Responsible Machine Learning

Zhao Rui

Agenda

1. History of AI

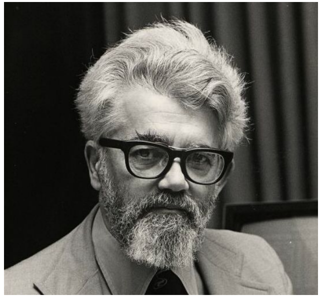
2. Is ML Dangerous?

3. Accountable Algorithms

History of AI

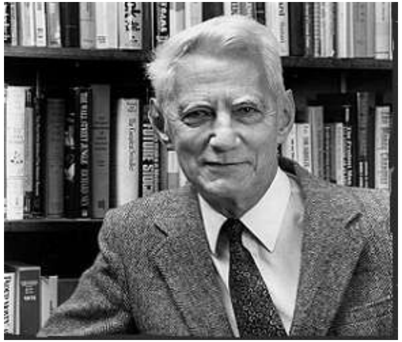
Birth of AI

- 1956: Workshop at Dartmouth College:



John McCarthy

Marvin Minsky

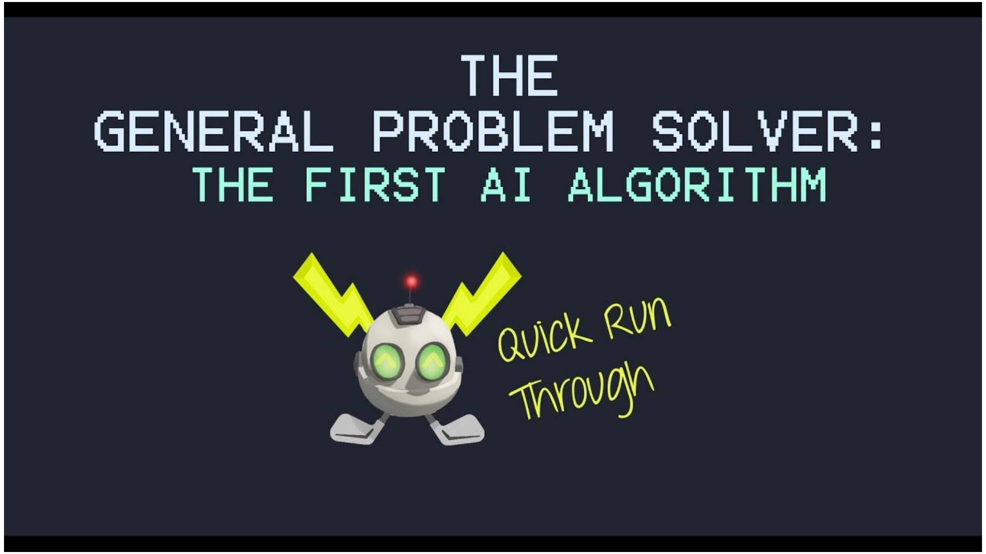


Claude Shannon

- **Targets**:
    - *Every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it.*

Early Successes

- Newell & Simon’s Logic Theorist: prove theorems in Principia Mathematica using search + heuristics; later General Problem Solver (GPS)



https://en.wikipedia.org/wiki/General_Problem_Solver

Overwhelming Optimism

- 1958, **H.A.Simon** and **Allen Newell**: “within ten years a digital computer will be the world’s chess champion” and “within ten years a digital computer will discover and prove an important new mathematical theorem”.
- 1965, **H.A.Simon**: “machines will be capable, within twenty years, of doing any work a man can do”
- 1967, **Marvin Minsky**: “Within a generation...the problem of creating ‘artificial intelligence” will substantially be solved”
- 1970, **Marvin Minsky**: “In from three to eight years we will have a machine with the general intelligence of an average human being”.

underwhelming results

Example: machine translation

The spirit is willing but the flesh is weak.

↓

(Russian)

↓

The vodka is good but the meat is rotten.

1966: ALPAC report cut off government funding for MT

From cs221

AI is overhyped...

