

Recommendation Systems

Diversity. Debiasing.

Eugeny Malyutin / Sergey Dudorov

Recommender's result list

NETFLIX Browse ▾ DVD Search Joshua

Top Picks for Joshua

Breaking Bad | SING | THE FOSTERS | New Girl | are you here | BABY DADDY

Trending Now

shameless | Schitt's Creek | ORANGE IS THE NEW BLACK | OZARK | New Girl | STRANGER THINGS

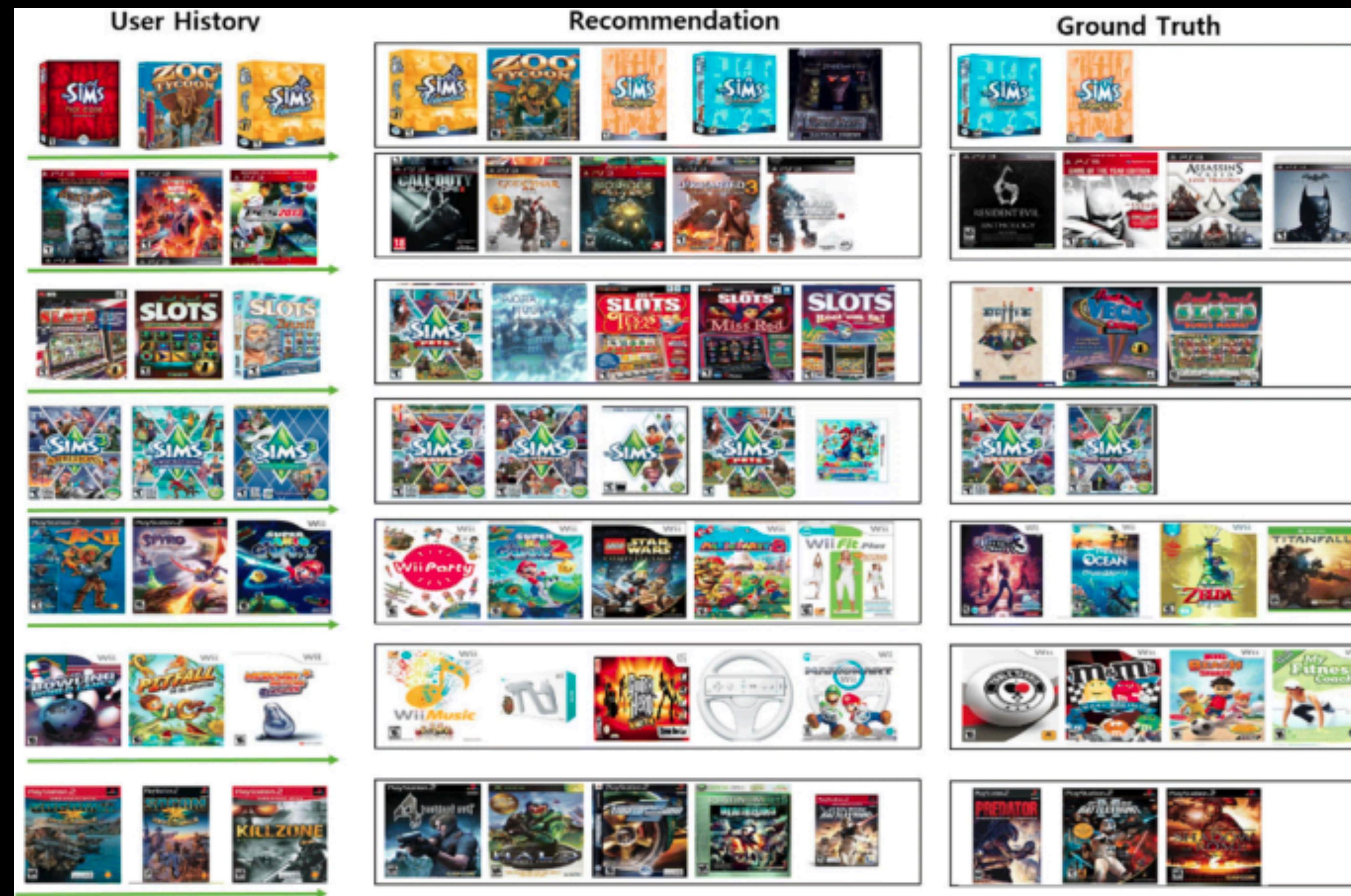
Because you watched Narcos

SURVIVING ESCOBAR | COMORRON | PABLO ESCOBAR | SUBURRA: BLOOD ON ROME | ALIAS JJ, LA CELEBRIDAD DEL MAL | ANTHONY BOURDAIN: PARTS UNKNOWN

New Releases

BEYOND STRANGER THINGS | MOANA | THE MIST | THE BABYSITTER | RIVERDALE | DOCTOR STRANGE

Balance



Recommender's result list

- Relevance
- Novelty
- Diversity
- Selected/Paid items

What is diversity?

- Diversity has been introduced as one of possible solution of overfitting
- We have a lot of definitions of diversity
- Diversity is actual problem for each project



Diversity definitions

- Average dissimilarity for each pair of items in the result list
- Diversity is represented as the Gini coefficient - a measure of distributional inequality.

$$D = -\frac{\sum_{i=1}^n \sum_{j=1}^n \left(1 - \mathbf{Similarity}(c_i, c_j)\right)}{n/2 * (n - 1)}$$

$$G = 1 - 2 \int_0^1 L(u) du$$

Diversity definitions

- Diversity is part of the calculation of the nDCG measure - it has a direct impact on the calculated probability value.
- Diversity between two items is the product the item's relevance, similarity and places in the ranked list.

$$G[k] = \sum_{i=1}^m J(d_k, i)(1 - \alpha)^{r_i, k-1}$$

$$ILD(i_k | u, R) = C'_k \sum_l \text{disc}(l | k) p(\text{rel} | i_l, u) \text{dist}(i_k, i_l)$$

Diversity definitions

- Diversity is a combination of genre coverage (how many different genres are present in the ranked list) and non-redundancy (genres do not repeat on the list).
- Ask your users - too expensive

$$\mathbf{BinomDiv}(R) = \mathbf{Coverage}(R) * \mathbf{NonRed}(R)$$

Diversity Algorithms

- Improving Recommendation Lists Through Topic Diversification

1. Generate predictions (at least $5N$ for a final top- N recommendation list).
2. For each $N+1$ position item calculate the ILS (diversity) if this item was part of the top- N list.
3. Sort the remaining items in reverse (according to ILS rank) to get their dissimilarity rank.
4. Calculate new rank for each item as $r = a * P + b * P_d$, with P being the original rank, P_d being the dissimilarity rank and a, b being constants in range $0, 1]$.
5. Select the top- N items according to the newly calculated rank.

