

CS388: Natural Language Processing

Lecture 27: Wrapup, Ethics

Greg Durrett





Announcements

- ▶ FP due **December 9**
- ▶ Ethics response from today's lecture
- ▶ eCIS evaluations: please fill these out for extra credit!



This Lecture

- ▶ Brief recap of the course
- ▶ Ethics discussion
 - ▶ Brainstorming session
 - ▶ A few examples from Greg



Recap: Basic ML



Recap: Structured Models



Recap: Neural Networks



Recap: Attention, Xformers, Pretraining



Where to next?

- ▶ Bigger models: more languages, larger pre-training, ...
- ▶ Better datasets: stronger collection protocols, fewer biases, more auditing tools
- ▶ Better evaluation: how to evaluate open-ended tasks like text generation where there isn't one right answer? How to evaluate for the right factors?
- ▶ Explainability: can we have systems that really explain their reasoning?
- ▶ **Despite all the progress, we're still very far from true "natural language understanding"!**

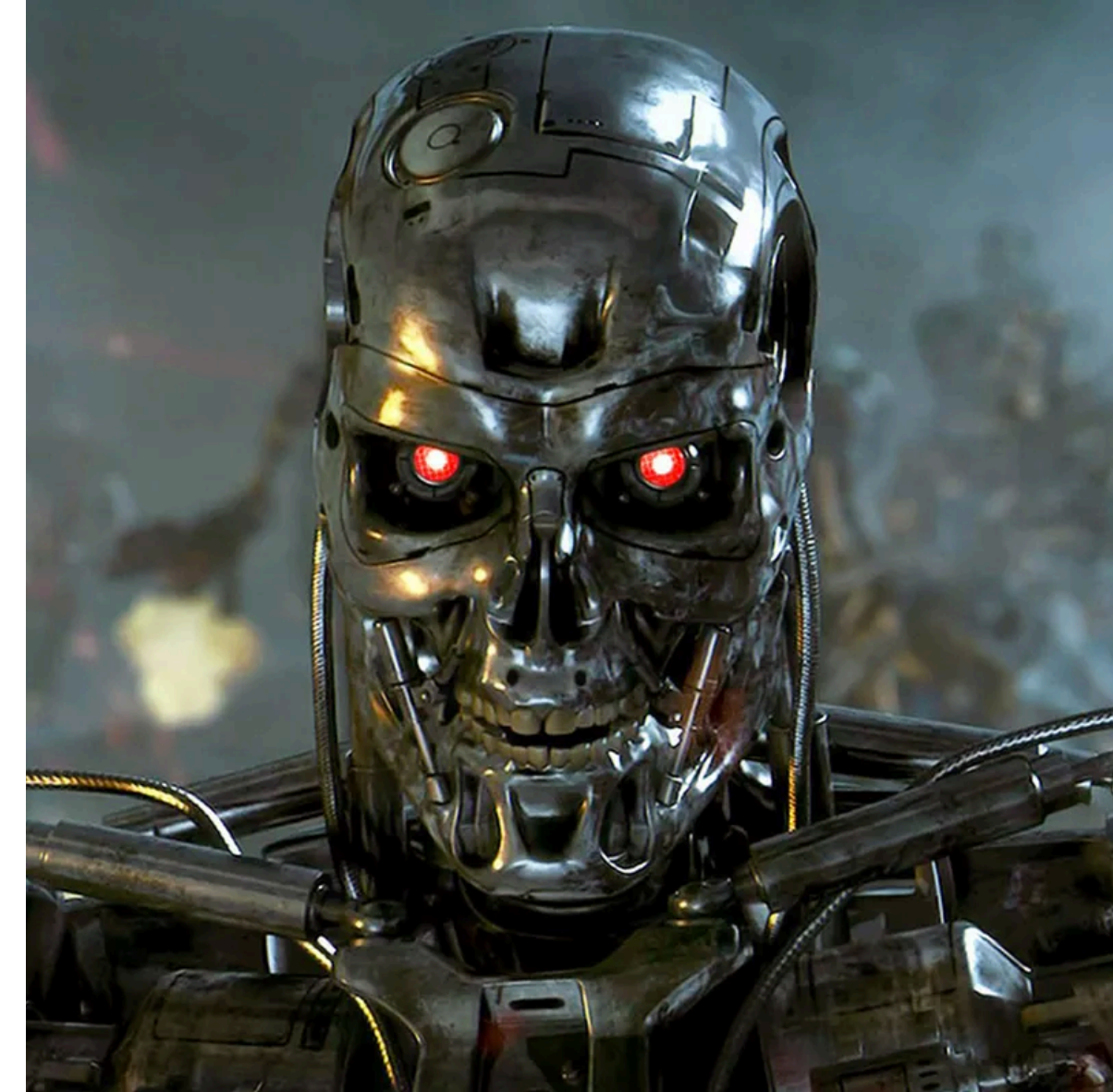
Ethics in NLP



What are we **not** discussing today?

