

Popularity Bias in Recommendation

Anastasiia Klimashevskaja, PhD Candidate

WP2: User Modelling, Personalization and Engagement

Supervisor: Assoc. Prof. Mehdi Elahi (UiB)

Co-supervisors: Prof. Christoph Trattner (UiB), Prof. Dietmar Jannach (AAU)

Research Centre for Responsible
Media Technology & Innovation

Project number 309339



Undesired Effects

- Echo chambers
- Filter bubbles
- Popularity bias
- Unfairness
- Discrimination
- Lack of diversity

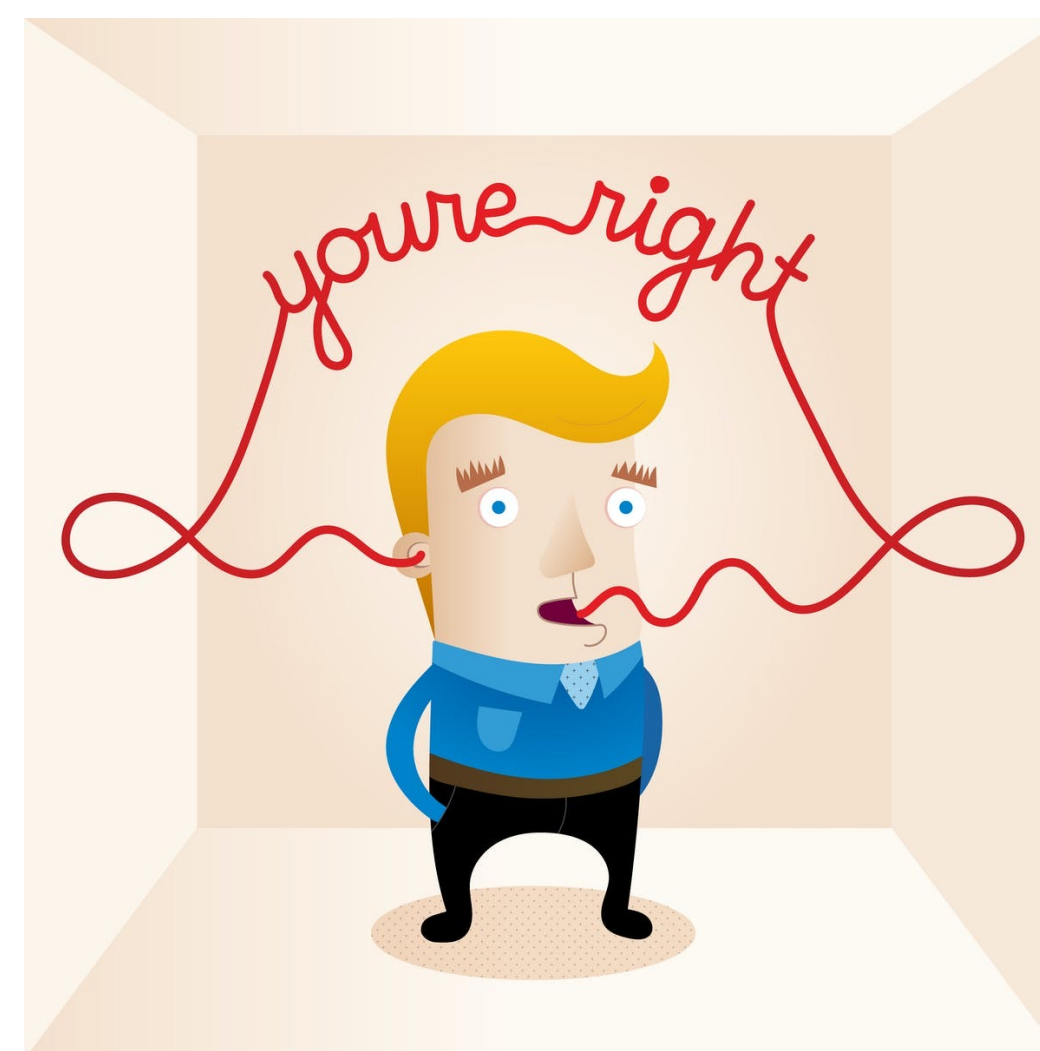


Image source: <https://medium.com/the-graph/popularity-vs-diversity-c5bc22c253ee>, <https://www.nbcnews.com/better/lifestyle/problem-social-media-reinforcement-bubbles-what-you-can-do-about-ncna1063896>, <https://theconversation.com/the-problem-of-living-inside-echo-chambers-110486>

Can we recommend more diverse items in terms of popularity, which are still engaging, relevant and interesting to people?

