

ANNOUNCEMENTS

Next Tuesday (11/4) will be a review of the concepts covered in the last couple of weeks. **Happy Halloween** for those perusing the class website on 10/31!

ALGORITHMIC LIVING

The idea and the processing of algorithms have become a feature of cultural life; we must understand ourselves to be objects of algorithmic attention.



ONLINE DATING WEBSITE PROFILES

Users fill out a profile and algorithms present it to others using keywords/textual commodities Drawback! A negative attitude toward the keywords will still be a "match"

Algorithms couldn't read the context

MY PROFILE

I dislike Harry Potter and camping.

MATCH!

LOOKING FOR

People who like Harry Potter

OCCUPY WALL STREET & TWITTER

Participants thought they were being censored by Twitter because it never became a "trending" topic How could Kim Kardashian and Justin Bieber be more important?

Twitter didn't intend censorship but could not provide evidence to the contrary All rankings are done via algorithms, which are constantly running

No one person has a complete understanding of Twitter's algorithms for trending topics Marked an important point in history

Social media presence was just as important as traditional media

e.g. front page of New York Times

Twitter had become an important "measure" of how the movement was doing

Now it was necessary for algorithms to be "fair and honest"

ALGORITHMS

Algorithms are ever-changing, vast, and different at any moment in time

Evolution: School Theory to National to Cultural Significance

We are all objects of algorithmic attention

There needs to be more emphasis on becoming algorithm-literate

EXAMPLE OF CULTURAL LITERACY

Showing a PC user interface on TV

Requires an understanding of a computer UI to understand what's happening

Being "culturally literate"

e.g. hearing two clicks of a mouse and understanding that an action was taken

WHAT ALGORITHMS DO

Matching/recommendations (e.g. Twitter, Netflix)

Selection (e.g. Facebook News Feed)

Statistics from user data (e.g. GPA)

Image processing (e.g. facial recognition)

Predictions (e.g. weather, crime)

Personality tests

GPS/routing

Searches (e.g. Google)

WHY ARE ALGORITHMS VALUABLE?

They help provide an efficient, accurate, and unbiased method of evaluating data

ALGORITHMS

impersonal

objective

literal

"black box"

ability to handle large scope

predictable

absence of bias

accuracy

speed

HUMANS

personal

subjective

patterning

transparent

limited scope

unpredictable

tendency toward bias

can make mistakes

physical limitations

GROUP WORK Still, there may be bias/inaccuracy within algorithms. List at least five.

Censorship/selectivity of data

Integrity

Variation

User error

Hardware limitations

Language/architecture

GROUP 14 PRESENTATION :: CREDIT SCORING

Note: Please reference the slides from Group 14 for a more accurate/complete picture of their presentation.

FICO: FAIR ISAAC AND COMPANY

Most widely used credit score

Range of 300 - 850

Predicts an estimate on future level of risk

Some employers check the scores of their employees

Based off of credit history (can have 3 different scores at once)

A good or "low risk" score is higher than 650

HISTORY OF CREDIT SCORING

In the 1950s, credit scoring was done through scorecards

Designed by asking questions printed on tables separated into difference categories Used as an "unbiased" method, as any person could be reduced to a number e.g. someone could be judged without considering ethnic/racial backgrounds

MEASURED

NOT MEASURED

payment history new credit length ofhistory race salary
religion employer
gender job title
age

IMPORTANCE OF CREDIT SCORES

"Pretty Good" vs best rating can mean a \$40,000 difference in mortgages

A lower score means more interest paid

A single missed payment can lower the score by 100 points

Creates a form of trust between the user and lenders

HARD CHECK When companies look at your credit score (hurts your score with each check)

SOFT CHECK A credit check done through a website (will not hurt your score)

Society requires good credit scores to provide reliable finances

Drawback! Not all people have access to means of fostering good credit

TYPES OF CREDIT

Installment

Revolving

Must utiliaze both to have "good credit"

FICO DOMINANCE OVER OTHER ALGORITHMS

Replaces racial bias with a single number

Drawback! Single company has too much power (potential monopoly)

Operates on data sets that might not be clean/pure

3 different scores due to each score having different data on the user

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THE TEAM

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