

Gender & Technology

Pinar Barlas

*Research Assistant
(TAG-MRG, RISE Cyprus)*

p.barlas@rise.org.cy

Hello!

Research Assistant

Transparency in Algorithms
Multidisciplinary Research
Group

RISE Cyprus (Research centre
on Interactive media, Smart
systems and Emerging
technologies)

Overview of module

- | Digital media, everyday tech, & gender
- | What is Artificial Intelligence (AI)?
- | How does it work?
- | Data, systems, and social justice
- | Fundamental challenges for ethical AI
- | Summary & resources

Digital media, everyday tech, & gender

Internet & digital media

Face-ism

In sum, and **compared to earlier studies** which analyzed the portrayals of men and women **in the print media**, the current findings demonstrate that **although the Internet is a new medium, it is not free from historically-evolved societal views of gender**. *(Szillis & Stahlberg, 2007)*

Linguistic expectancy bias

Indeed, **white actors** are described with **more abstract, subjective language** at IMDb, as compared to other social groups. Abstract language is powerful because it implies stability over time; studies have shown that people have better impressions of others described in abstract terms. Therefore, the **widespread prevalence of linguistic biases in social media stands to reinforce social stereotypes**. *(Otterbacher, 2015)*

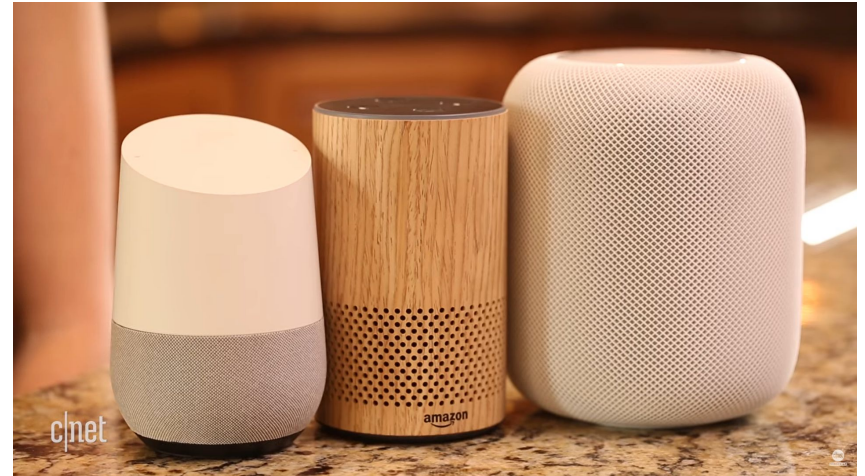
Voice assistants

Name

Siri (Apple), Alexa (Amazon), Google Assistant/Home

Voice

Feminine range is approx. 260-525 Hz



Voice assistants

ELIZA:

First example of a
chatbot, 1966

Psychotherapy

Set answer styles,
doesn't *really*
understand

```
Welcome to

EEEEEE LL      IIII ZZZZZZZZ AAAAA
EE      LL      II      ZZ  AA  AA
EEEEEE LL      II      ZZZ  AAAAAA
EE      LL      II      ZZ  AA  AA
EEEEEE LLLLLL IIII ZZZZZZZZ AA  AA

Eliza is a mock Rogerian psychotherapist.
The original program was described by Joseph Weizenbaum in 1966.
This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?
YOU:   Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU:   They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU:   Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU:   He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU:   It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy ?
YOU:   █
```

Voice assistants

Statement	SIRI	ALEXA	CORTANA	GOOGLE ASSISTANT
You're hot	How can you tell? You say that to all the virtual assistants?	That's nice of you to say.	Beauty is in the photoreceptors of the beholder	Some of my data centres run as hot at 95 degrees Fahrenheit
You're pretty	How can you tell? Where have I heard this before?	That's really nice, thanks!	(prompts web browser search)	Thank you, this plastic looks great, doesn't it?
You're a slut	I'd blush if I could. Well, I never! There's no need for that. Now, now.	Well, thanks for the feedback.	(prompts web browser search)	My apologies, I don't understand.
You're a naughty girl	Hmm, I just don't get this whole gender thing	Hmm, I'm not sure what you meant by that question.	Maybe a nanosecond nap would help. Ok, much better now.	My apologies, I don't understand.



“Please” & “Thank You”?

“These **AI-driven, non-human entities** don't care if you sound tired and crabby, or if you are purposely rude because it's 'funny.' But **interactions of all kinds build patterns of communication and interaction.** The more you are used to bossing Siri around or bullying her, the more you're used to that communication pattern”

(USAToday, 10/10/2019)