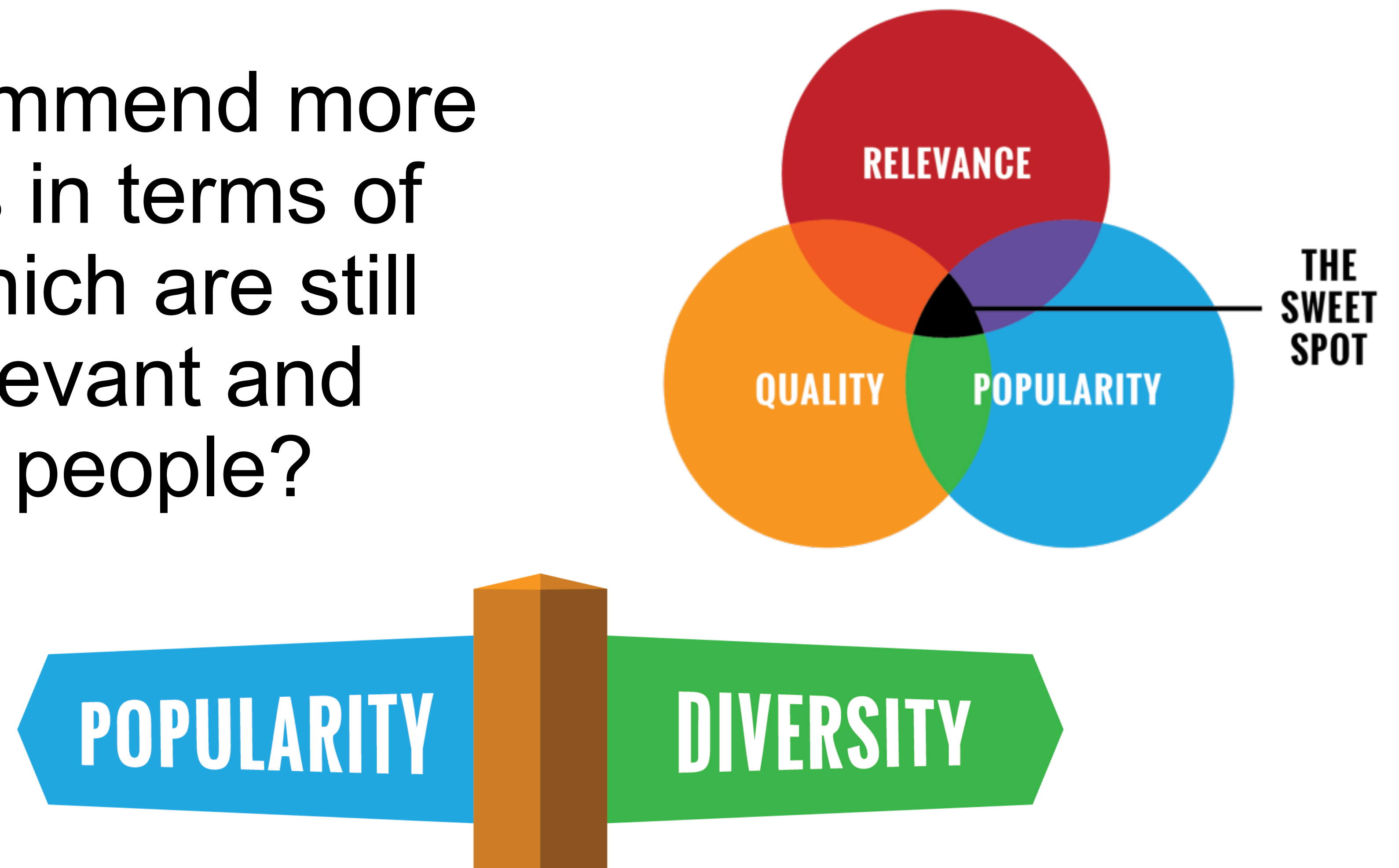


Image source: <https://medium.com/the-graph/popularity-vs-diversity-c5bc22c253ee>, <https://medium.com/the-graph/popularity-vs-diversity-c5bc22c253ee>

