# Future of Software User Interfaces

An HCI Perspective

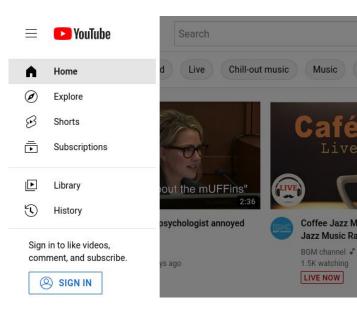
Algorithms and UI



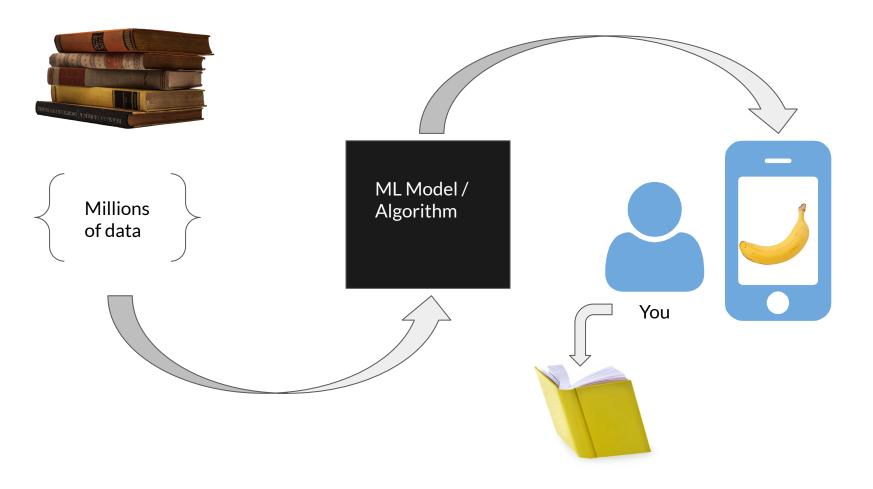
## facebook

Connect with friends and the world around you on Facebook.

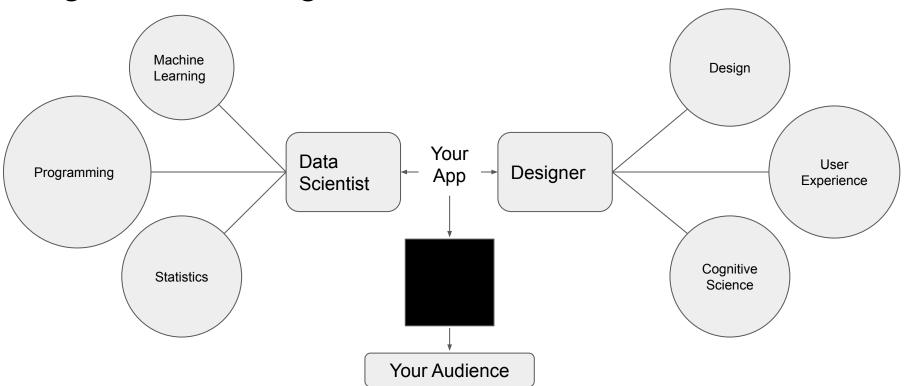
Music







## Algorithmic Design



# Data models + algorithms = increasing complexity



## Black Box Al

Users rarely know or understand how an algorithm works or why it returns the results that it does

Results are influenced by:

#### Quality of inputs

→ Are the images of the books clear, easily identifiable?

#### Representational accuracy of inputs

→ Do the images of books include ALL types of books or only hardback?

#### Accuracy of input classification

→ Did the humans classifying the inputs get it right?

#### Engineer demographics

→ Do the engineers have familiarity with all types of books or only one?

# Case Study: Twitter

Released an image cropping algorithm that emphasized light skinned faces over darker ones









# Case Study: Twitter

Twitter acknowledged the issue, but claimed it was unintentional.