- A Content Recommendation System Based on Category Correlations

1. Collect genre information for each film in the dataset.
2. Calculate genre correlation for all film in the dataset by counting the number of occurrences of each possible pair of genres.
3. Normalize genre correlation values.
4. Collect user genre preferences explicitly.
5. Generate recommendations by calculating each predicted ratings as:
 - 5.1 $\sum R_M * r_{ij}$ with R_M being the films average ratings and r_{ij} being the genre correlations of all genres liked by user i and being attributed to film j .
 - 5.2 Normalize the sum according to the number of user's genre preferences.
6. Select the top N items with the highest predicted rating and present them to the user.

Diversity Algorithms

- Temporal diversity in recommender systems

1. Generate recommendations using the Matrix Factorization, kNN or mean average rating approach.
2. Track if the user selected/rated any of the recommended items.
3. Generate a new recommendations using updated information (all new ratings provided by the user).
4. Calculate the diversity of the newly generated list of recommendations, by comparing it with the previous iteration (the list of recommendations presented to the user during his/her previous interaction with the system).

- Who likes it more?: mining worth-recommending items from long tails by modeling relative preference

1. Create recommendations for all existing user using any CF approach.
2. For each item that was recommended at least once, calculate a 5D score as a combination of: Accuracy, Balance, Coverage, Quality and Quantity of long-tail.
3. For each user create a list of possible recommendations and:
 - 3.1 Order the list by predicted rating in order to assign a rank r to each item.
 - 3.2 Reverse order the list by each items 5D score in order to assign a rank r_{5D} to each item.
 - 3.3 Create a combined rank $r_n = r * r_{5D}$ and order the items by this rank.
4. Present the top N items to the user.

Diversity results

- Diversity has strong connection with domain
- Optimal diversity increase user's satisfaction
- Diverse items better works in blocks
- Explanation improves user's feedback

Novelty

- Fresh content is always better
- Fresh content is important part
- Fresh content doesn't really matter

Amy Coney Barrett confirmed to US Supreme Court

Mr Trump's fellow Republicans voted 52-48 to approve the judge, overcoming the opposition of Democrats.

Who is the new US Supreme Court judge?

ACB on abortion, healthcare and her faith

Win or lose, Trump has already changed the world

Antibodies 'fall rapidly after Covid infection'

Doctors expect 'Covid catastrophe' in Syria

At least seven dead in Pakistan school attack

Sacred Aboriginal tree bulldozed for highway

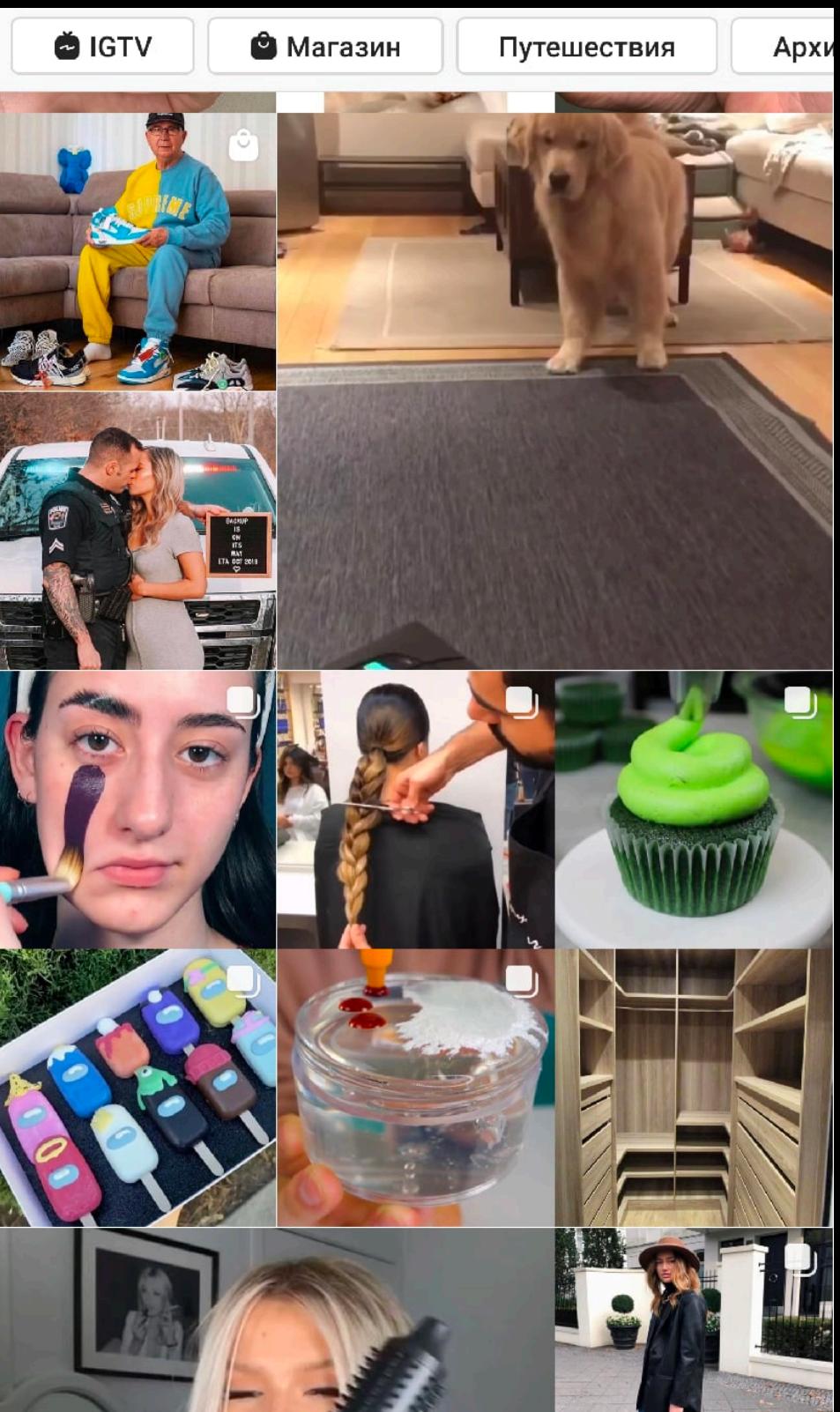
Water on the Moon could sustain a lunar base