Research Track

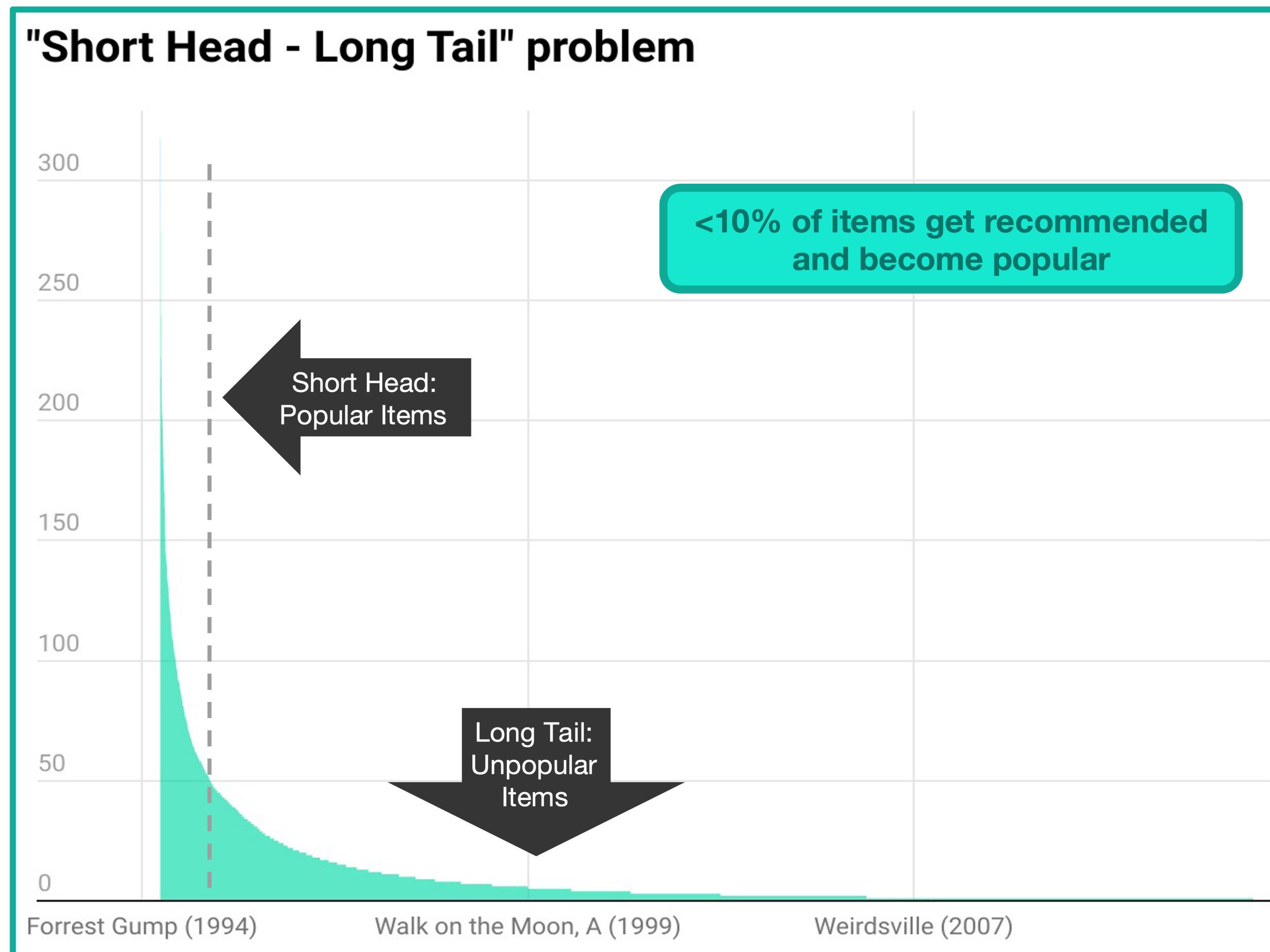
- 1** Identify the issue
- 2** Research state of the art
- 3** Pick / Upgrade a method
- 4** Offline testing and experiments
- 5** Deployment and online testing