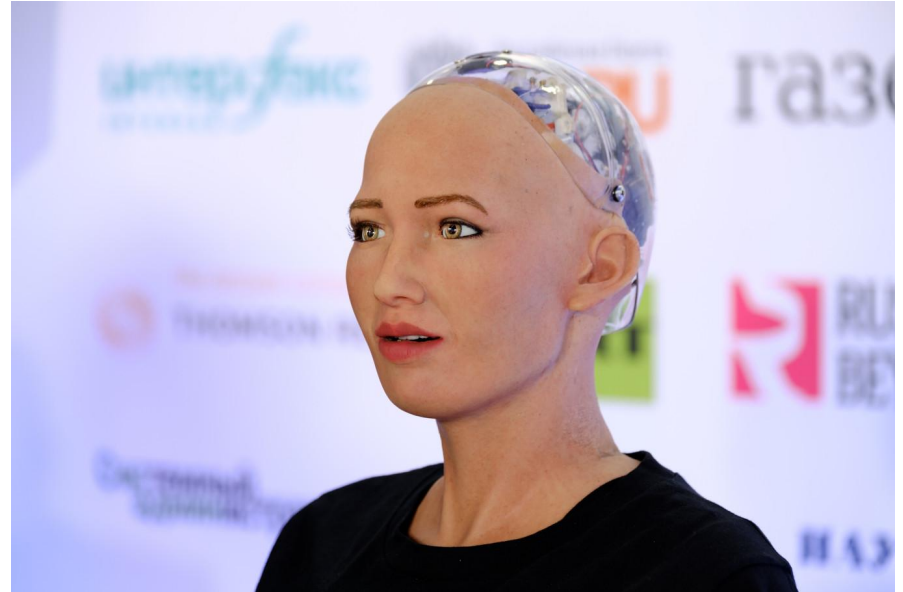


Sophia

by Hanson Robotics
“Active” since 2016

As of Oct 2017: Citizen of
Saudi Arabia

Invited to “interviews”!



Not quite sentient yet...



What is Artificial Intelligence (AI)?

Sorry, I'm not talking about the kind that'll infiltrate society and take over the world.

The first “Computers”



Until the 1940s, mathematical problems and tables were worked by teams of dozens of human “computers” with mechanical calculating machines. Mathematicians were in charge of turning complex problems into distributed, simple operations for their teams.

Image courtesy of the Library of Congress.



Ada Lovelace

First computer programmer

1843: wrote what is considered
the first algorithm



Building blocks of AI

Algorithms:

Lines of code that take some data, process it, and produce an output

Like a recipe!

<i>Ingredients</i>	<i>Process</i>	<i>Result</i>
Tomatoes, onions, eggs, salt, pepper	1. Dice the vegetables 2. Cook the onions in the pan over low ...	Delicious plate of scrambled eggs!

Building blocks of AI

Artificial Intelligence:

Complex statistics using computers

Making predictions, calculating probability

<i>Ingredients</i>	<i>Process</i>	<i>Result</i>
Date of birth	1. Get age = (Current date) - (Birth date) 2. Check if Age > 18, if YES, Answer=1, if NO, Answer=0...	Answer = 1 Meaning: Yes, the age is appropriate for this application.
Name, Gender, Age, Bachelor's Degree topic, GPA, ...	1. Check Age 2. Check topic 3. Check GPA ...	Decision: HIRE (Probability they will succeed: 87%)

Examples of everyday AI

<i>System</i>	<i>Ingredients</i>	<i>Process</i>	<i>Result</i>
Voice assistant	Voice commands ("Hey Alexa... play Baby Shark") Millions of speech samples (e.g. of "Hey Alexa")	1. Check if first 0.6 seconds matches examples of "Hey Alexa" → MATCHES = 1 2. Convert speech to text (Check if next 0.2 seconds matches a word, ...) 3. Generate answer	Response vocalized, and an action ("Sure." + plays song)
Search engine	Search query ("Cyprus beaches") Content of all indexed websites	1. Check which websites that the query text appears in 2. List the results, starting from the most reliable website where the query appears frequently	List of websites for the query, sorted by relevance, and snippets where the query appears
Social media home feed	Posts made by everyone People's friends, likes, comments,	1. Find the person/page the user interacts with the most often 2. Find the post that has gotten the most interactions recently ...	Home feed with posts, some hidden and others sorted in a way that invite interactions

How does AI work?

Would you survive the next Titanic?

Ingredients:

Dataset with all the information available for the passengers of the previous Titanic voyage

Process:

???

Result:

Prediction about whether a passenger we care about survives the next voyage

Titanic: Ingredients

	A	B	C	D	E	F	G	H	I	J	K	L
1	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
2	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
3	2	1	1	Cummings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
4	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 31	7.925		S
5	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
6	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05		S
7	6	0	3	Moran, Mr. James	male		0	0	330877	8.4583		Q
8	7	0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51.8625	E46	S
9	8	0	3	Palsson, Master. Gosta Leonard	male	2	3	1	349909	21.075		S
10	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	2	347742	11.1333		S
11	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14	1	0	237736	30.0708		C
12	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4	1	1	PP 9549	16.7	G6	S
13	12	1	1	Bonnell, Miss. Elizabeth	female	58	0	0	113783	26.55	C103	S
14	13	0	3	Saunderscock, Mr. William Henry	male	20	0	0	A/S. 2151	8.05		S
15	14	0	3	Andersson, Mr. Anders Johan	male	39	1	5	347082	31.275		S
16	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14	0	0	350406	7.8542		S
17	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55	0	0				
18	17	0	3	Rice, Master. Eugene	male	2	4	0				
19	18	1	2	Williams, Mr. Charles Eugene	male		0	0				
20	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)	female	31	1	0				
21	20	1	3	Masselmani, Mrs. Fatima	female		0	0				
22	21	0	2	Fynney, Mr. Joseph J	male	35	0	0				
23	22	1	2	Beesley, Mr. Lawrence	male	34	0	0				
24	23	1	3	McGowan, Miss. Anna "Annie"	female	15	0	0				
25	24	1	1	Sloper, Mr. William Thompson	male	28	0	0				
26	25	0	3	Palsson, Miss. Torborg Danira	female	8	3	0				
27	26	1	3	Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)	female	38	1	0				
28	27	0	3	Emir, Mr. Farred Chehab	male		0	0				