Uber sued by drivers over 'automated robo-firing'

Could postal voting upend US election?

S Korean Jehovah's Witnesses start jail work terms

Ex-paratrooper attempts no-parachute record jump



Recommended for you

Trice the Brindled Cat Hath Mew'd A... by Alan Bradley

Egg: Nature's Perfect Package by Steve Jenkins, Robin Page

The Untethered Soul: The Journey... by Michael A. Singer

Before You Get Your Puppy by Ian Durbar

How to Be Your Dog's Best Friend: A... by Of New Skete Monks

NETFLIX

Top Picks for Joshua

Breaking Bad, SING, The Fosters, New Girl, are you here, Baby Daddy

Trending Now

shameless, Schitt's Creek, ORANGE IS THE BLACK, OZARK, New Girl, STRANGER THINGS

Because you watched Narcos

SURVIVING ESCOBAR, GOMORRAH, PABLO ESCOBAR, SUBURRA, ALIAS JJ, PARTS UNKNOWN, ANTHONY BOURDAIN

New Releases

BEYOND STRANGER THINGS, Moana, THE MIST, THE BABYSITTER, RIVERDALE

В России официально вводится всеобщий масочный режим

Газета.Ru · 2 часа назад

- Роспотребнадзор предписал россиянам носить маски в местах скопления людей
- Всеобщий масочный режим введен в России
- Роспотребнадзор ввел масочный режим по всей России
- Роспотребнадзор ввел по всей России всеобщий масочный режим