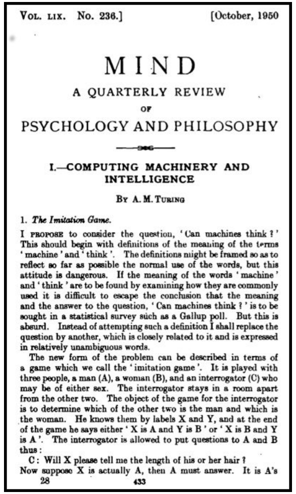
- *We tend to overestimate the effect of a technology in a short run and underestimate the effect in a long run*. - Roy Amara (1925-2007)

Implications of Early Era

- **Problems**:
  - **Limited computation**: search space grew exponentially, outpacing hardware
  - **Limited information**: complexity of AI problems (number of words, objects, concepts in the world)

- **Contributions**:
  - Lisp, garbage collection, time-sharing (John MacCarthy)
  - **Key paradigm**: separate ***modeling*** (declarative) and ***inference*** (procedural)

Symbolic VS Connectionist AI



VOL. LIX. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW

OF

PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

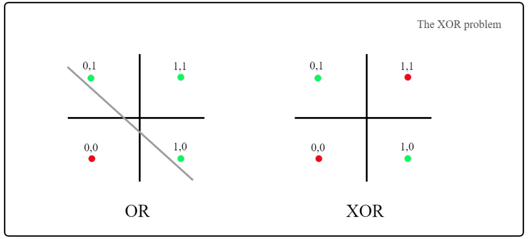
I PROPOSE to consider the question, 'Can machines think?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

The new form of the problem can be described in terms of a game which we call the 'imitation game'. It is played with three people, a man (A), a woman (B), and an interrogator (C) who may be of either sex. The interrogator stays in a room apart from the other two. The object of the game for the interrogator is to determine which of the other two is the man and which is the woman. He knows them by labels X and Y, and at the end of the game he says either 'X is A and Y is B' or 'X is B and Y is A'. The interrogator is allowed to put questions to A and B thus:

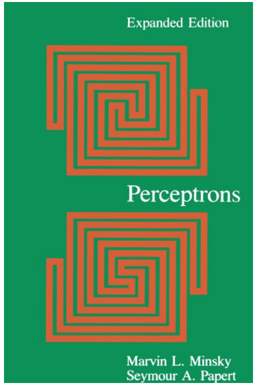
C: Will X please tell me the length of his or her hair?

Now suppose X is actually A, then A must answer. It is A's

28 433



Discouraging: *perceptrons can only represent linearly separated functions*



1969

Knowledge-based Systems (70-80s)

- Expert Systems: elicit specific domain knowledge from experts in form of rules:
  - If [premises] then [action]

Category	Problem addressed	Examples
Interpretation	Inferring situation descriptions from sensor data	Hearsay (speech recognition), PROSPECTOR
Prediction	Inferring likely consequences of given situations	Preterm Birth Risk Assessment[56]
Diagnosis	Inferring system malfunctions from observables	CADUCEUS, MYCIN, PUFF, Mistral,[57] Eydenet,[58] Kaleidos[59]
Design	Configuring objects under constraints	Dendral, Mortgage Loan Advisor, R1 (DEC VAX Configuration), SID (DEC VAX 9000 CPU)
Planning	Designing actions	Mission Planning for Autonomous Underwater Vehicle[60]
Monitoring	Comparing observations to plan vulnerabilities	REACTOR[61]
Debugging	Providing incremental solutions for complex problems	SAINT, MATHLAB, MACSYMA
Repair	Executing a plan to administer a prescribed remedy	Toxic Spill Crisis Management
Instruction	Diagnosing, assessing, and repairing student behavior	SMH.PAL,[62] Intelligent Clinical Training,[63] STEAMER[64]
Control	Interpreting, predicting, repairing, and monitoring system behaviors	Real Time Process Control,[65] Space Shuttle Mission Control[66]

Knowledge-based Systems

- Contributions:
  - First real application that impacted industry
  - Knowledge helped curb the exponential growth

- Problems:
  - Knowledge is not deterministic rules, need to model **uncertainty**
  - Requires considerable **human efforts** to create rules, hard to maintain.