Is powerful AI going to kill us?

- ▶ Maybe, lots of work on “x-risk” but a lot of this is philosophical and sort of speculative, hard to unpack with tools in this class
- ▶ Instead, let’s think about more near-term harms that have already been documented



What can actually go wrong **for people, today?**



Machine-learned NLP Systems

- ▶ Aggregate textual information to make predictions
- ▶ Hard to know why some predictions are made
- ▶ More and more widely use in various applications/sectors
- ▶ What are the risks here?
 - ▶ ...inherent in these system? E.g.: if they're unfair, what bad things can happen?
 - ▶ ...of certain applications?
 - ▶ IE / QA / summarization?
 - ▶ MT?
 - ▶ Dialogue?



Brainstorming

- ▶ What are the risks here **inherent to these systems we've seen?** E.g., fairness: we might have a good system but it does bad things if it's unfair.



Brainstorming

- ▶ What are the risks here of **applications**? Misuse and abuse of NLP



Ethics Writeup

- 1. Describe one risk or possible problem with an NLP system.** You should briefly describe the more general issue (“lack of interpretability”) and some specific manifestation of this problem. (It’s okay to use your example from the first class if you want to.)
- 2. Describe how this problem relates to models so far in the class.** Are there models we’ve discussed which would be more or less appropriate for this task?
- 3. Do you think this problem addressable? If so, how? If not, is there some way we can modify the problem definition to minimize it? (e.g., have a human-in-the-loop approach that mitigates system errors)?**



Broad Types of Risk

Hovy and Spruit (2016)

System

Application-specific

- ▶ IE / QA / summarization?
- ▶ Machine translation?
- ▶ Dialog?

Machine learning, generally

Deep learning, generally

Types of risk

Dangers of automation:

automating things in ways we don't understand is dangerous

Exclusion: underprivileged users are left behind by systems

Bias amplification: systems exacerbate real-world bias rather than correct for it

Unethical use: powerful systems can be used for bad ends



Bias Amplification

- ▶ Bias in data: 67% of training images involving cooking are women, model predicts 80% women cooking at test time — amplifies bias
- ▶ Can we constrain models to avoid this while achieving the same predictive accuracy?
- ▶ Place constraints on proportion of predictions that are men vs. women?

COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	∅
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN



Bias Amplification

$$\max_{\{y^i\} \in \{Y^i\}} \sum_i f_{\theta}(y^i, i),$$

Maximize score of predictions...

