Bias in Facial Recognition

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Facial Recognition Systems

- There are two very effective types of facial recognition systems
  - Deep learning models
  - You!
- An example facial recognition task

Input → FR system subjects image to learned ideas about faces → Output

"Dr. Tom Goldstein"
Project goals

1. Compare areas of weaknesses/bias between humans and A.I.
   a. Design an empirical study

2. Along the way, identify issues with datasets that might lead to bias in A.I. systems, and create a clean dataset
Bias in Machine Learning Systems

- Gender Shades
- Discrimination in Online Ad Delivery
- Robustness Disparities in Commercial Face Detection
Bias in Human Recognition

- Research shows that humans perform facial recognition tasks with bias.
- People are better able to identify others belonging to their own racial group.
  - Cross-Race Effect
- Similar effects can be seen across gender and age groups.
- Raises the question: Is there a significant difference in the bias of facial recognition systems and human recognition?
Our Study

● The mission of our study is to quantify the extent of human bias in a way that is comparable to that of leading facial recognition algorithms.
  ○ Our verification test asks participants to verify whether two images are the same person
  ○ Our identification test asks participants to select a particular person’s face from a lineup of 9 images.

● The same test will be performed on leading facial recognition technologies, and the results between humans and computer will be compared.
App

- Built a Flask web application with Bootstrap 5 to make the survey website
  - Flask is a Python web framework which allows rapid development of websites
  - Bootstrap 5 is a CSS library that defines many useful stylized classes
  - Uses vanilla JavaScript for dynamic elements

- Used the agile framework to develop the application ([link to the repo here](#))
  - Agile is a development framework that focuses on self-defined tasks, a task board, and frequent communication with the stakeholders
Kanban board used to track survey development progress
Datasets

- Use **Labelled Faces in the Wild (LFW)** as initial source of test question images.
- Supplemented set of LFW images with photos from **Celeb-A** dataset.
- Both datasets are research standards, contain photos of celebrities.
- Chose LFW as **main** dataset due to manageable size and mostly accurate labelled identities.
Datasets

• Some **issues** with both LFW and Celeb-A
  ○ Low representation of certain groups (LFW particularly)
    ■ Comparatively lower percentage of women
    ■ Small range of ethnicities
    ■ Minimal to no children and babies.
  ○ Duplicate pairs of images.
  ○ Images with more than one person.
  ○ Images with the face being blocked.
  ○ Images clearly taken on the same occasion
    ■ particularly unsuitable for human testing
Datasets

- **Tagged** issues with images in LFW.
  - ATT/BACK/BW/DUP/MULT/OBS
- **Filtered** out images with issues for human test design.
  - Interesting (but preliminary finding): disparities in mean number of image issues depending on gender of image subject.
Datasets

- Since our study is concerned with sensitive attributes of images, we require labels for these attributes.
  - Some label datasets exist for LFW (such as MSU’s LFW+), and Celeb-A comes with attribute labels, but these are incomplete and contain several clear mislabellings.
- We manually labelled all images for subject’s **birthdate**, **country** of origin, **gender** presentation, and **skin tone**.
  - Only kept images for which these attributes could be exhaustively verified (i.e. through media articles or official biographies).
  - Classified skin tones by **Fitzpatrick scale**. Ultimately decided by a 2/3 majority vote.
  - Skin tone does not correlate perfectly with race, but more objective than race.
Datasets

- Final dataset to contain approximately **7500** images.
  - At least **100** pairs for each combination of gender presentation (male, female, other), and Fitzpatrick skin tone (1 to 6).
  - Strong coverage across ages within each gender-skin group too.

- **Beneficial Outcome:** **Cleaned-up and methodically-labelled** dataset
  - Could be useful for future facial recognition studies, in addition to this one.
Database Model

- Records survey responses
  - Unique user ids
  - Stores question metadata (images included, difficulty)
  - User identification information (age, skin tone, country)

- SQL database setup on UMIACS
  - Python API communicates between Flask and SQL
  - Flask submits form response to API
  - API validates data and inserts into database

- Next steps
  - Gather survey responses
  - Aggregate data to test hypothesis and produce statistics
LOOK! IT WORKS!
Anecdotal Evidence

- Identification is much more difficult than verification
- Some found caucasians harder to identify than people of other demographics
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Design Decisions

● Survey format
  ○ Verification and Identification
  ○ Gallery of 9 (difficult but not overwhelming). Corresponds closely to police lineup.

● Number of questions
  ○ Internal trials for length
  ○ Try to shoot for equal number of each demographic bucket
  ○ Make questions as difficult as possible (same Fitzpatrick in gallery, same gender, similar age window)

● Collecting user information
  ○ Age, gender presentation, Fitzpatrick tone, country of origin.
  ○ Fitzpatrick images.
Ideas for Analysis/Future Plans

Recap - we are interested in comparing AI and human performance in a way that highlights weak areas for each.

- Once we get responses:
  - Compare AI vs. Human overall for each task
  - Look at target groups and see which have worst performance on them
  - Compare human test-taking groups to see if there is in-group/out-group bias.
- Share our dataset and welcome discussion
Thanks for Listening

Suggestions/Feedback/Comments?