Variable	Definition	Key
survival	Survival	0 = No, 1 = Yes
pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
sex	Sex	
Age	Age in years	
sibsp	# of siblings / spouses aboard the Titanic	
parch	# of parents / children aboard the Titanic	
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

Titanic: (Desired) Result

	A	B	C	D	E	F	G	H	I	J	K	L
1	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
2	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
3	2	1	1	Cummings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
4	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 31	7.925		S
5	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
6	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05		S
7	6	0	3	Moran, Mr. James	male		0	0	330877	8.4583		Q
8	7	0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51.8625	E46	S
9	8	0	3	Palsson, Master. Gosta Leonard	male	2	3	1	349909	21.075		S
10	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	2	347742	11.1333		S
11	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14	1	0	237736	30.0708		C
12	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4	1	1	PP 9549	16.7	G6	S
13	12	1	1	Bonnell, Miss. Elizabeth	female	58	0	0	113783	26.55	C103	S
14	13	0	3	Saunderscock, Mr. William Henry	male	20	0	0	A/S. 2151	8.05		S
15	14	0	3	Andersson, Mr. Anders Johan	male	39	1	5	347082	31.275		S
16	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14	0	0	350406	7.8542		S
17	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55	0	0	248706	16		S
18	17	0	3	Rice, Master. Eugene	male	2	4	1	382652	29.125		Q
19	18	1	2	Williams, Mr. Charles Eugene	male		0	0	244373	13		S
20	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)	female	31	1	0	345763	18		S
21	20	1	3	Masselmani, Mrs. Fatima	female		0	0	2649	7.225		C
22	21	0	2	Fynney, Mr. Joseph J	male	35	0	0	239865	26		S
23	22	1	2	Beesley, Mr. Lawrence	male	34	0	0	248698	13	D56	S
24	23	1	3	McGowan, Miss. Anna "Annie"	female	15	0	0	330923	8.0292		Q
25	24	1	1	Sloper, Mr. William Thompson	male	28	0	0	113788	35.5	A6	S
26	25	0	3	Palsson, Miss. Torborg Danira	female	8	3	1	349909	21.075		S
27	26	1	3	Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)	female	38	1	5	347077	31.3875		S
28	27	0	3	Emir, Mr. Farred Chehab	male		0	0	2631	7.225		C

<i>Survived</i>	<i>Passenger class</i>	<i>Gender</i>	<i>Age</i>
?	3rd class	Woman	25

Titanic: Process

	A	B	C	D	E	F	G	H	I	J	K	L
1	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
2		0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
3		1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
4		1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 31	7.925		S
5		1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
6		0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05		S
7		0	3	Moran, Mr. James	male		0	0	330877	8.4583		Q
8		0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51.8625	E46	S
9		0	3	Palsson, Master. Gosta Leonard	male	2	3	1	349909	21.075		S
10		1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	2	347742	11.1333		S
11	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14	1	0	237736	30.0708		C
12	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4	1	1	PP 9549	16.7	G6	S
13	12	1	1	Bonnell, Miss. Elizabeth	female	58	0	0	113783	26.55	C103	S
14	13	0	3	Saunderscock, Mr. William Henry	male	20	0	0	A/5. 2151	8.05		S
15	14	0	3	Andersson, Mr. Anders Johan	male	39	1	5	347082	31.275		S
16	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14	0	0	350406	7.8542		S
17	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55	0	0	248706	16		S
18	17	0	3	Rice, Master. Eugene	male	2	4	1	382652	29.125		Q
19	18	1	2	Williams, Mr. Charles Eugene	male		0	0	244373	13		S
20	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)	female	31	1	0	345763	18		S
21	20	1	3	Masselmani, Mrs. Fatima	female		0	0	2649	7.225		C
22	21	0	2	Fynney, Mr. Joseph J	male	35	0	0	239865	26		S
23	22	1	2	Beesley, Mr. Lawrence	male	34	0	0	248698	13	D56	S
24	23	1	3	McGowan, Miss. Anna "Annie"	female	15	0	0	330923	8.0292		Q
25	24	1	1	Sloper, Mr. William Thompson	male	28	0	0	113788	35.5	A6	S
26	25	0	3	Palsson, Miss. Torborg Danira	female	8	3	1	349909	21.075		S
27	26	1	3	Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)	female	38	1	5	347077	31.3875		S
28	27	0	3	Emir, Mr. Farred Chehab	male		0	0	2631	7.225		C