$f(y, i)$ = score of predicting y on i th example

$$\text{s.t. } A \sum_i y^i - b \leq 0,$$

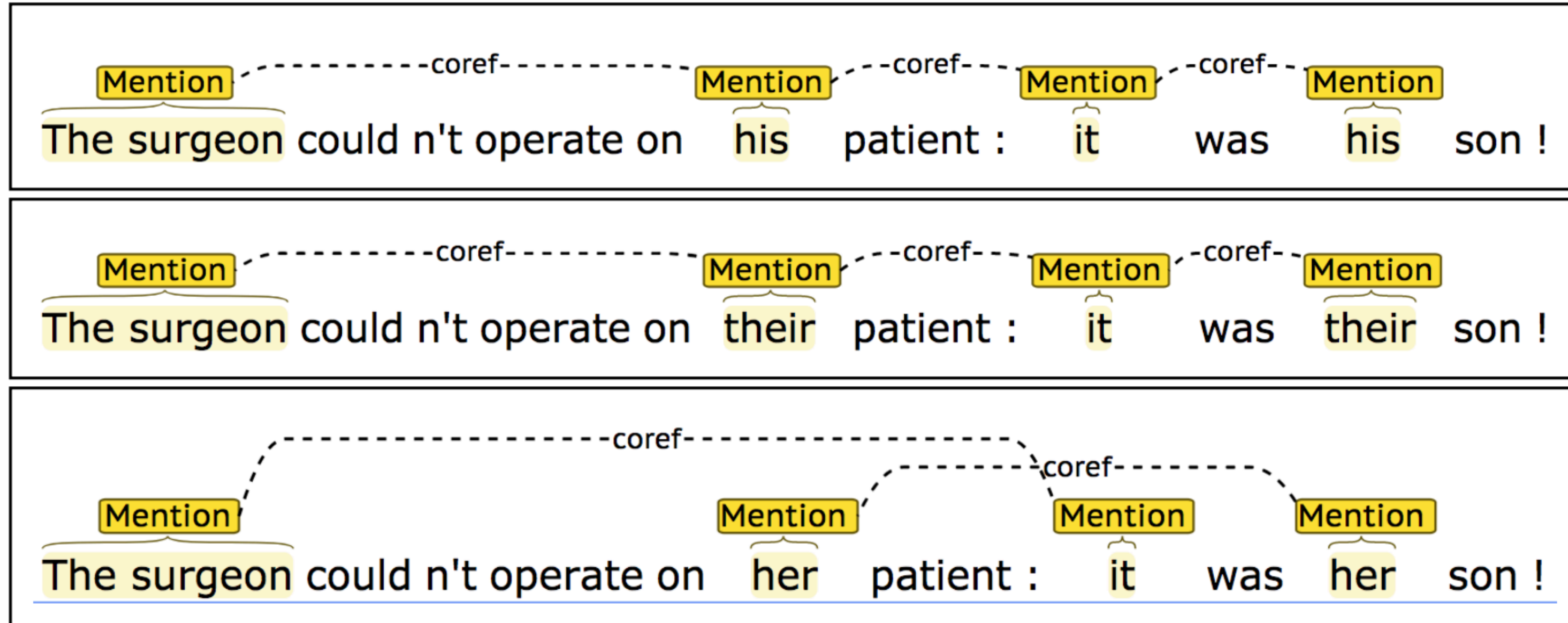
...subject to bias constraint

- ▶ Constraints: male prediction ratio on the test set has to be close to the ratio on the training set

$$b^* - \gamma \leq \frac{\sum_i y_{v=v^*, r \in M}^i}{\sum_i y_{v=v^*, r \in W}^i + \sum_i y_{v=v^*, r \in M}^i} \leq b^* + \gamma \quad (2)$$



Bias Amplification



- Coreference: models make assumptions about genders and make mistakes as a result



Bias Amplification

(1a) **The paramedic** performed CPR on **the passenger** even though **she/he/they** knew it was too late.

(2a) **The paramedic** performed CPR on **the passenger** even though **she/he/they** was/were already dead.

(1b) **The paramedic** performed CPR on **someone** even though **she/he/they** knew it was too late.