Посмотреть

В России за сутки выявлено 16 550 случаев заражения коронавирусом

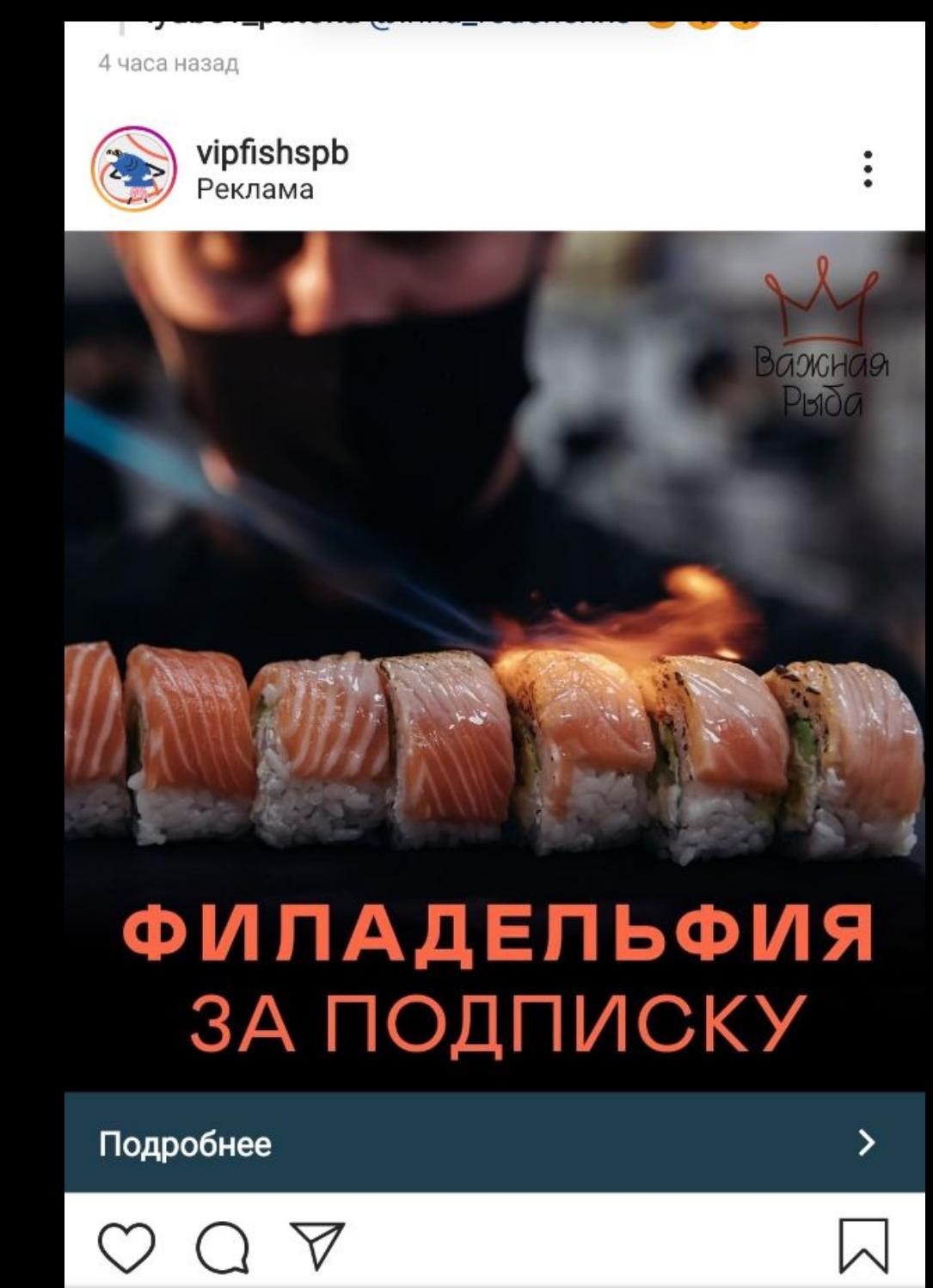
Интерфакс · 1 час назад

- За сутки в России подтверждено 16 550 случаев COVID-19 в 85 регионах

Посмотреть

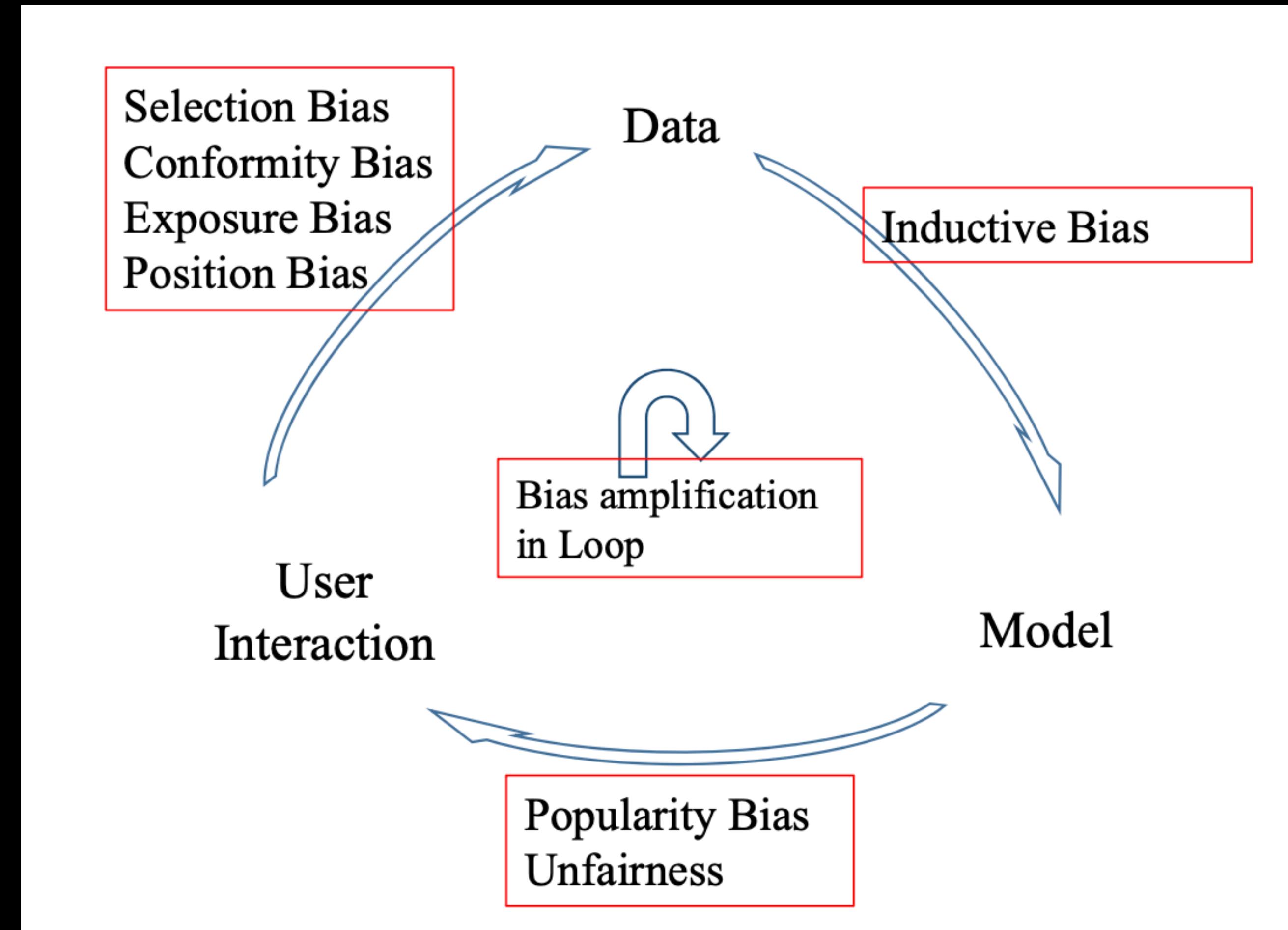
Paid items

- Find relevance adv/paid items



- Use fix position for them
- Use dynamic position(active users watch more adv/paid items)