Popularity Bias

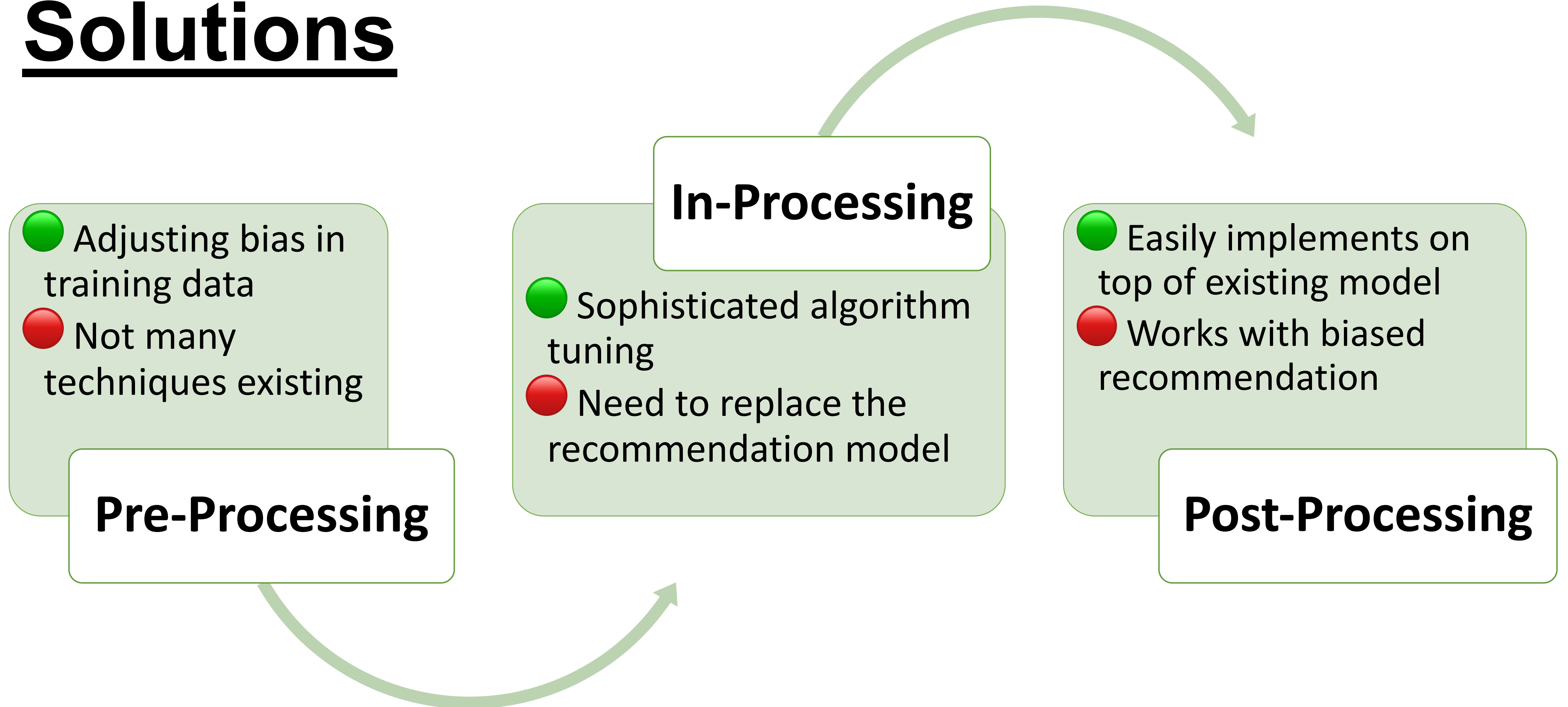
- “Matthew Effect”
- “Rich Getting Richer”

Why is it bad?