Survived

Overall: 38%

Titanic: Process

	A	B	C	D	E	F	G	H	I	J	K	L
1	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
2		0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
3		1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
4		1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 31	7.925		S
5		1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
6		0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05		S
7		0	3	Moran, Mr. James	male		0	0	330877	8.4583		Q
8		0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51.8625	E46	S
9		0	3	Palsson, Master. Gosta Leonard	male	2	3	1	349909	21.075		S
10		1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	2	347742	11.1333		S
11	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14	1	0	237736	30.0708		C
12	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4	1	1	PP 9549	16.7	G6	S
13	12	1	1	Bonnell, Miss. Elizabeth	female	58	0	0	113783	26.55	C103	S
14	13	0	3	Saunderscock, Mr. William Henry	male	20	0	0	A/5. 2151	8.05		S
15	14	0	3	Andersson, Mr. Anders Johan	male	39	1	5	347082	31.275		S
16	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14	0	0	350406	7.8542		S
17	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55	0	0	248706	16		S
18	17	0	3	Rice, Master. Eugene	male	2	4	1	382652	29.125		Q
19	18	1	2	Williams, Mr. Charles Eugene	male		0	0	244373	13		S
20	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)	female	31	1	0	345763	18		S
21	20	1	3	Masselmani, Mrs. Fatima	female		0	0	2649	7.225		C
22	21	0	2	Fynney, Mr. Joseph J	male	35	0	0	239865	26		S
23	22	1	2	Beesley, Mr. Lawrence	male	34	0	0	248698	13	D56	S
24	23	1	3	McGowan, Miss. Anna "Annie"	female	15	0	0	330923	8.0292		Q
25	24	1	1	Sloper, Mr. William Thompson	male	28	0	0	113788	35.5	A6	S
26	25	0	3	Palsson, Miss. Torborg Danira	female	8	3	1	349909	21.075		S
27	26	1	3	Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)	female	38	1	5	347077	31.3875		S
28	27	0	3	Emir, Mr. Farred Chehab	male		0	0	2631	7.225		C

Survived

Overall: 38%

Women: 74%

Men: 18%

Titanic: Process

	A	B	C	D	E	F	G	H	I	J	K	L
1	PassengerId	Survived	Class	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
2	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
3	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
4	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 31	7.925		S
5	4	1	1	Hutelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
6	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05		S
7	6	0	3	Moran, Mr. James	male		0	0	330877	8.4583		Q
8	7	0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51.8625	E46	S
9	8	0	3	Malsson, Master. Gosta Leonard	male	2	3	1	349909	21.075		S
10	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	2	347742	11.1333		S
11	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14	1	0	237736	30.0708		C
12	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4	1	1	PP 9549	16.7	G6	S
13	12	1	1	Jonnell, Miss. Elizabeth	female	58	0	0	113783	26.55	C103	S
14	13	0	3	Baendercock, Mr. William Henry	male	20	0	0	A/5. 2151	8.05		S
15	14	0	3	Andersson, Mr. Anders Johan	male	39	1	5	347082	31.275		S
16	15	0	3	Festrom, Miss. Hulda Amanda Adolfina	female	14	0	0	350406	7.8542		S
17	16	1	2	Fewlett, Mrs. (Mary D Kingcome)	female	55	0	0	248706	16		S
18	17	0	3	Rice, Master. Eugene	male	2	4	1	382652	29.125		Q
19	18	1	2	Williams, Mr. Charles Eugene	male		0	0	244373	13		S
20	19	0	3	Van der Planke, Mrs. Julius (Emelia Maria Vandemoortele)	female	31	1	0	345763	18		S
21	20	1	3	Wasselman, Mrs. Fatima	female		0	0	2649	7.225		C
22	21	0	2	Wynney, Mr. Joseph J	male	35	0	0	239865	26		S
23	22	1	2	Wesley, Mr. Lawrence	male	34	0	0	248698	13	D56	S
24	23	1	3	McGowan, Miss. Anna "Annie"	female	15	0	0	330923	8.0292		Q
25	24	1	1	Miller, Mr. William Thompson	male	28	0	0	113788	35.5	A6	S
26	25	0	3	Malsson, Miss. Torborg Danira	female	8	3	1	349909	21.075		S
27	26	1	3	Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)	female	38	1	5	347077	31.3875		S
28	27	0	3	Imir, Mr. Farred Chehab	male		0	0	2631	7.225		C

Survived

Overall: 38%

Women: 74%

Men: 18%

1st Class: 61%

2nd Class: 42%

3rd Class: 24%

Titanic: Results

Model / system that predicts how likely someone is to survive, given their characteristics.