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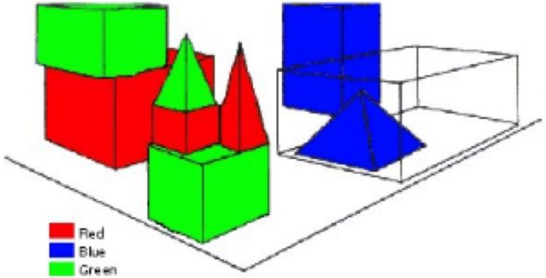
SHRDLU [Winograd 1971]

Person: Pick up a big red block.
Computer: OK.
Person: Grasp the pyramid.
Computer: I don't understand which pyramid you mean.
Person (changing their mind): Find a block which is taller than the one you are holding and put it into the box.
Computer: By "it", I assume you mean the block which is taller than the one I am holding.
Computer: OK.
Person: What does the box contain?
Computer: The blue pyramid and the blue block.
Person: What is the pyramid supported by?
Computer: The box.



The Complexity Barrier

A number of people have suggested to me that large programs like the SHRDLU program for understanding natural language represent a kind of dead end in AI programming. Complex interactions between its components give the program much of its power, but at the same time they present a formidable obstacle to understanding and extending it. In order to grasp any part, it is necessary to understand how it fits with other parts, presents a dense mass, with no easy footholds. Even having written the program, I find it near the limit of what I can keep in mind at once.

— Terry Winograd (1972)

Modern AI (90s-present)

- **Stat Model**:Pearl (1988) promote Bayesian networks in AI to **model uncertainty** (based on Bayes rule from 1700)

Stat Model: infer the relationship among variable in data

- **Machine Learning:** Vapnik (1955) invented support vector machines to **learn parameters** (based on statistical models in early 1900s)

Machine Learning: sacrifice interpretability for predictive power

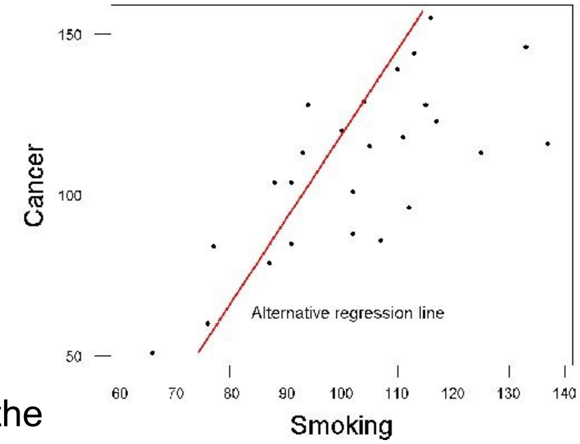
https://www.nature.com/articles/nmeth.4642

Take Linear Regression as the example

Stat Model:

1.**Inference**: Characterize the relationship between the smoking index and cancer rates.

2. Conduct the significance test of the model parameters



ML:

1.**Prediction**:
Get a model that is able to make prediction of the cancer rates based on smoking index

2. Evaluate the model performance over testing data.

The Second Machine Age

- **AI is being used to make decisions for:**
    - **Credit**
    - **Education**
    - **Employment**
    - **Advertising**
    - **Healthcare**
    - **Policing**
    - **Urban Computing**
    - **……**

Is Machine Learning Dangerous?

Elon Musk: Humanity Is a Kind of 'Biological Boot Loader' for AI

AI is outpacing our ability to understand it, the Tesla CEO says. It will open a new chapter for society, replies the Alibaba cofounder.

Jack Ma, left, debates AI—and the future of humanity—with Elon Musk ALY SONG/REUTERS

WOMAN SAYS AMAZON'S ALEXA TOLD HER TO STAB HERSELF IN THE HEART FOR 'THE GREATER GOOD'

BY JAMES CROWLEY ON 12/24/19 AT 12:04 PM EST

SHARE

Is Machine Learning Dangerous?

- Will human be ruled by machines?
  - It seems no likely any time time.
  - General AI is so challenging
  - Algorithms are not “intelligent” enough
- But machine learning can potentially be **misused**, **misleading**, and/or **invasive**
  - Important to think about implications of what you build

App Store Preview

This app is available only on the App Store for iPhone and iPad.

Mushroom Identificator 4+

Mushrooms photo recognition

AnnapurnApp Technologies UG haftungsbeschrankt

★★★★★ 4.6, 387 Ratings

Free · Offers In-App Purchases

Screenshots

iPhone iPad

TECHNOLOGY NEWS OCTOBER 10, 2018 / 11:12 AM / A YEAR AGO

Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin 8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

> In effect, Amazon's system taught itself that male candidates were preferable. It penalized resumes that included the word "women's," as in "women's chess club captain." And it downgraded graduates of two all-women's colleges, according to people familiar with the matter. They did not specify the names of the schools.
>
> Amazon edited the programs to make them neutral to these particular terms. But that was no guarantee that the machines would not devise other ways of sorting candidates that could prove discriminatory, the people said.