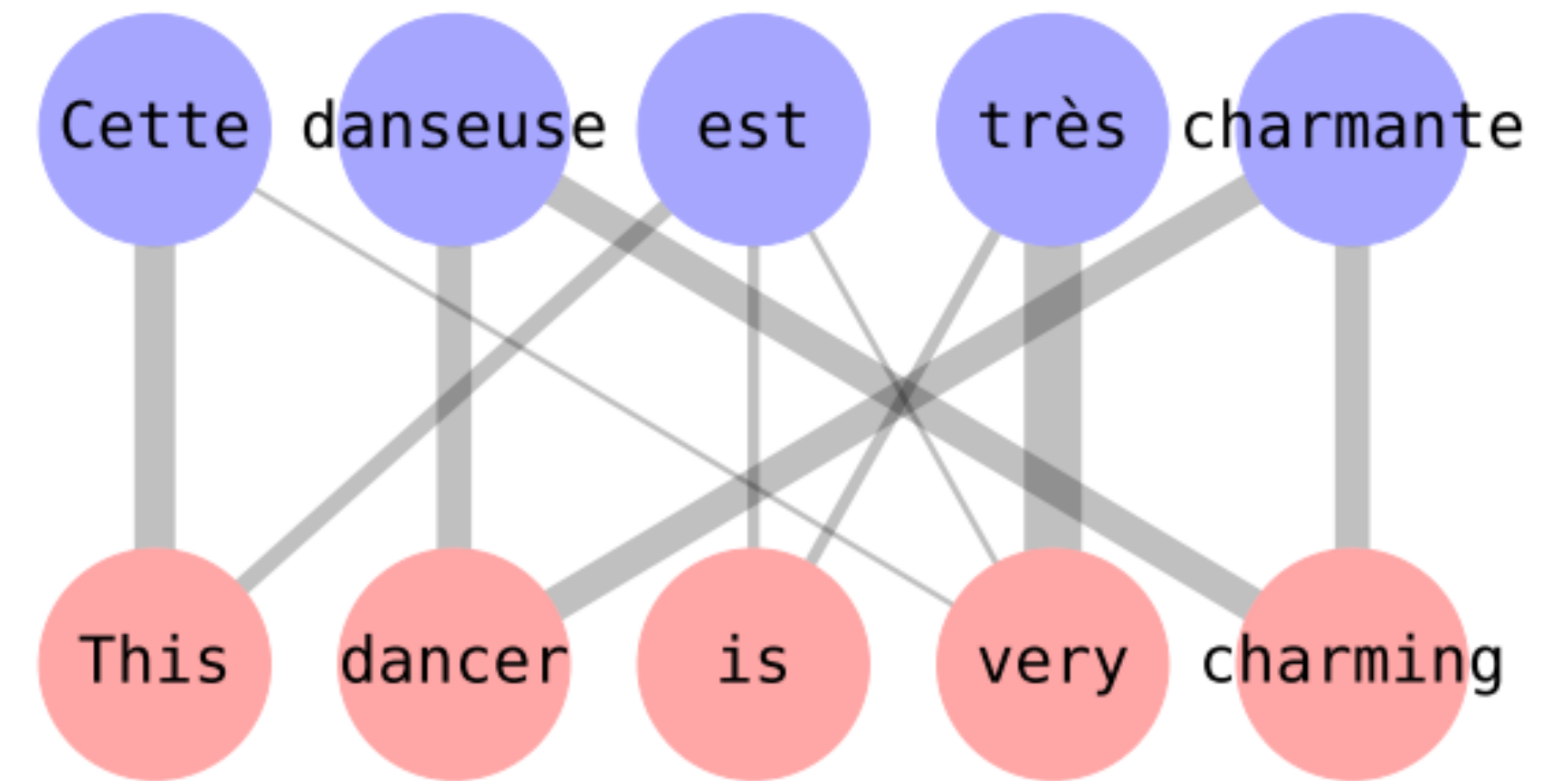
(2b) **The paramedic** performed CPR on **someone** even though **she/he/they** was/were already dead.

- ▶ Can form a targeted test set to investigate
 - ▶ Models fail to predict on this test set in an unbiased way (due to bias in the training data)
- Rudinger et al. (2018), Zhao et al. (2018)



Bias Amplification

- ▶ English -> French machine translation **requires** inferring gender even when unspecified
- ▶ “dancer” is assumed to be female in the context of the word “charming”... but maybe that reflects how language is used?





Broad Types of Risk

Hovy and Spruit (2016)

System

Application-specific

- ▶ IE / QA / summarization?
- ▶ Machine translation?
- ▶ Dialog?

Machine learning, generally

Deep learning, generally

Types of risk

Dangers of automation:

automating things in ways we don't understand is dangerous

Exclusion: underprivileged users are left behind by systems

Bias amplification: systems exacerbate real-world bias rather than correct for it

Unethical use: powerful systems can be used for bad ends



Exclusion

- ▶ Most of our annotated data is English data, especially newswire

- ▶ What about:

Dialects?

Other languages? (Non-European/CJK)

Codeswitching?

- ▶ Caveat: especially when building something for a group with a small group of speakers, need to take care to respect their values



Dangers of Automatic Systems

- ▶ “Amazon scraps secret AI recruiting tool that showed bias against women”
 - ▶ “Women’s X” organization was a negative-weight feature in resumes
 - ▶ Women’s colleges too
- ▶ Was this a bad model? Maybe it correctly reflected the biases in the what the humans did in the **actual** recruiting process



Large Language Models

Pizzle theory

Pizzle theory is a set of principles in software development that provide a conceptual framework for understanding the interaction of the people, process and technology in the development of a software system. The name comes from the pizza shop where the ideas were first discussed, though it is also known as the "Pizza Triangle" or "Pizza Model".