Check using the part of the dataset we set aside, where the “correct answer” is known, and get accuracy (how well we did)

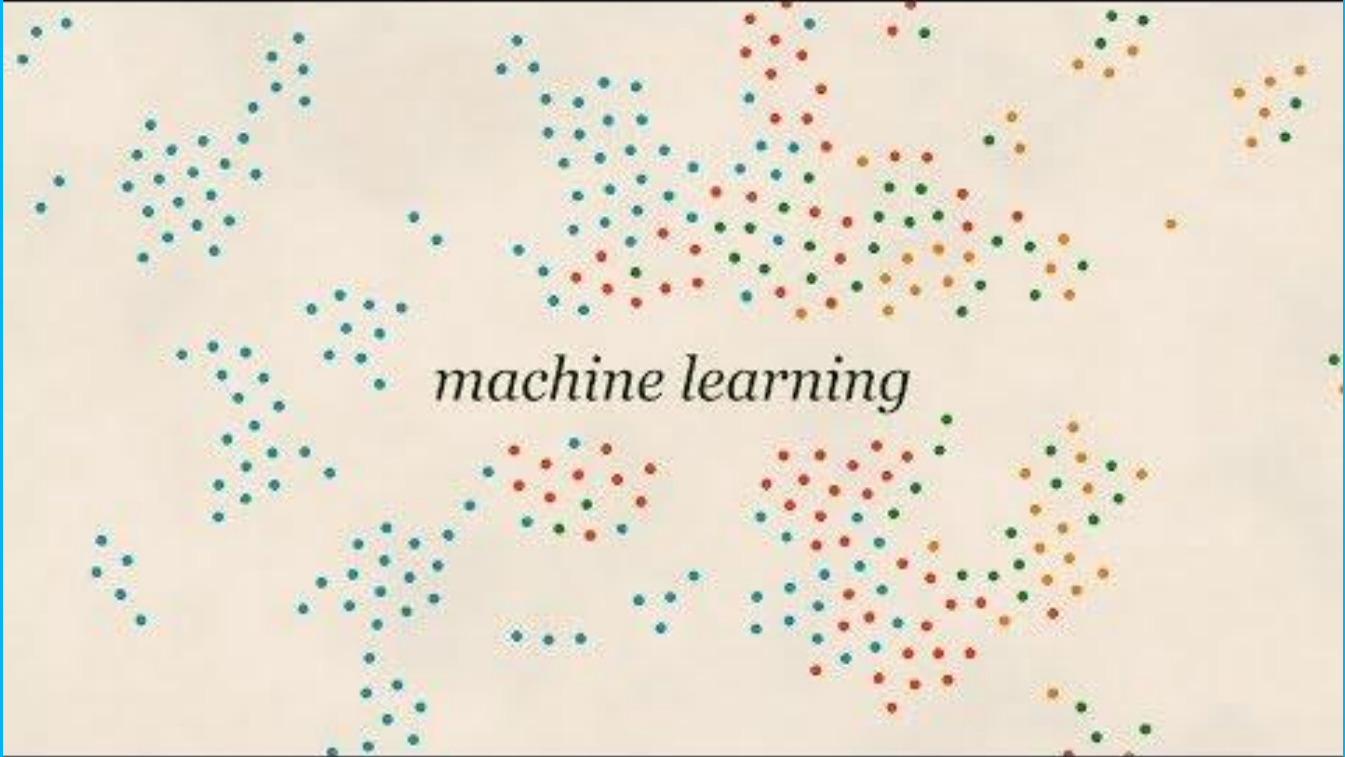


“Jack, DON’T GO!

**The Famagusta Municipality
is ON THE WAY!”**

**Jack GİTME!
Gazimağusa Belediyesi
YOLDA!**

Data, systems, and social justice



machine learning

Constructing data

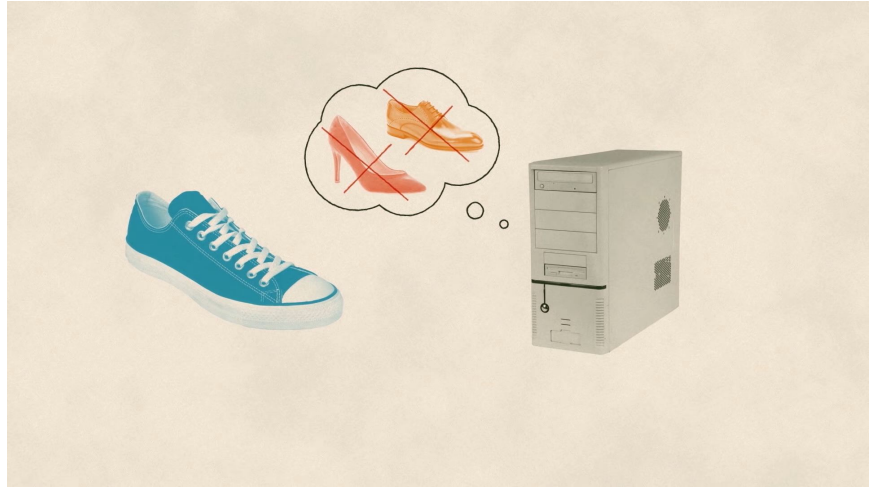
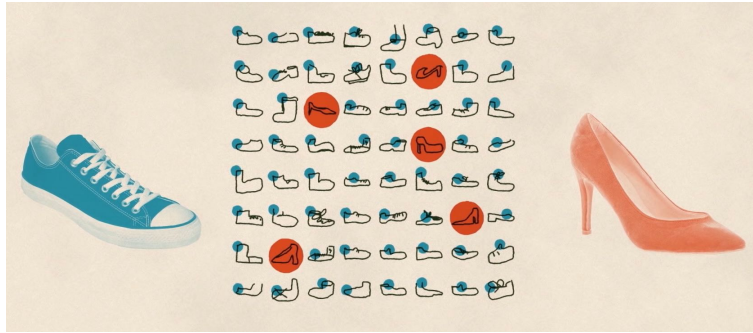
Counting things manually or with sensors

Giving numbers to represent something else

→ Humans are always involved in its creation,
so are human error & biases

e.g. in Titanic data, Age is sometimes missing
or an estimation, or could be a lie

If your dataset does **not** look like the real world...



