PERSONA.TECH

ALGORITHMS TRAINED WITH ONLINE HUMAN BEHAVIOR

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ALGORITHMS

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- Many learning systems fit to this description, but we will focus on algorithmic presentation at digital services, of—perhaps personalized— content based on previous user behavior, e.g., clicks.
- Typical examples are ranking results and recommendations, and any type of content curated algorithmically (e.g., at the home page)
- A particular focus will be on digital marketplaces

WHEN MACHINE LEARNING DOES NOT WORK
/
OR WHY WE SHOULDN'T RELY ON CLICK DATA

- All supervised learning theory is based on "empirical risk minimization"
- We assume by fitting to training data, we can learn a model that can generalize
- The prerequisite is that the training data should constitute a random sample for the entire population

User behavior in interaction with the system, however, is by no means random!
Further, it does not truly reflect user preferences.


USER FEEDBACK IS INCOMPLETE


HUMAN BEHAVIOR IS BIASED


BIASES - 1


SOME OF YOUR CLICKS, OR LACK
THEREOF,
ARE DUE TO
MERE EXPOSURE

SAMPLING BIASES IN USER FEEDBACK

EXPOSURE BIAS

- Users can only click on the items they see
- These might be the items their friends advise, the restaurants they see on their way, or the items shown by the system/application due to an algorithm.
- In a data set of user clicks, and assuming they are indeed indicative of positive feedback, the absence of click is ambiguous.

SAMPLING BIASES IN USER FEEDBACK

POSITION BIAS

- A special case is the position bias
- Refers to user's tendency to ignore the items that are ranked lower
- That is, regardless of its relevance, the position of an item has an effect on the click event: items ranked lower are more likely to be ignored.

MOST OF YOUR RATINGS ARE SUBJECT
TO
SELF-SELECTION,
AND THEY ARE
MOSTLY HIGH

SAMPLING BIASES IN USER FEEDBACK

SELF-SELECTION

- Users selectively rate items (probably the ones that they think they would like)
- Marlin et al. (2007) previously showed that when the users choose the movies they rate, they tend to choose the movies they would rate very high or low.

SAMPLING BIASES IN USER FEEDBACK

COLLECTING MORE DATA IS NOT A FIX

Statistical learning theory does not work, and collecting more data does not fix the problem.

- **Due to self-selection or algorithmic exposure, the behavior data sets are subject to sampling biases.**
- **User-item pairs included in training data sets do not constitute a random sample of user-item pairs.**
- **Such data sets *do not qualify* as training data sets.**


BIASES - 2

USERS
TRUST THE PLATFORM,
THEY
FOLLOW THE ALGORITHM'S
RECOMMENDATIONS

BIASES THAT CHANGE USER BEHAVIOR

TRUST

- Trust bias refers to “the users have substantial trust in the search engine’s ability to estimate the relevance of a page, which influences their clicking behavior” (Joachims et al., 2005)
- Confirmed in actual eye-tracking studies


PEOPLE TRUST OTHER PEOPLE

BIASES THAT CHANGE USER BEHAVIOR

CONFORMITY

- **A bias that occurs when a user's feedback is affected by other people's opinions.**
- **The user might adjust their original, negative feedback to an item after seeing that it is high-rated by other users, friends and social circles alike (Wang & Wang, 2014; Liu et al., 2016; Krishnan et al., 2014, Wang et al., 2017)**
- **They might avoid clicking a cold-started item, which would be interpreted as negative feedback**