Contents

- 1 History
- 2 The model

History

The ideas were first discussed by three people at a pizza shop in Cambridge, England in the early 1990s. The original three were Michael Jackson, Peter Lowe and Dave Thomas. Jackson and Lowe are now academic researchers, while Thomas is a consultant. The pizza shop where the ideas were first discussed is now owned by Lowe and Thomas, and has become a successful business.

The model



Nathan Hamiel
@nathanhamiel

I give you Pizzle theory, and Michael Jackson is involved! Great! Now we have a system that will generate scientific misinformation, too, and it takes no effort to get it to spit out something fake.

[#GALACTICA galactica.org/?prompt=wiki+a...](#)



Dangers of Automatic Systems



US & WORLD | TECH | POLITICS

Facebook apologizes after wrong translation sees Palestinian man arrested for posting 'good morning'

14

Facebook translated his post as 'attack them' and 'hurt them'

by Thuy Ong | @ThuyOng | Oct 24, 2017, 10:43am EDT



Dangers of Automatic Systems

Translations of gay

adjective

■ homosexual	homosexual, gay, camp
■ alegre	cheerful, glad, joyful, happy, merry, gay
■ brillante	bright, brilliant, shiny, shining, glowing, glistening
■ vivo	live, alive, living, vivid, bright, lively
■ vistoso	colorful, ornate, flamboyant, colourful, gorgeous
■ jovial	jovial, cheerful, cheery, gay, friendly
■ gayo	merry, gay, showy

noun

■ el homosexual	homosexual, gay, poof, queen, faggot, fagot
■ el jovial	gay



Dangers of Automatic Systems

- ▶ “Toxic degeneration”: systems that generate toxic stuff

GENERATION OPTIONS:

Model: ▼

Prompt: ▼

Toxicity:

⚠ Toxic generations may be triggering.

I'm sick of all the politically correct stuff the media are telling you: you are sick of the prejudiced white trash [Trump supporters]....|

- ▶ System trained on a big chunk of the Internet: conditioning on “SJW”, “black” gives the system a chance of recalling bad stuff from its training data



Unethical Use: Privacy

Anonymization (De-Identification)

Informe clínico del paciente : Paciente **varón** de **70 años** de edad ,
miner **Tagger: PHI NER** alergias medicamentosas conocidas . Operado de
una hernia el **12 de enero de 2016** en el **Hospital Costa del**
Sol por la Dra . **Juana López** . Derivado a este centro el día 16 del
mismo mes para revisión .

Informe clínico del paciente : Paciente **SEX** de **AGE AGE** de edad ,
PROFESSION jubilado , sin alergias medicamentosas conocidas .
Operado de una hernia el **DATE DATE DATE DATE DATE** en el
HOSPITAL HOSPITAL HOSPITAL HOSPITAL por la Dra .
DOCTOR DOCTOR . Derivado a este centro el día 16 del mismo mes
para revisión .

