

PERSONA.TECH

ALGORITHMS  
TRAINED WITH  
ONLINE HUMAN BEHAVIOR

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The image features a dark, moody background with the silhouettes of several people. A bright light source on the right side creates a strong glow and lens flare, illuminating the scene from the side. The overall atmosphere is mysterious and artistic.

# ALGORITHMS

# ALGORITHMS TRAINED WITH ONLINE HUMAN BEHAVIOR

- **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.**

The background of the image shows the dark silhouettes of several people sitting around a table in a meeting or conference room. The lighting is dim, with some highlights on the table and the people's profiles. The overall mood is professional and collaborative.

USER FEEDBACK IS INCOMPLETE

The background of the image shows the dark silhouettes of several people sitting around a table in a meeting room. The scene is dimly lit, with a light source from the right creating a soft glow on the table and the people's profiles. The overall mood is professional and focused.

HUMAN BEHAVIOR IS BIASED

A group of people is silhouetted against a bright, low-angle light source, creating a dramatic, high-contrast scene. The light source is positioned on the right side of the frame, casting long, golden rays across the scene. The people are standing in a line, their forms dark against the bright background. The overall mood is contemplative and artistic.

# 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.**

The image features a group of people, likely a choir or a group of performers, silhouetted against a bright, low-angle light source. The light creates a strong glow and lens flare, particularly on the right side of the frame. The overall mood is dramatic and artistic. The text "BIASES - 2" is centered over the image in a white, serif font.

# 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**



A dark, low-key photograph of a group of people in a hallway. The scene is dimly lit, with a strong light source from the right creating a bright, diagonal beam of light across the floor and the side of a person in the foreground. The silhouettes of several people are visible in the background, some looking towards the camera. The overall mood is mysterious and contemplative.

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

The background of the image shows the dark silhouettes of several people sitting around a table in a meeting or conference room. The scene is dimly lit, with some light reflecting off the table surface, creating a professional and collaborative atmosphere. The text is overlaid on this background.

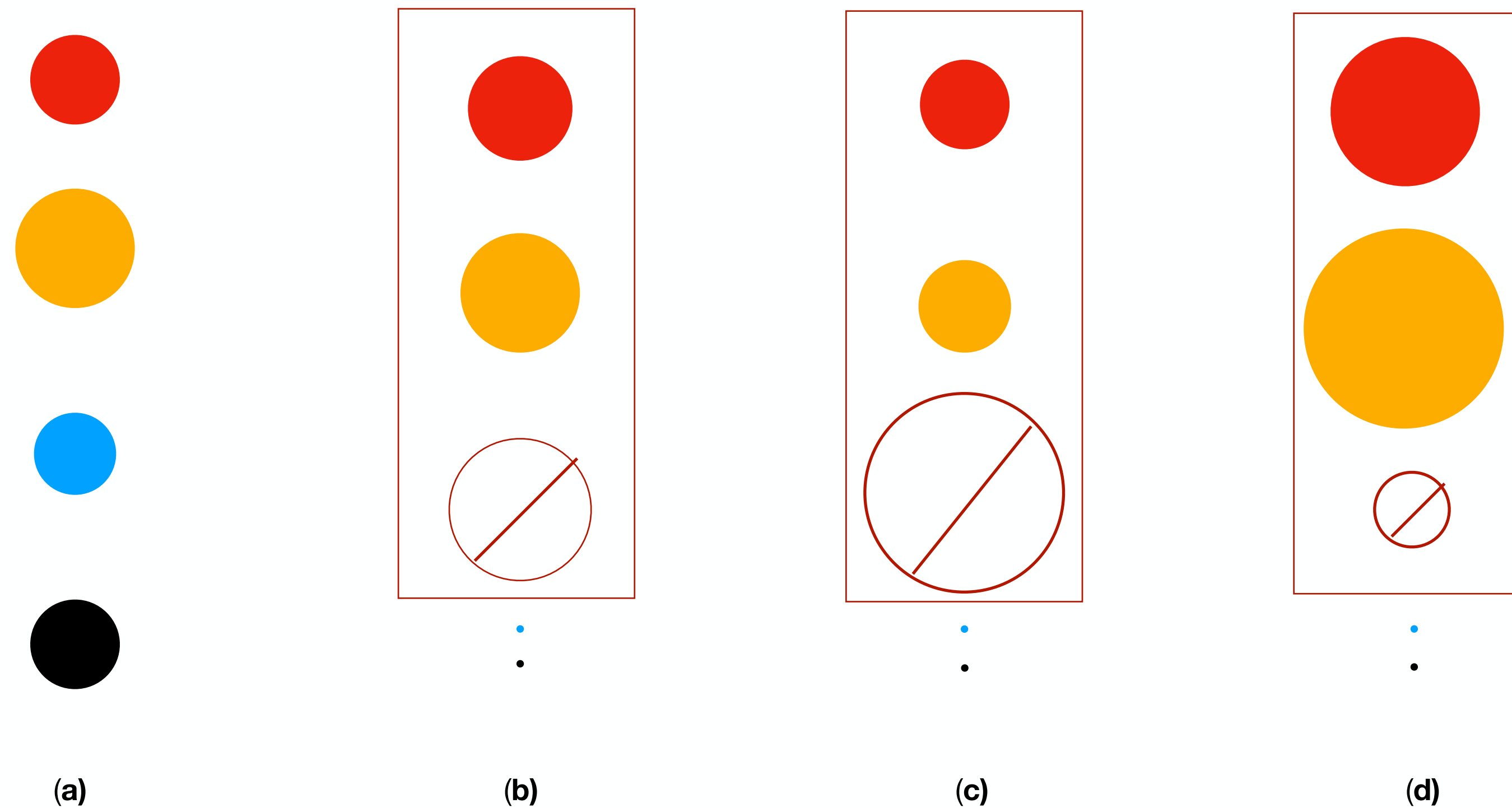
USERS PUT  
THE LEAST EFFORT,  
THEY DO NOT BOTHER TO EXPLORE  
FURTHER

# 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



**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 image features a group of people, likely a family, silhouetted against a bright, low-angle light source, possibly a sunset or sunrise. The light creates a strong glow and lens flare, illuminating the scene from the right. The overall mood is contemplative and dramatic. The title 'THE CONSEQUENCES' is overlaid in a clean, white, sans-serif font across the center of the image.

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 image features a dark, moody scene with several silhouetted figures. A bright light source on the right side creates a strong glow and lens flare, illuminating the edges of the people. The overall atmosphere is somber and mysterious.

# 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

The background of the image shows the dark silhouettes of several people sitting around a table in a meeting or conference room. The lighting is dim, with some highlights on the table and the people's profiles, creating a professional and collaborative atmosphere.

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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