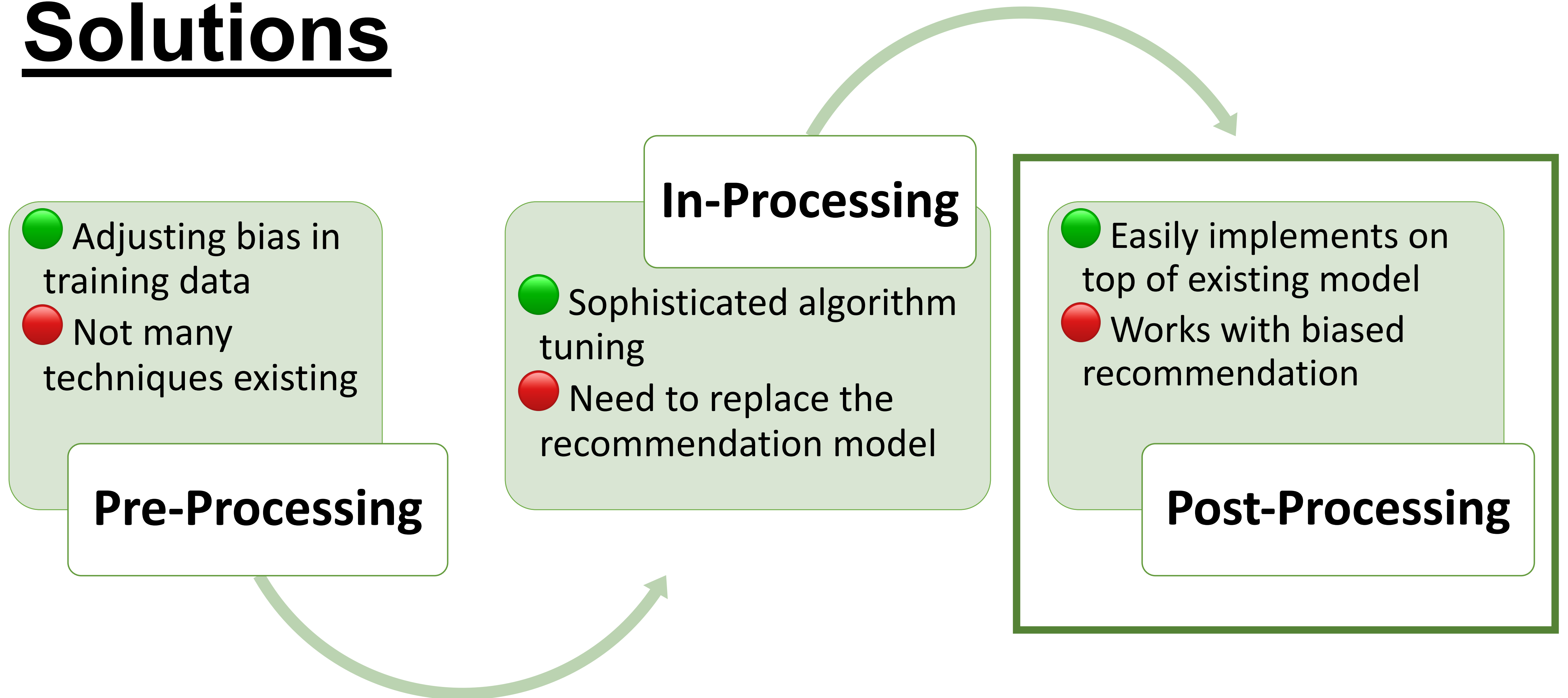
- Decreases diversity of recommendation
- Can potentially lead to user dissatisfaction and lower engagement
- Can lead to provider withdrawal from the platform that makes the recommendation