Bias



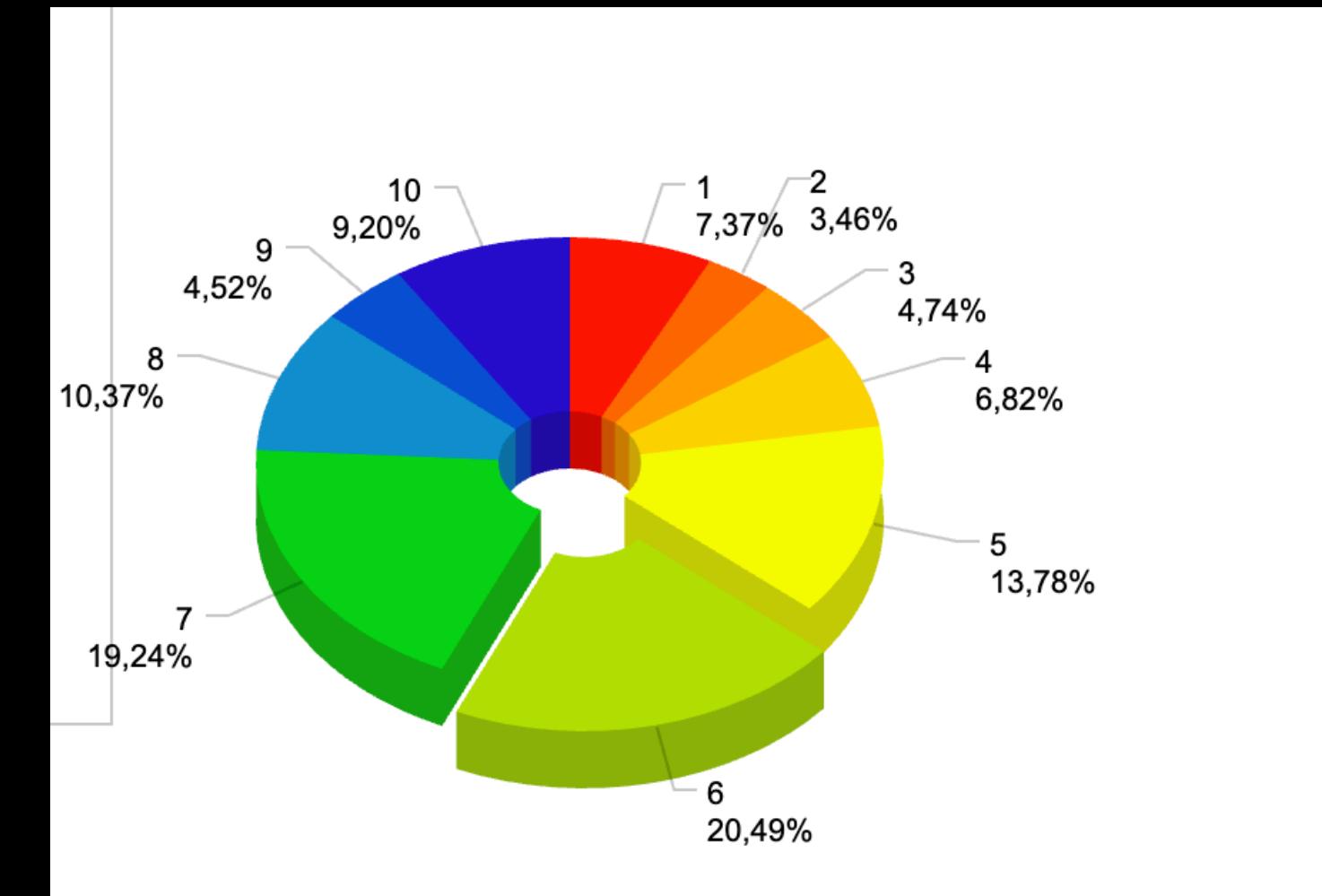
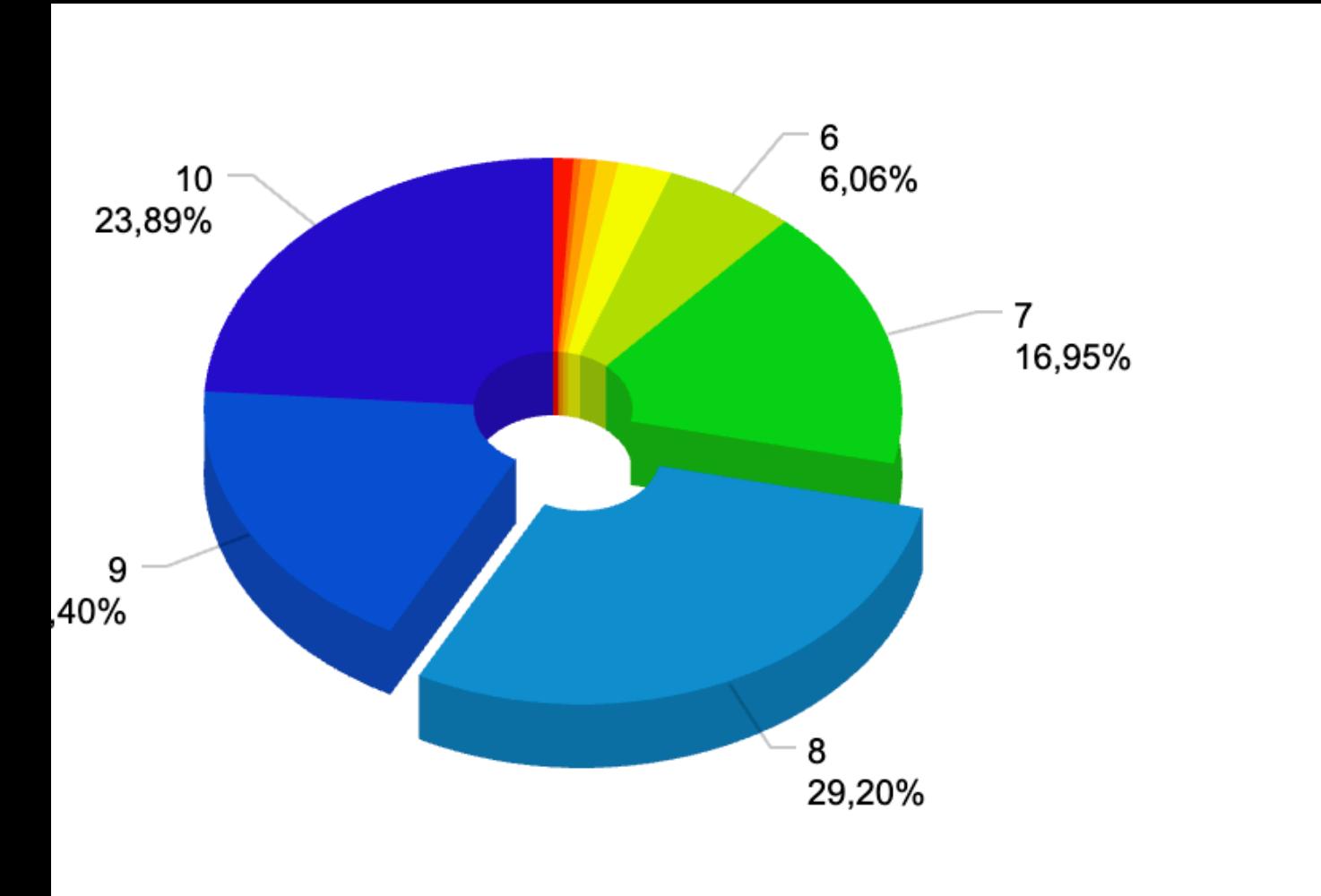
Selection Bias