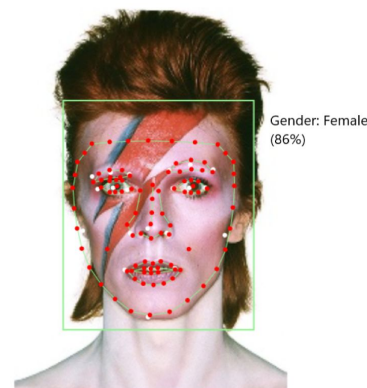
If your dataset does **not** look like the real world...

Commercial facial recognition algorithms claim to infer gender from someone's face

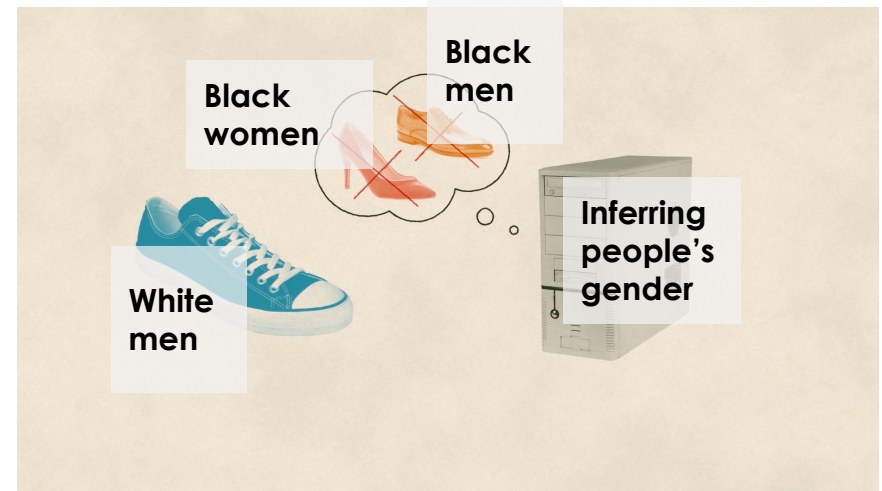
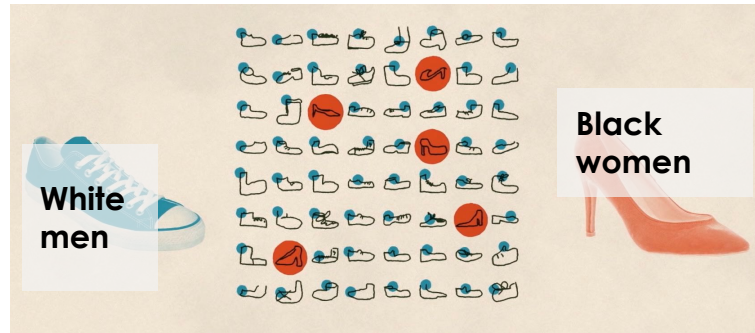
Researchers found that **men with light skin** were misgendered around **0.8%** of the time... while **women with dark skin** were misgendered **34.7%** of the time.

(Buolamwini & Gebru, 2018)

Reason? Most likely because their training dataset overrepresented white men and underrepresented black women

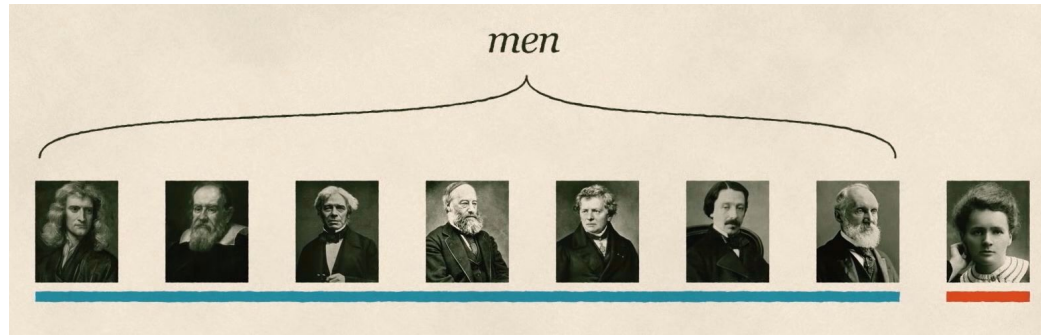


If your dataset does **not** look like the real world...



If your dataset looks **too much** like the real world...

Famous, successful physicists:



If your dataset looks **too much** like the real world...

Not all patterns in the data are useful, or desirable

e.g. Selling insurance to Titanic passengers: make insurance more expensive for those with higher risk... i.e. for men? Third class? Not fair!

The system may pick up on the **discriminatory pattern** in the world and **replicate it**.