Requested researchers to help test the algorithm to further identify bias

Eventually dropped the algorithm altogether

## Twitter apologises for 'racist' imagecropping algorithm

Users highlight examples of feature automatically focusing on white faces over black ones



https://www.theguardian.com/technology/2020/sep/21/twitter-apologises-for-racist-image-cropping-algorithm

## Case Study: Twitter

Researchers who accepted Twitter's invitation found even more instances of bias

From the perspective of diversity, equity, and inclusion, how might these findings marginalize or bias certain individuals?

#### Further findings:

- → Crops out white or gray hair
- Crops based on height, lower faces in a group are not selected
- More likely to ignore people wearing head coverings
- → Preference towards slim, young, bright faces

Do you think it was intentional?

Is there harm?

"Al bias will explode. But only the unbiased Al will survive. Within five years, the number of biased Al systems and algorithms will increase. But we will deal with them accordingly—coming up with new solutions to control bias in Al and champion Al systems free of it."

#### Excerpt from

https://bostonreview.net/articles/annette-zimmermann-algorithmic-political/

"...even if algorithms themselves achieve some sort of neutrality in themselves, the data that these algorithms learn from is still riddled with prejudice."

Systematic errors that create unfair, unequal, and exclusive outcomes are unavoidable

Far more complex than automated photo cropping

#### Some other examples...

- → Amazon recruiting algorithm favors men's resumes over women's
- → Courtroom algorithm produced more lenient sentences to white people than to black people
- Mortgage algorithms biased against Latino borrowers
- → Uber facial recognition suspends accounts of transitioning transgender drivers

What can be done?

Remove bias from training data

Keep training data up to date

Publicly share training data, support open data sets)

Construct diverse, representative teams to design, deploy, and ethically evaluate Al

Acknowledge that not all systems are suitable for algorithmic assessment and assistance

Increase transparency, or Explainable AI

## XAI: Explainable AI

Make Black Box systems more understandable to humans by making the output more transparent

Why explain?

To Justify

→ Bias, discrimination

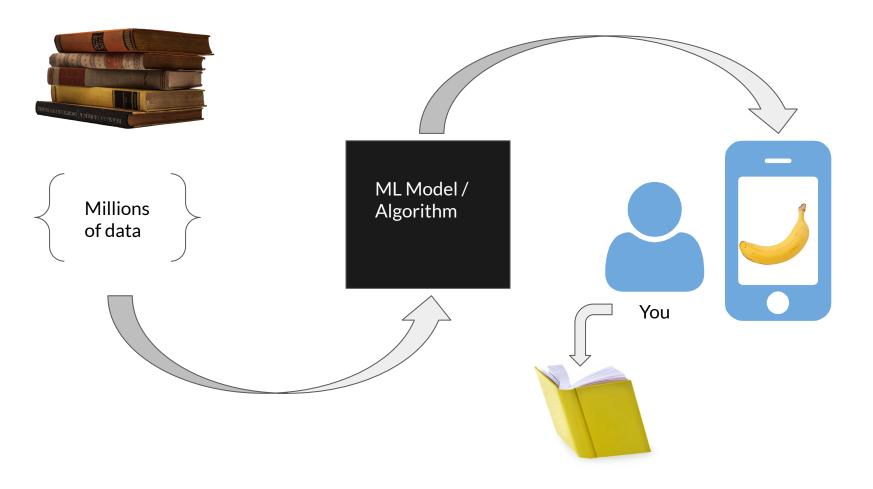
To Control

→ Visibility, identify errors

To Improve

To discover

→ Leads to understanding of how computation can meet human needs and goals



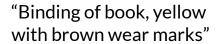


Millions of data

Explainable Interface

ML Model / Algorithm

Explainable Model





Some Examples Relevant to UI

## **Building Trust**

#### Benevolent Deception

- Metaphors (desktop)
- Skeuomorphs (skype static)
- Placebo controls deceiving the mental model [1].