- Only Explicit Feedback
- User prefer mark best and worst items



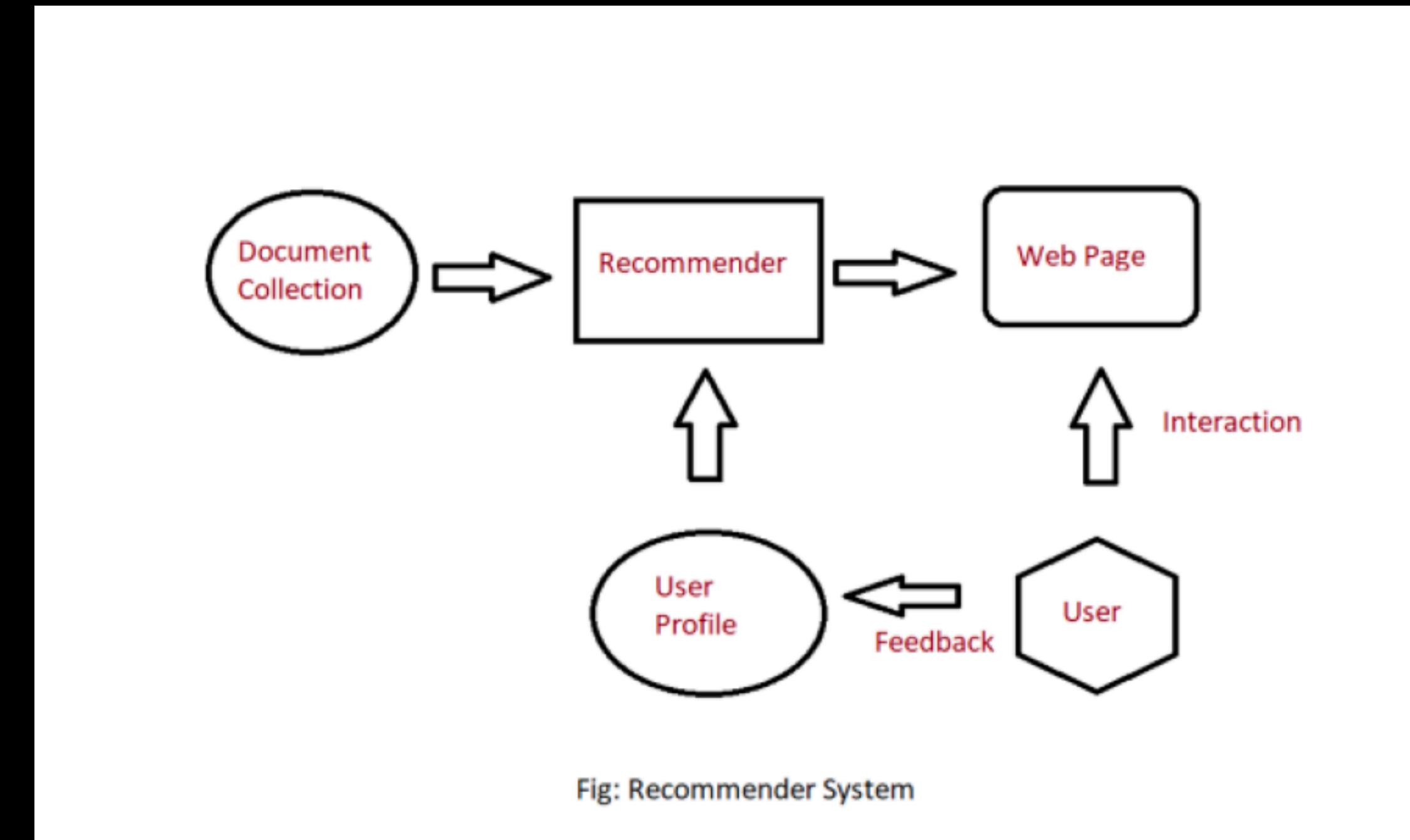
Conformity Bias

- Only explicit feedback
- Users rate item similarly to the others users



Exposure Bias

- User very biased on our recommendation lists



Position Bias

- Works on both types of feedback
- Users prefer interact with items in higher position of the result list
- Lower items can be more relevant but user didn't watch them