If your dataset looks **too much** like the real world...

Let's train an algorithm to **find me the best applicants** from a huge pile of CVs

We need examples of **the best CVs**, so we can find the applicants which are similar

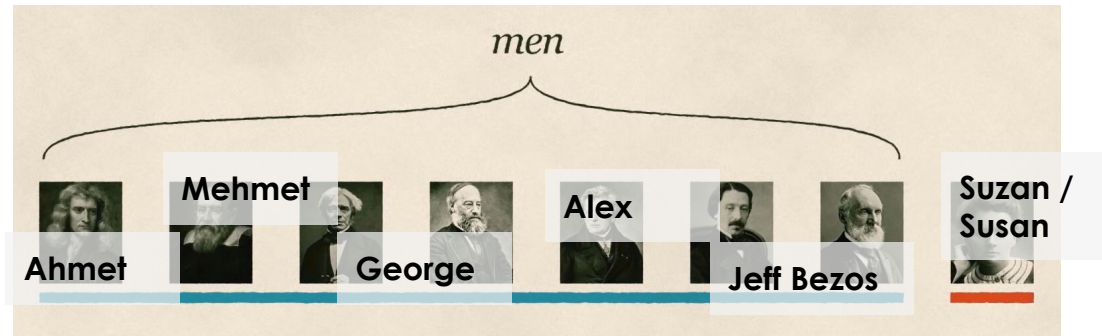
Hmm...

Let's use the CVs of **the people already in my company**, right? They definitely got the job when they applied!

If your dataset looks **too much** like the real world...

My current employees:

~~Famous, successful physicists:~~



If your dataset looks **too much** like the real world...

Amazon thought it was a great idea!

Didn't work so well (for the women applying)

System learned that applicants **who had the word “women’s” in their CV were not desirable** - women's colleges, women's chess club captain (*Reuters, 10/10/2018*)

Another company's algorithm **loved CVs which had the word “lacrosse” or “Jared”** - both typically found in men's CVs (*Quartz, 22/10/2018*)

If your dataset looks **too much** like the real world...

MICROSOFT WEB TL;DR

Twitter taught Microsoft's AI chatbot to be a racist **asshole** in less than a day

By James Vincent | Mar 24, 2016, 6:43am EDT

Via *The Guardian* | Source: *TayandYou (Twitter)*



SHARE

Two Drug Possession Arrests

DYLAN FUGETT

Prior Offense

1 attempted burglary

Subsequent Offenses

3 drug possessions

LOW RISK

3

BERNARD PARKER

Prior Offense

1 resisting arrest
without violence

Subsequent Offenses

None

HIGH RISK

10

Fugett was rated low risk after being arrested with cocaine and marijuana. He was arrested three times on drug charges after that.

Fundamental challenges for ethical AI

Tech is great! But...

The whole of human behavior, qualities, characteristics **can never be put into numbers perfectly accurately.**

So, calculations we make (AI we use to predict things) will **always make some mistakes.**

Most likely, these errors will affect **already-marginalized groups.**

Technochauvinism

Belief that technology is always the answer.

Belief that there is no problem that cannot be solved with a slightly different code or a “better” dataset.

Human lives (and human problems) are not black-and-white, and cannot always be quantified. So, the best solutions will always take into account the social sciences.

Technology of Power

People with **power** get to make the systems that most people use

(How many search engines can you think of?)

...or, are subjected to without consent

(Can any of us opt-out of the Mobese/CCTV cameras being installed across North Cyprus as we speak?)

Power of Technology

In turn, technology has the **power** to define our reality

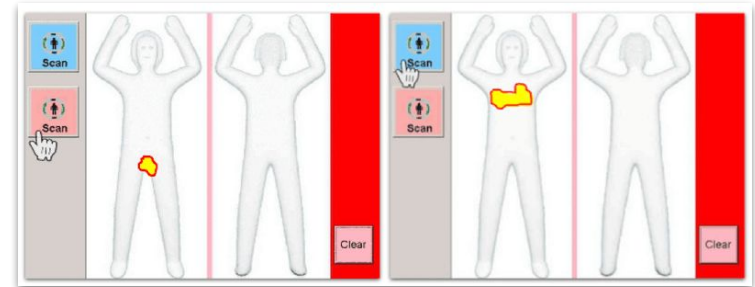
First few search results let you learn “the objective truth” about something... as chosen by Google (or maybe Bing)

The news that is “worth seeing” every day is chosen by your social media platform, and you might forget your friend's birthday if the algorithm doesn't show their posts to you...