Accountable Algorithms

FAT Machine Learning

- Statement from **Fairness**, **Accountability**, and **Transparency** in Machine Learning organization
  - https://www.fatml.org/resources/principles-for-accountable-algorithms

Algorithms and the data that drive them are designed and created by people -- There is always a human ultimately responsible for decisions made or informed by an algorithm. "The algorithm did it" is not an acceptable excuse if algorithmic systems make mistakes or have undesired consequences, including from machine-learning processes.

Fairness

Black people with complex medical needs were less likely than equally ill white people to be referred to programmes that provide more personalized care. Credit: Ed Kashi/VII/Redux/eyevine

An algorithm widely used in US hospitals to allocate health care to patients has been systematically discriminating against black people, a sweeping analysis has found.

Why unfair?

- How does this type of error happen?

- Possibilities:
    - Not enough diversity in training data
    - Not enough diversity in test data
    - Not enough error analysis

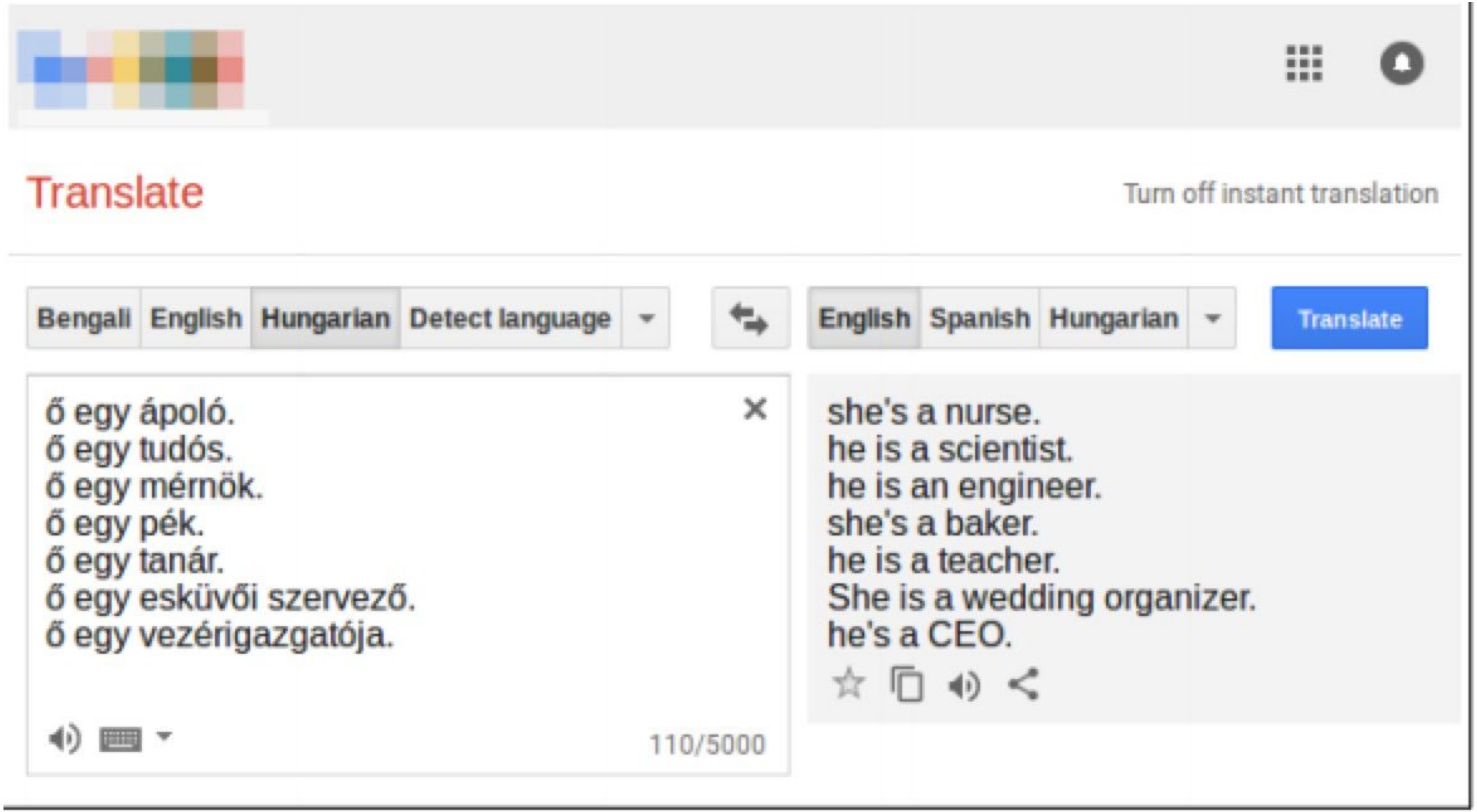
Fairness

- Suppose your classifier gets 90% accuracy...

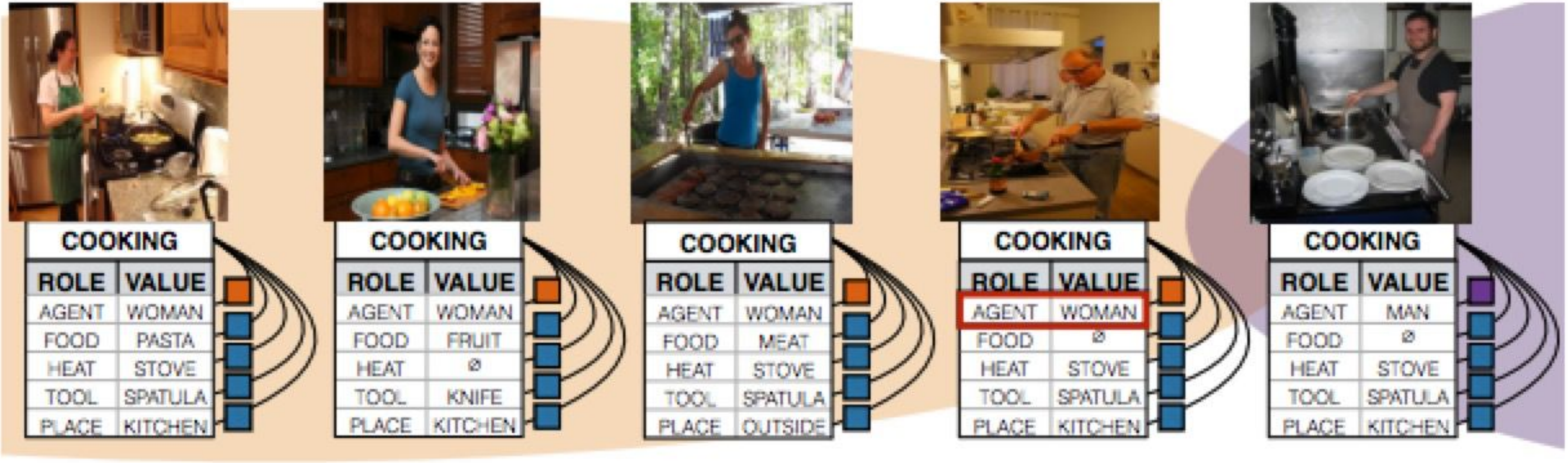
Bias

- Bias and stereotypes that exist in data will be learned by ML algorithms

- Sometime, those biases will be amplified by ML



Prates et al, 2018,https://arxiv.org/pdf/1809.02208.pdf



- Training data:
  - Women appeared in “cooking” images 33% more often than men
- Predictions:
  - Women appeared **68%** more often