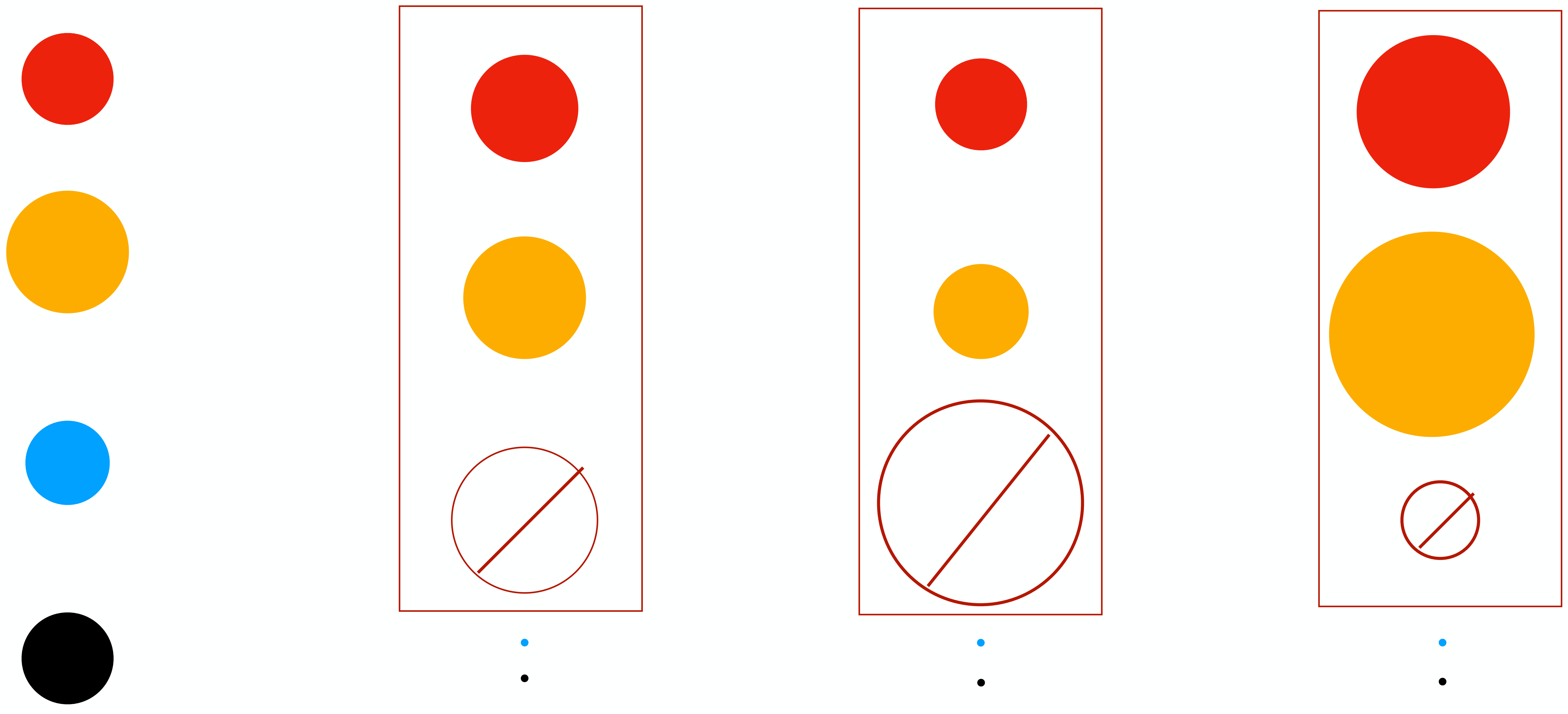

USERS PUT
THE LEAST EFFORT,
THEY DO NOT BOTHER TO EXPLORE
FURTHER

BIASES THAT CHANGE USER BEHAVIOR

THE LEAST EFFORT

- The principle of least effort (Zipf, 1949) states that humans, with the least effort, pick from their choices, unless they are too unsatisfactory
- The principle indicates that the user would choose in the most convenient way, i.e., they simply choose from what is recommended (shortlisted, shown in the first page, etc.)
- Zipf's Law is due to this principle

EXAMPLE: BIASES IN ONLINE HUMAN BEHAVIOR DUE TO INTERACTION WITH RANKING ALGORITHMS



(a) (b) (c) (d)

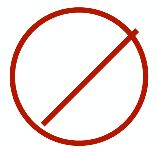
Figure.

(a) The system's ranking of 4 different items with sizes proportional to their actual choice probabilities

(b) The system recommends 2 of them, and the click probabilities are adjusted with trust bias

(c) Position bias: when an item is shown at lower positions, the likelihood to click decreases

(d) User puts little effort into exploring

 denotes 'opting not to choose'


THE CONSEQUENCES

WHAT HAPPENS?

**Most of algorithmic presentation, e.g., ranking results or recommendations, are off.
In fact, the lists based on basic statistics (top-rated, most-liked, popular, etc.) are biased.**

- **Example scenario:** A product is ranked high, it is clicked because it is ranked high, you are happy (with your decision), you reinforce your belief on the item being relevant.
- **Example scenario:** All restaurants are high-rated (this is because of self selection). The metric is useless.

WHAT HAPPENS?

“The system writes its own future” (Baeza-Yates, 2018).

- A “vicious cycle of biases” occurs due to user interaction with algorithms in a feedback loop:
    - The user feedback on the system's presentation is biased
    - Based on this biased feedback, the system updates its belief on user preferences
    - The system’s estimate of user preferences from such data will be biased (Liang et al., 2016; Sinha et al., 2016; Sun et al., 2019) and inconsistent (Schmit & Riquelme, 2018)
    - The user, in turn, provides biased feedback to the systematic decision based on biased estimates of user preferences, reinforcing the system's initial, biased belief.

WHAT HAPPENS?

Examples abound.

- Same product listing, higher purchases for items listed at the top positions
- Some products/sellers are virtually unseen, and they stay unseen
- Ratings follow initial ratings
- Things that are newly introduced to the system are not noticed at first, and they stay unnoticed
- Initial preferences of users are exaggerated


THE HARM

THE COST OF BIAS

Systematic presentation is harmful for the users

- Systematic exposure causes filter bubbles (Pariser, 2011)
- A group of users' behavior tends to homogenize due to algorithmic confounding (Chaney et al., 2018)
- A user's interest may even degenerate over time (Jiang et al, 2019)

THE COST OF BIAS

Systematic presentation is harmful for the sellers

- Causes early-exposure and early-luck advantage
- It is super difficult to be selected by an algorithm if a product is new:
    - As the product is not shown, it is not clicked, as it is not clicked, it is not shown
    - Not only the first-movers, content that is found favorable out of luck might stay overestimated forever
- Lots of good products are under-presented, and they get lost

THE COST OF BIAS

Systematic presentation is harmful for the platform.

- Rich gets richer—killing a healthy competition
- Algorithmic biases lead to monopolies—the marketplace inevitably fails in the long term
- The platform would never know: the evaluation metrics are mostly delusional


REMEDIES

WE SHOULD INVEST IN BETTER ALGORITHMS

REMEDIES

We should invest as much, if not more, in better algorithms, as we do in more sophisticated ones.

- Clicks/ratings are not as reliable, we need to be careful
- What we need to optimize for is counterfactual, and cannot be measured directly
- There are techniques:
  - Combinations of causal reasoning and online learning

REMEDIES

We should invest as much, if not more, in better algorithms, as we do in more sophisticated ones.

- This has serious implications, and cannot be overlooked
    - “Algorithms are black boxes,” this is not an excuse
    - “This is the standard way of doing things” also not an excuse
    - Computational convenience—not an excuse

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