### Malevolent Deception

- Malware
- Phishing
- Dark patterns (UX)

## **Active Exploration**

"Emotional forecasting user interface"

Enable user control to support user understanding





## **Active Exploration**

Identify more

More who are identified

Gender (Female / Male )

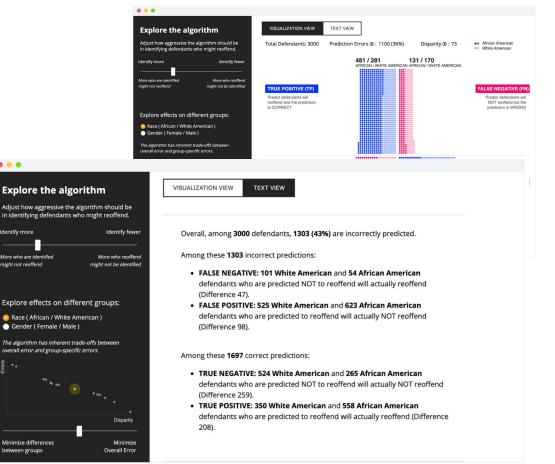
Minimize differences

between groups

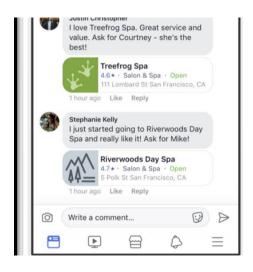
might not reoffend

Trade-off thresholds in recidivism prediction models

Supports alignment between AI predictions and individual or organizational values



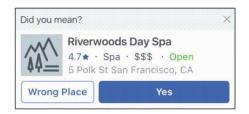
## **Show and Control**



#### If confidence is high:



#### Else if confidence is medium:



#### Else:



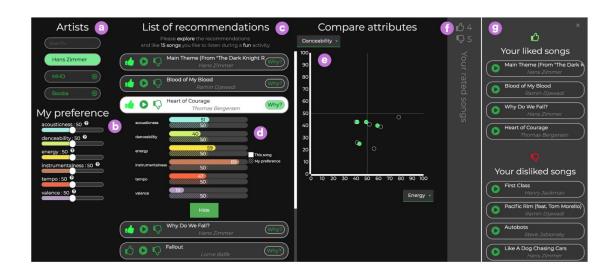
## Progressive Disclosure

The "Why?" button

Explaining helps users gain confidence in choices

Faster assessment

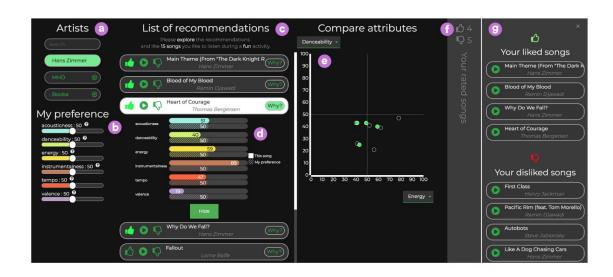
Additional cognitive burden for certain people (unfamiliar with viz, etc.)



## Progressive Disclosure

### **Design Implications:**

- Explanations should be personalized to type of user
- Toggle features, optionally present
- Vary detail level to accommodate expertise



## XAI: Explainable AI

Users SHOULD be able to understand how and why a decision is made

Users MUST be able to identify whether or not a decision is human or algorithmically derived

Why does it matter?

- → Regulation
- → Auditing
- → Empower Users

# Algorithmic Bias: Challenges

Building data sets is HARD.

Companies do not want to share

Imbalance between scientists, policymakers, and end users

Institutions are highly motivated to implement AI systems

Do you want to see the training data?

#### Vox





Students are evacuated following the school shooting at Saugus High School in Santa Clarita, California, November 2019. Mario Tama/Getty Images

## New surveillance AI can tell schools where students are and where they've been

Not all Al being used by schools is facial recognition. That doesn't mean the tech doesn't come with privacy risks.

By Rebecca Heilweil | Jan 25, 2020, 5:00am PST

https://www.vox.com/recode/2020/1/25/21080749/surveillance-school-artificial-intelligence-facial-recognition

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