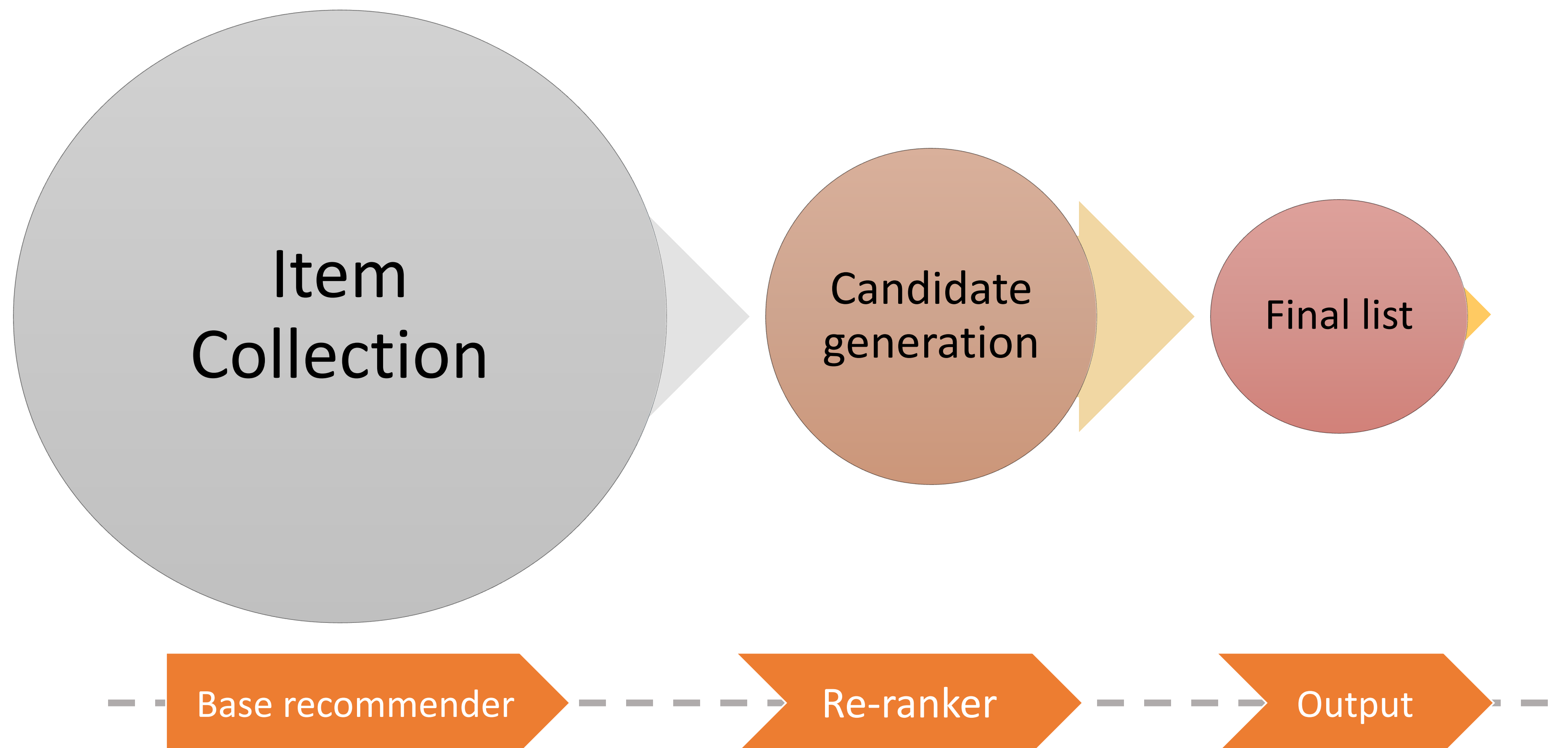
Solutions



Solutions

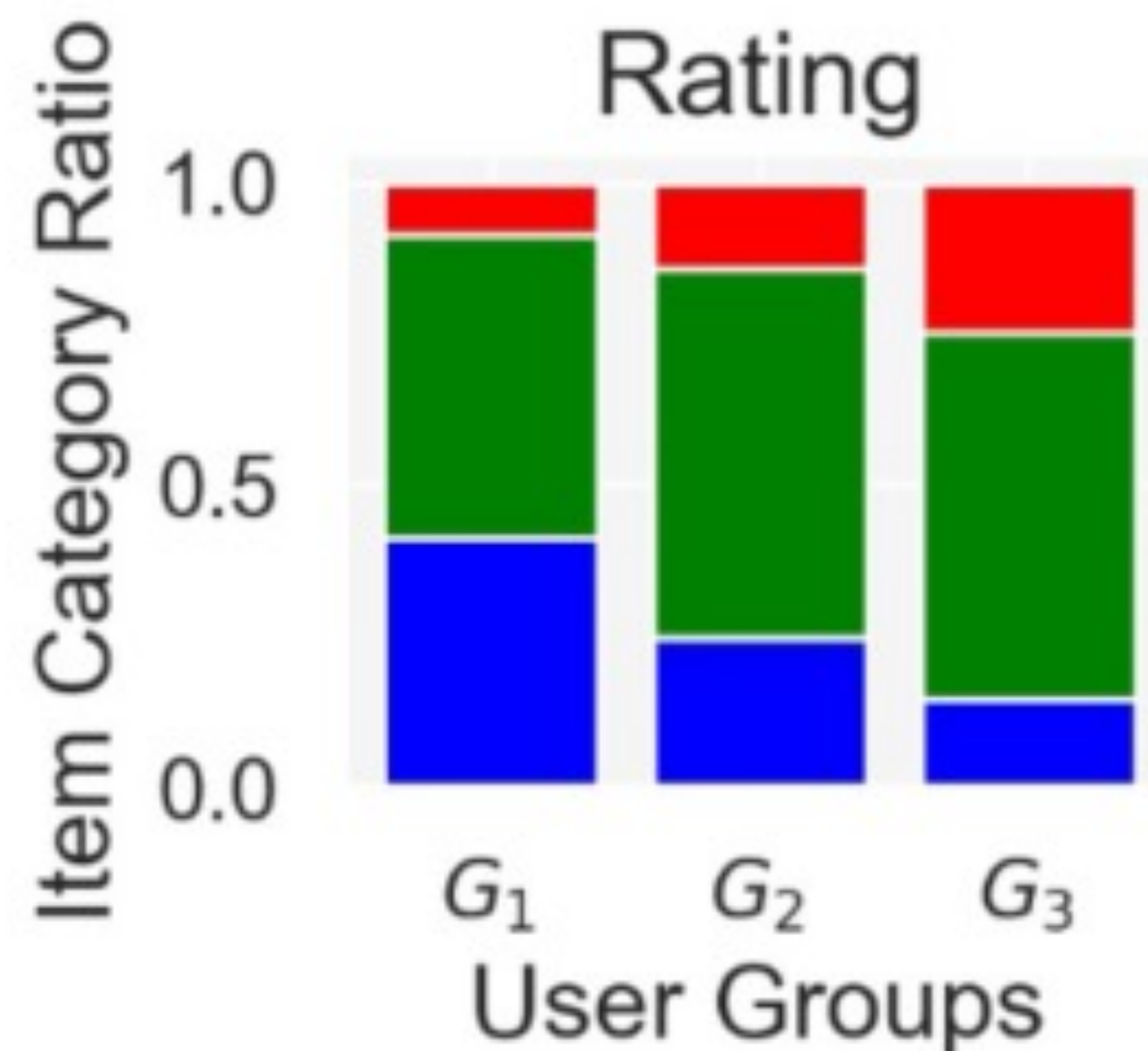


Post-Processing: Re-ranking



Calibrated Popularity

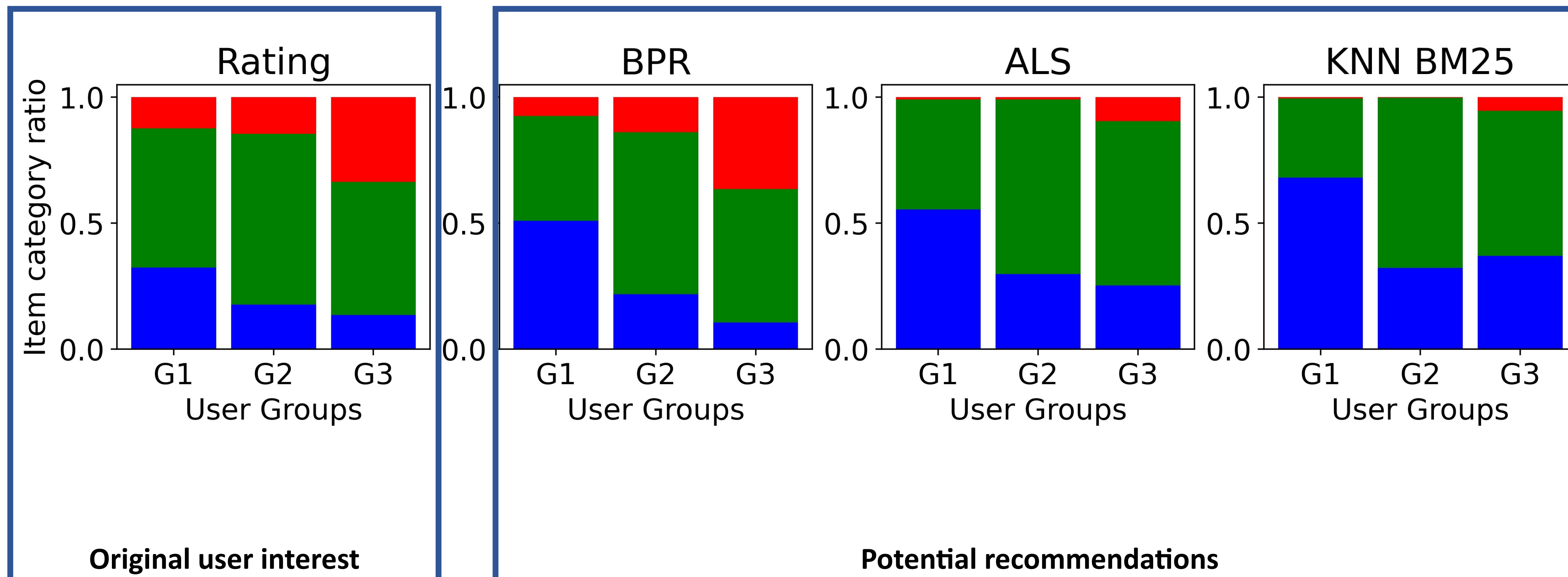
- (G1) - “Mainstream” lovers
- (G2) - Users with diverse preferences