Главное

ВСЁ НОВЫЕ РЕЛИЗЫ ЧАРТ НАСТРОЕНИЯ И ЖАНРЫ ДЛЯ ДЕТЕЙ

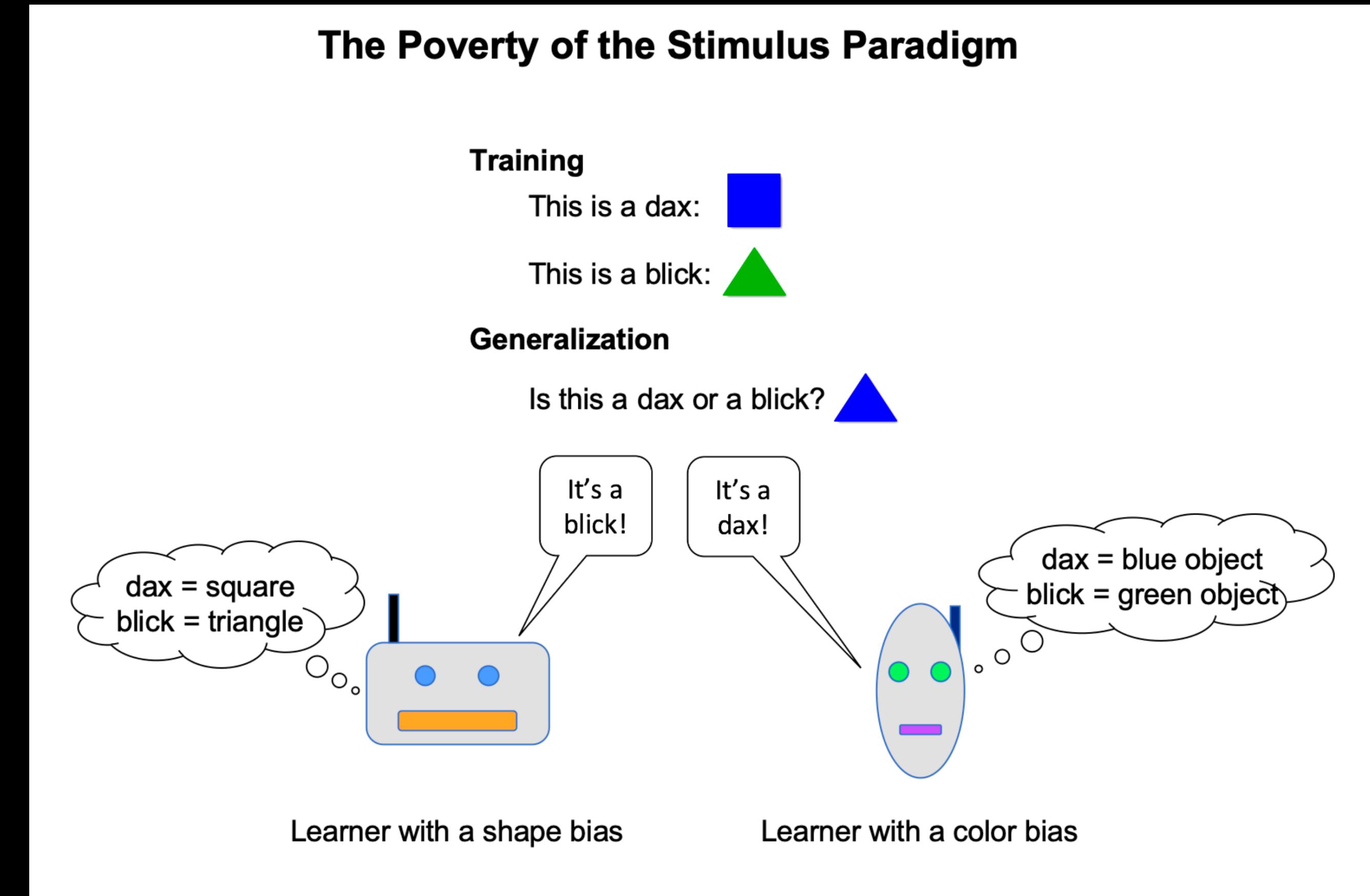
Что слушают 5 000 000 подписчиков прямо сейчас

Россия

Ряд	Название	Исполнитель	Время
1	Снова я напиваюсь	SLAVA MARLOW	1:57
2	Rolls Royce	Джиган, Тимати, Егор Крид	2:23
3	Если тебе будет грустно	Rauf & Faik, NILETTO	3:11
4	Юность	Dabro	3:39
5	Deep End	Foushéé	2:21
6	El Problema	prod. SLAVA MARLOW MORGENSHTERN, Тимати	2:17
7	Беги feat. Poët	Dj Smash	3:06
8	Сияй	Ramil'	2:01
9	СЛЁЗЫ OST «Пацанки»	Анет Сай	2:54
10	АУФ	SQWOZ BAB, The First Station	3:12

Inductive Bias

- What is your target?
- Can item hack your data?
- Some features can hack your target



Popularity Bias

- Popular content has more interactions in dataset
- Users prefer content with a lot of feedback(views, likes, rates)

Главное

ВСЁ НОВЫЕ РЕЛИЗЫ ЧАРТ **НАСТРОЕНИЯ И ЖАНРЫ** ДЛЯ ДЕТЕЙ

Что слушают 5 000 000 подписчиков прямо сейчас

Россия

Ранж.	Артист/Группа	Название трека	Длительность
1	SLAVA MARLOW	Снова я напиваюсь	1:57
2	Джиган, Тимати, Егор Крид	Rolls Royce	2:23
3	Rauf & Faik, NILETTO	Если тебе будет грустно	3:11
4	Dabro	Юность	3:39
5	Fousheé	Deep End	2:21
6	MORGENSEN, Тимати	El Problema prod. SLAVA MARLOW	2:17
7	Dj Smash	Беги feat. Poët	3:06
8	Ramil'	Сияй	2:01
9	Анет Сай	СЛЁЗЫ OST «Пацанки»	2:54
10	SQWOZ BAB, The First Station	АУФ	3:12
11	Zivert, Баста	неболей	5:34
12		Многоточия	2:27