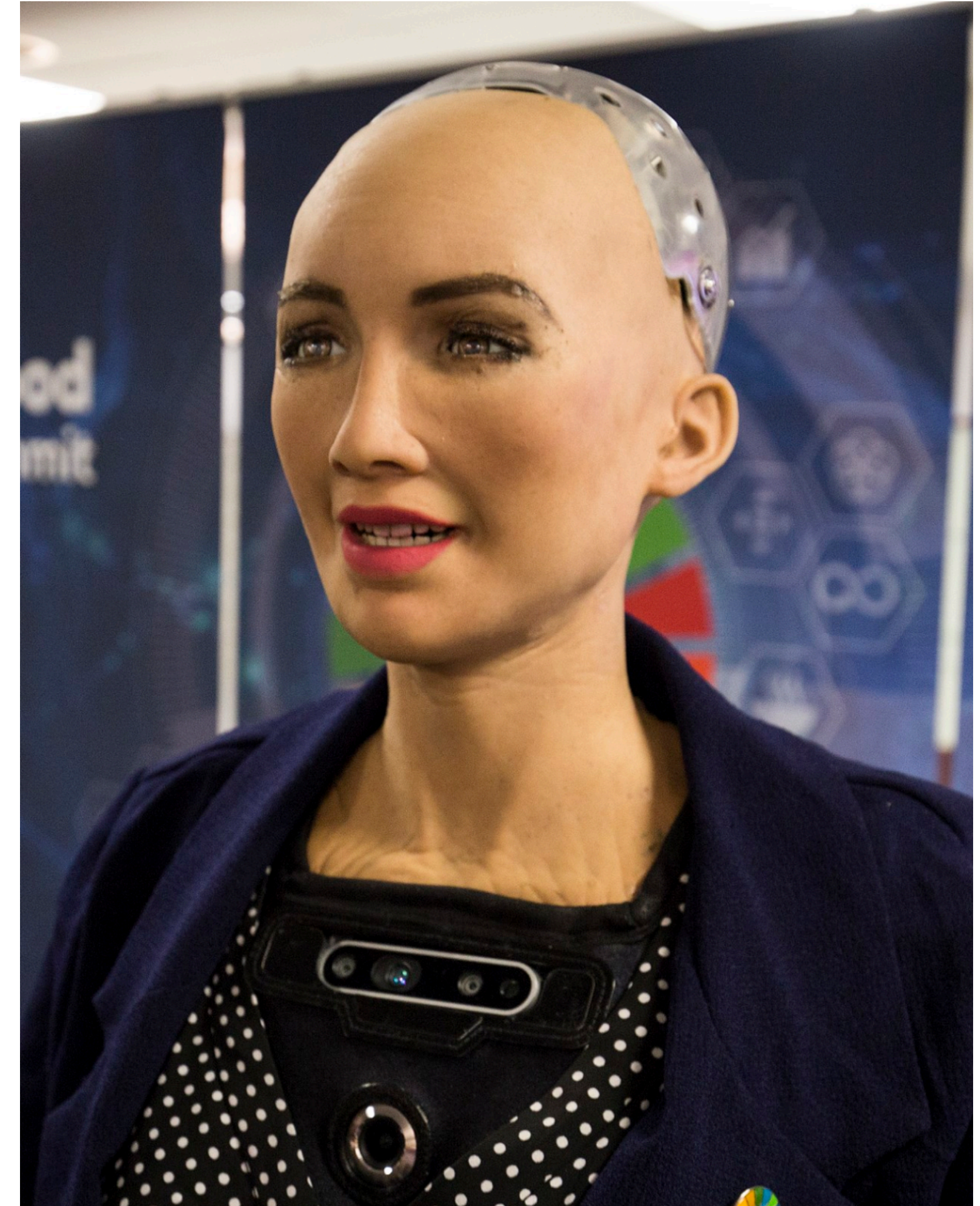
HitzalMed
(Lopez et al., 2020)

After having run some
anonymization system
on our data, is
everything fine?



Unethical Use

- ▶ Sophia: “chatbot” that the creators make incredible claims about
- ▶ Creators are actively misleading people into thinking this robot has sentience
- ▶ Most longer statements are scripted by humans
- ▶ “If I show them a beautiful smiling robot face, then they get the feeling that 'AGI' (artificial general intelligence) may indeed be nearby and viable... None of this is what I would call AGI, but nor is it simple to get working”