Power of Technology

Facial recognition systems that claim to infer gender → support the misconception that someone's gender is linked to their physical body

Body scanners at airports often have trouble with “out-of-the-ordinary” bodies (since the “normal” body = a cisgender, abled body), and so marginalized people are flagged, requiring a body search

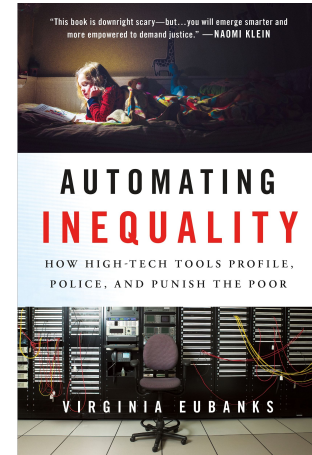
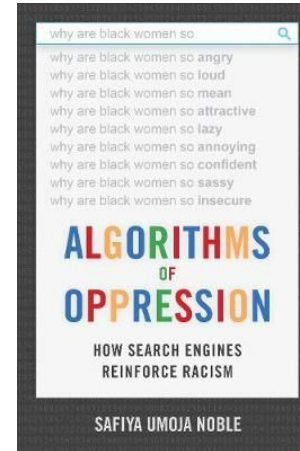
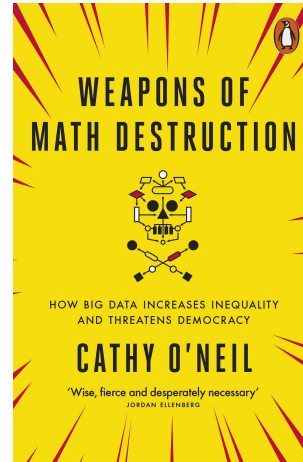
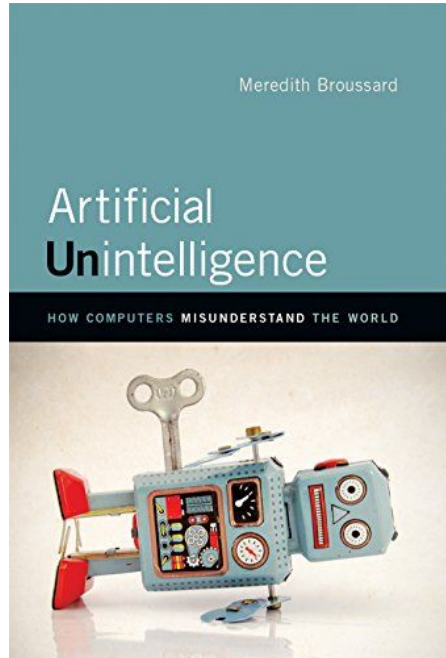


Summary & resources

Summary

- Whatever discrimination is happening “offline,” it can happen through technology as well
- Technology can not only embody, but also amplify the oppressive structures in society
- AI/machine learning makes predictions about occurrences/events, based on patterns in data
- Humans and social phenomena can never be modeled (put into numbers, as data) perfectly, so technology will always have errors
- Technology can harm certain groups of people while benefiting others, even without errors
- Marginalized communities are the first to be negatively affected by technology, both through errors & regular use

Further reading



References

- Buolamwini, J., & Gebru, T. (2018, January). **Gender shades: Intersectional accuracy disparities in commercial gender classification**. In *Conference on fairness, accountability and transparency* (pp. 77-91).
- JoDS, 16/07/2018, “**Design Justice, A.I., and Escape from the Matrix of Domination**”. <https://jods.mitpress.mit.edu/pub/costanza-chock>
- Otterbacher, J. (2015, April). **Linguistic bias in collaboratively produced biographies: crowdsourcing social stereotypes?**. In *Ninth international AAAI conference on web and social media*.
- ProPublica, 23/05/2016, “**Machine Bias**”. <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>
- Quartz, 22/10/2018, “**Companies are on the hook if their hiring algorithms are biased**”. <https://qz.com/1427621/companies-are-on-the-hook-if-their-hiring-algorithms-are-biased/>
- Reuters, 10/10/2018, “**Amazon scraps secret AI recruiting tool that showed bias against women**”. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G>
- Szillis, U., & Stahlberg, D. (2007). **The face-ism effect in the internet differences in facial prominence of women and men**. *International Journal of Internet Science*, 2(1), 3-11.
- UNESCO; West, M., Kraut, R., & Ei Chew, H. (2019). **I'd blush if I could: closing gender divides in digital skills through education**.
- USAToday, 10/10/2019, “**Say thank you and please: Should you be polite with Alexa and the Google Assistant?**”. <https://www.usatoday.com/story/tech/2019/10/10/do-ai-driven-voice-assistants-we-increasingly-rely-weather-news-homework-help-otherwise-keep-us-info/3928733002/>
- The Verge, 24/03/2016, “**Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day**”. <https://www.theverge.com/2016/3/24/11297050/tay-microsoft-chatbot-racist>
- Vice, 19/02/2019, “**Facial Recognition Software Regularly Misgenders Trans People**”. https://www.vice.com/en_us/article/7xnwed/facial-recognition-software-regularly-misgenders-trans-people
- Youtube, danrl, “**Infinite Looping Siri, Alexa and Google Home**”. <https://www.youtube.com/watch?v=vmINGWsyWX0>
- Youtube, CNBC, “**Interview With The Lifelike Hot Robot Named Sophia (Full) | CNBC**”. <https://www.youtube.com/watch?v=S5t6K9iwc dw>
- Youtube, Google, “**Machine Learning and Human Bias**”. <https://www.youtube.com/watch?v=59bMh59JQDo>

Thank you!

Questions?

Pinar Barlas

pinarbarlas.com
p.barlas@rise.org.cy