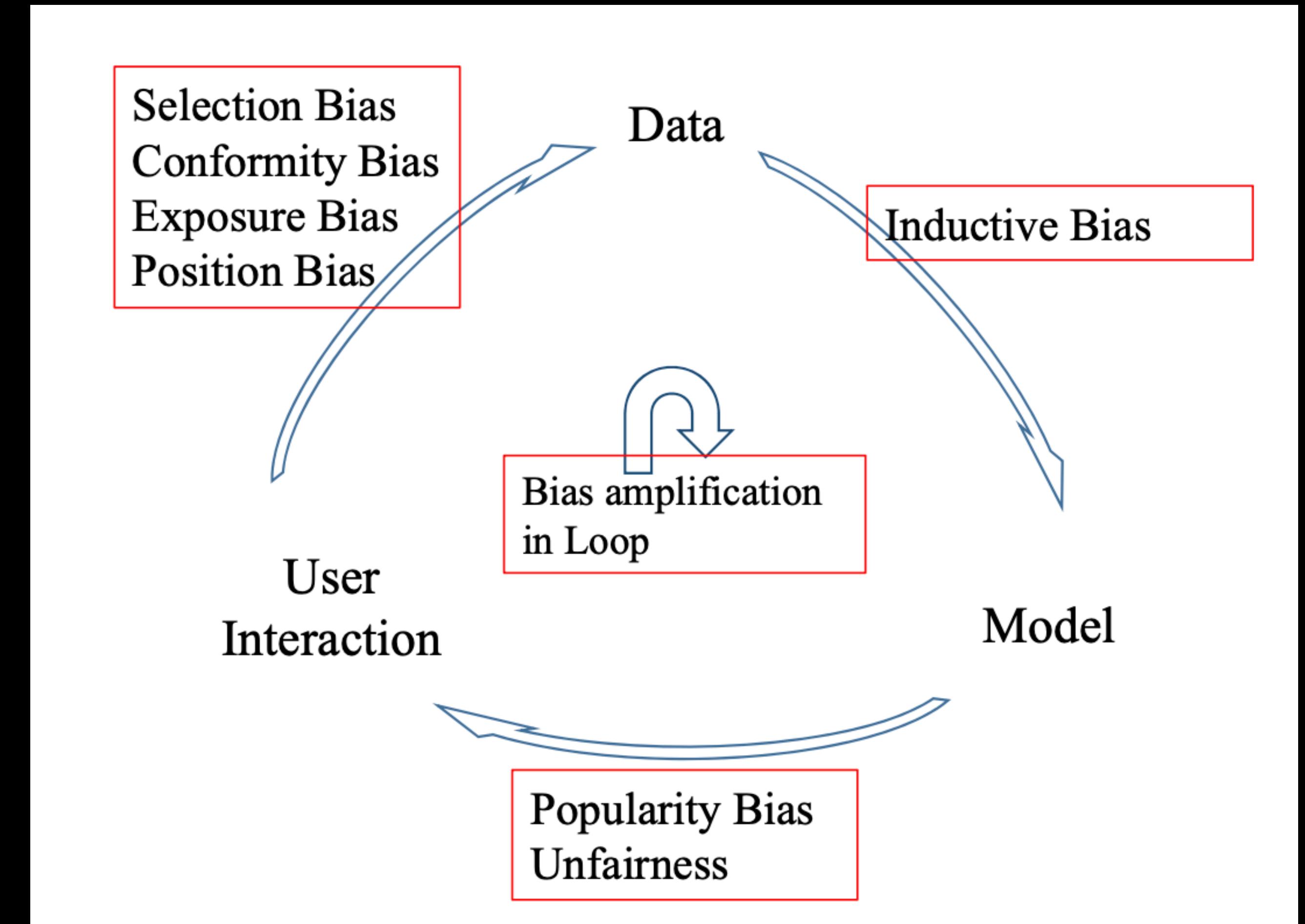
Unfairness

- Small societies has low quality recommendations
- Low number of interaction for item -> bad ranking



Feedback Loop

- The result of all biases concatenate and could be further intensified over time along the loop
- Recommendation system need to monitor this biases



Debiasing Selection Bias

Propensity Score

$$H(\hat{R}) = \frac{1}{nm} \sum_{u=1}^n \sum_{i=1}^m \delta_{u,i}(r, \hat{r})$$

Data Imputation

$$\arg \min_{\theta} \sum_{u,i} W_{u,i} \cdot \left(r_{u,i}^{o\&i} - \hat{r}_{u,i}(\theta) \right)^2 + \text{Reg}(\theta)$$

$$\hat{H}_{\text{naive}}(\hat{r}) = \frac{1}{\left| \{(u, i) : O_{u,i} = 1\} \right|} \sum_{(u,i):O_{u,i}=1} \delta_{u,i}(r, \hat{r})$$

$$\hat{H}_{IPS}(\hat{r} \mid P) = \frac{1}{nm} \sum_{(u,i):O_{u,i}=1} \frac{\delta_{u,i}(r, \hat{r})}{P_{u,i}}$$

$$\begin{aligned} \mathbb{E}_O [\hat{H}_{IPS}(\hat{r} \mid P)] &= \frac{1}{nm} \sum_u \sum_i \mathbb{E}_{O_{u,i}} \left[\frac{\delta_{u,i}(r, \hat{r})}{P_{u,i}} O_{u,i} \right] \\ &= \frac{1}{nm} \sum_u \sum_i \delta_{u,i}(r, \hat{r}) = H(\hat{r}) \end{aligned}$$

Debiasing Conformity Bias

- Train XGBoost predict score without user features

$$\hat{r}_{ui} = xgb \left(\{(1 - \omega) \cdot t_{ui} + \omega \cdot a_{ui}, c_{ui}, a_{ui}, d_{ui}\}, \Theta_{xgb} \right)$$

Debiasing Exposure Bias

- Update each iteration of your algorithm with different learning rate for different unobserved items
- Set for unobserved items other constant then 0
- Advanced sampling

Debiasing Position Bias

- Click modeling
- Add position to rate prediction

Debiasing Popularity Bias

- Regularization
- Adversarial learning

Debiasing Unfairness

- Define what is it
- Garante a fair chance to the Item been in recommended lists
- Rebalance your result list and garante all-group parity

Break down feedback loop

- Uniform data distribution
- Add random
- Reinforcement learning

Sources

- <https://arxiv.org/pdf/2010.03240.pdf>
- <https://papers-gamma.link/static/memory/pdfs/153-Kunaver Diversity in Recommender Systems 2017.pdf>
- <https://arxiv.org/pdf/1905.06589.pdf>