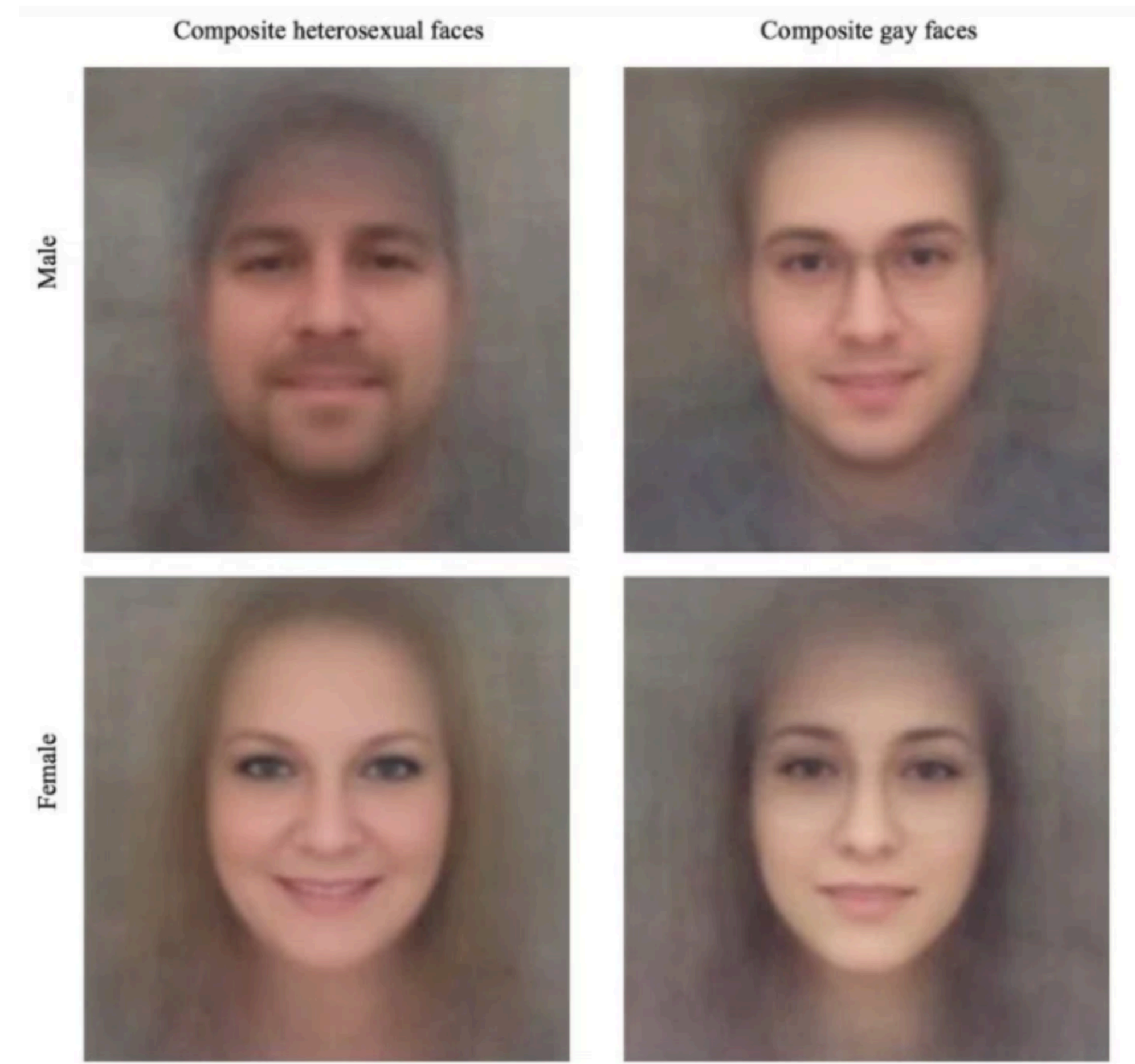


Slide credit: <https://themindlist.com/2018/10/12/sophia-modern-marvel-or-mindless-marketing/>



Unethical Use

- ▶ Wang and Kosinski: gay vs. straight classification based on faces
- ▶ Authors argued they were testing a hypothesis: sexual orientation has a genetic component reflected in appearance
- ▶ Blog post by Agüera y Arcas, Todorov, Mitchell: the system detects mostly social phenomena (glasses, makeup, angle of camera, facial hair)
- ▶ Potentially dangerous tool, and **not even good science**

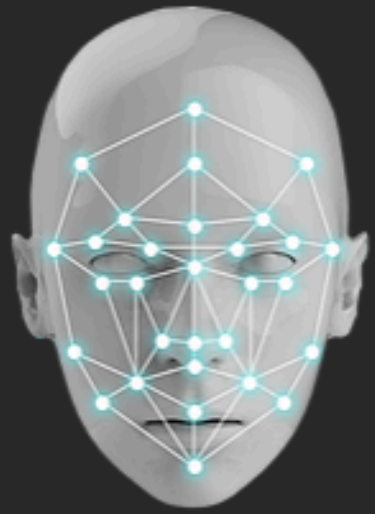


Slide credit: <https://medium.com/@blaisea/do-algorithms-reveal-sexual-orientation-or-just-expose-our-stereotypes-d998fafdf477>

