Small groups → higher penalty on errors [weight = 1/frequency]
- K-fold cross validation → stratified each time
- Check fairness → accuracy same across groups

Labeling bias

- Provide detailed instructions
- Ensure diverse labelers at start → be aware of your labelers
- Get everything labelled by more than one person
  - Multiple annotators + consensus reduces subjectivity
- Bias-aware training → treat certain labels with caution (e.g., in terms of weighting)

What about historical bias?

- Awareness & auditing: Examine datasets for underrepresentation or historical patterns.
- Rebalancing / reweighting: Give more weight to underrepresented groups or outcomes.
- Counterfactual or synthetic data: Generate data to represent fairer scenarios.

Calibration / Measurement Bias

- Bias from sensors, instruments, or measurement errors.
  - Example: Facial recognition for darker skin tones / evening images
- Improve measurement quality: Better sensors / procedures.
- Normalize / preprocess inputs: Reduce systematic differences in inputs across groups.
- Calibration techniques: Adjust model outputs so probabilities match reality per group.
- Continuous monitoring: Track performance across groups and recalibrate regularly.

Feature Awareness

- Be aware of *sensitive attributes* (gender, race, age, caste, …)
- Sometimes you want to exclude them (might contribute to bias)
- Sometimes you want to include them (for fairness)
- How do you know what to do?
    - Ask the domain expert / research the domain
    - Look for difference in accuracy across groups / ranges
    - Eliminate features to see if it reduces these gaps
    - Sometimes this can bring down overall accuracy
- To include, or not to include—that is the question!

Fairness metrics

- Statistical / demographic parity: Equal outcomes across groups
  - 90% Indians predicted “at risk”, 90% Americans also should be.
  - Unfair in some cases → what if one race is low risk compared to others?
- Equal opportunity / equal TP: Same true positive rate across groups
  - Among those who qualify as positive, the algorithm predicts +ve for same % in all groups.
  - Among all qualified, % men predicted qualified = % women predicted qualified
- Predictive parity: Same precision across groups
  - Among predicted as “qualified”, same % of qualified people across groups
  - Ensures trustworthiness of models for various groups
  - Some group’s yes is often wrong → people don’t pay attention to model

Fairness metrics

- Equalized odds: Equal true positive & true negative rates
  - Model doesn’t make more mistakes for one group than another
  - Example: If 80% of creditworthy men are approved (TPR) and 10% of non-creditworthy men are incorrectly approved (FPR), then the same rates should hold for women.
- Treatment Equality: Ratio of false negatives (FN) to false positives (FP) is equal across groups
  - Example: In medicine, we want to avoid FN, over FP
  - If FN/FP = 1/100 for Caucasians, should also be 1/100 for Indians.

Individual-based fairness tests

- Counterfactual fairness: same outcome if you swap a protected attribute, all else remaining fixed
  - Options to explore “What if” / counterfactuals typically provided in explainable systems.
  - Important to also ensure trust in systems
- Fairness through awareness (within group): Similar individuals (by relevant features) should have similar outcomes
  - Easily seen through clusters

Diversity / representation metrics

- Proportional representation – Each group’s representation matches its share in the population
- Ensure similar error rates, positive / deserved outcomes for each group
- Coverage / exposure – how much coverage do we get / how much exposure do we get
    - E.g., recommendations of just one kind than variety?

Some other metrics (Regression)

- Statistical difference / mean difference – Compare means of predictions or errors across groups
- Correlation with sensitive attributes – Measures how strongly predictions depend on protected features.

Fairness is contextual & conflicted

- No one size fits all fairness metric
- There are tensions between metrics
  - E.g., equal outcomes vs. equal opportunities
  - Minimize overall error vs. maintain parity in error rates
- We can’t satisfy all at once!
- Need careful thought + expert opinion
- Notion of fairness itself can be unfair
  - Who defines it? Who is affected by it?

In summary…

- Bias in data → bad, less robust models
  - Users lose trust
  - Social consequences
- Bias occur due to data sampling, labelling, calibration and historical reasons
- Systematic ways of minimizing them in data
- Focus on other metrics to also measure fairness when appropriate!

Homework

- Work in pairs
- Pick one dataset:
  - Multiple your roll numbers’ last digits.
  - If even: Predict Students' Dropout and Academic Success
  - Else: Absenteeism at work
- Train a simple model for the task (use libraries)
- Evaluate the biases in the dataset
- Evaluate the performance of the model (incl. for fairness)
- Use python; turn in Colab / Github links+ report (TBA on HelloIITK)

Readings

- Implications of AI Bias in HRI: Risks (and Opportunities) when Interacting with a Biased Robot
- Humans inherit artificial intelligence biases
- Fair ML Book, https://fairmlbook.org/pdf/fairmlbook.pdf (Chapter-7)

Additional (optional):

- How human–AI feedback loops alter human perceptual, emotional and social judgements

Next class…

- Dr. RS Sharma → Aadhaar and data privacy
- Final project annoncements