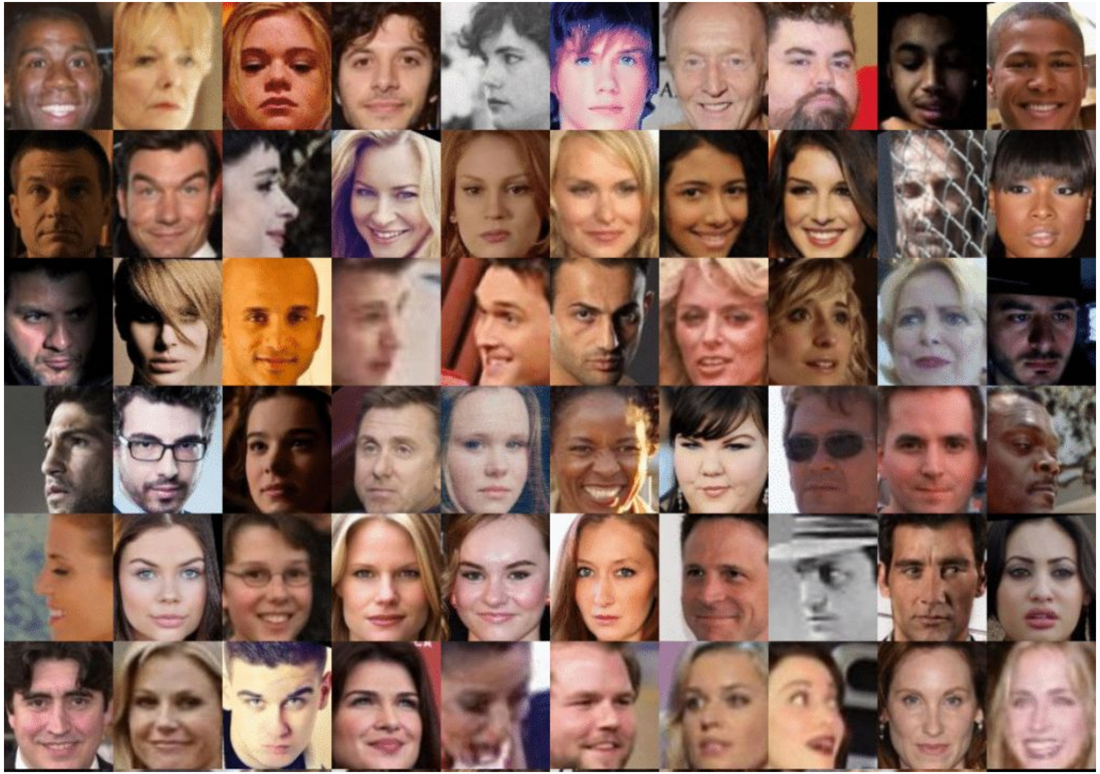
Zhao et al, 2017,https://arxiv.org/pdf/1707.09457.pdf

Privacy

- Training data is often scraped from the web

- Personal data may get scooped up by ML systems
  - Are users aware of this?
  - How do they feel about it?

- No reveal sensitive information (income, health, communication)



MegaFace Dataset:
4.7 million photos of
627,000 individuals,
from Flickr users

Use and Misuse

- Machine learning can predict:
    - If you are overweight
    - If you are transgender
    - If you have died

- People may build these classifiers for legitimate purposes, but could easily be misused by others

Criminal Machine Learning

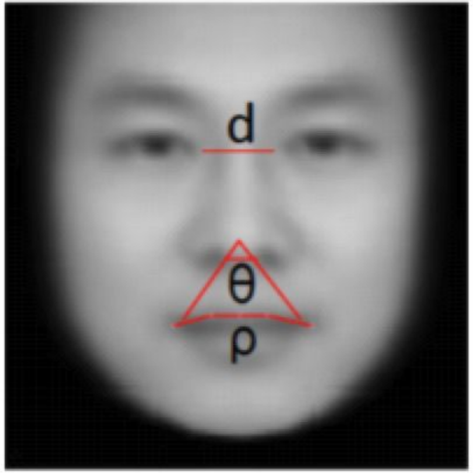
- Can we predict if someone is prone to committing a crime based on their facial structure?
- One of studies: Wu and Zhang (2016), “Automated Inference on Criminality using Face Images”, claims yes, with 90% accuracy.
- Good summary of why the answer is probably no:
    - https://callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

Figure 2. Criminal and non-criminal faces from Wu and Zhang (2016)

Use and Misuse

- How was the dataset created?
    - Criminal photos: government IDs
    - Non-criminal photos: professional headshots

- What did the classifier learn?
    - “The algorithm finds that criminals have shorted distances between the inner corners of the eyes, smaller angles between the nose and the corners of the mouth, and higher curvature of the upper lip.”



Case Study

- If your tool seems dystopian:
    - Consider whether this is really something you should be building…
        - One argument: someone will eventually build this technology, so better for researchers to do it first to understand it.
        - Still, proceed carefully: understand potential misuse
    - Be sure that your claims are correct
        - Solid error analysis is critical
        - Misuse of an inaccurate system even worse than misuses of an accurate system.

Course Summary