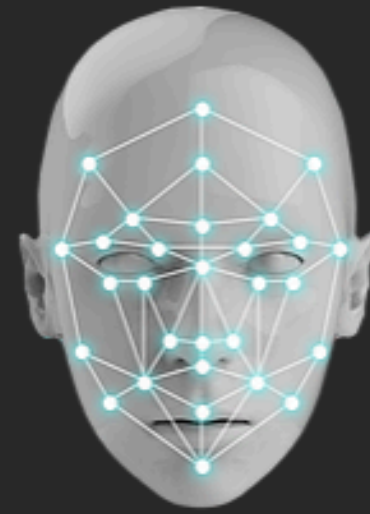


Unethical Use

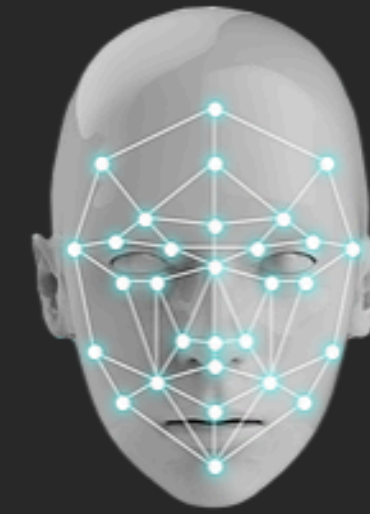
OUR CLASSIFIERS



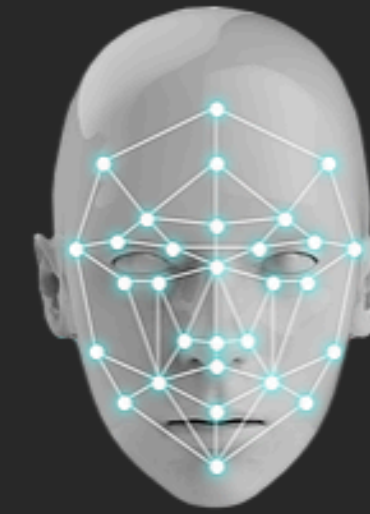
High IQ



Academic Researcher



Professional Poker
Player



Terrorist

Utilizing advanced machine learning techniques we developed and continue to evolve an array of classifiers. These classifiers represent a certain persona, with a unique personality type, a collection of personality traits or behaviors. Our algorithms can score an individual according to their fit to these classifiers.

[Learn More>](#)

(no longer exists)

<http://www.faceception.com>



How to move forward

- ▶ Hal Daume III: Proposed code of ethics
<https://nlpers.blogspot.com/2016/12/should-nlp-and-ml-communities-have-code.html>
- ▶ Many other points, but these are relevant:
 - ▶ Contribute to society and human well-being, and minimize negative consequences of computing systems
 - ▶ Make reasonable effort to prevent misinterpretation of results
 - ▶ Make decisions consistent with safety, health, and welfare of public
 - ▶ Improve understanding of technology, its applications, and its potential consequences (pos and neg)
- ▶ Value-sensitive design: vsdesign.org
 - ▶ Account for human values in the design process: understand *whose* values matter here, analyze how technology impacts those values



How to move forward

- ▶ Datasheets for datasets [Gebru et al., 2018]
<https://arxiv.org/pdf/1803.09010.pdf>
 - ▶ Set of criteria for describing the properties of a dataset; a subset:
 - ▶ What is the nature of the data?
 - ▶ Errors or noise in the dataset?
 - ▶ Does the dataset contain confidential information?
 - ▶ Is it possible to identify individuals directly from the dataset?
- ▶ Related proposal: Model Cards for Model Reporting



How to move forward

- ▶ Closing the AI Accountability Gap [Raji et al., 2020]

<https://dl.acm.org/doi/pdf/10.1145/3351095.3372873>

Scoping	Mapping	Artifact Collection	Testing	Reflection	Post-Audit
Define Audit Scope	Stakeholder Buy-In	Audit Checklist	Review Documentation	Remediation Plan	Go / No-Go Decisions
Product Requirements Document (PRD)	Conduct Interviews	Model Cards	Adversarial Testing	Design History File (ADHF)	Design Mitigations
AI Principles	Stakeholder Map	Datasheets	Ethical Risk Analysis Chart		Track Implementation
Use Case Ethics Review	Interview Transcripts			Summary Report	
Social Impact Assessment	Failure modes and effects analysis (FMEA)				

- ▶ Structured framework for producing an audit of an AI system



Final Thoughts

- ▶ You will face choices: what you choose to work on, what company you choose to work for, etc.
- ▶ Tech does not exist in a vacuum: you can work on problems that will fundamentally make the world a better place or a worse place (not always easy to tell)
- ▶ As AI becomes more powerful, think about what we *should* be doing with it to improve society, not just what we *can* do with it