- (G3) - “Niche” lovers



- Very popular items
- Mid-popular items
- Niche unpopular items

Preliminary Experiments

- Very popular items
- Mid-popular items
- Niche unpopular items



Offline Testing

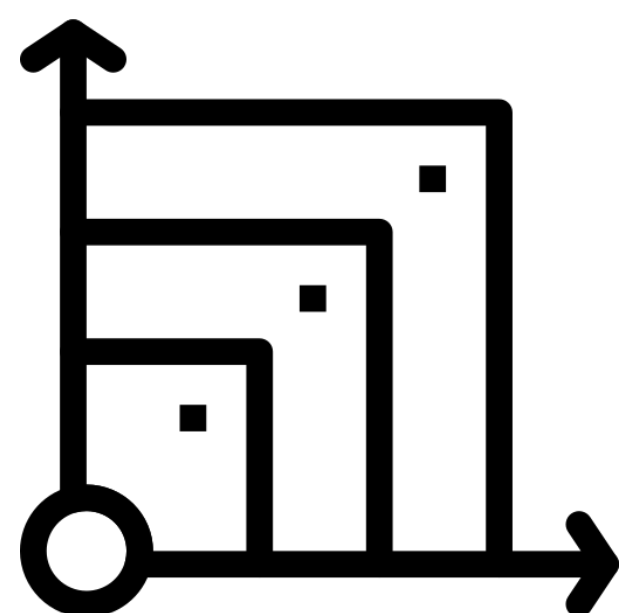
Dataset Algorithm		Metrics						
		Accuracy <i>Prec</i> ↑	Calibration <i>UPD</i> ↓	Long Tail Exposure			Equal Exposure	
				<i>ARP</i> ↓	<i>APLT</i> ↑	<i>ACLT</i> ↑	<i>Agg-Div</i> ↑	<i>Gini</i> ↓
TV 2	Pop	0.301	0.644	0.301	0.000	0.000	0.006	0.994
	Base (ALS)	0.875	0.286	0.143	0.639	0.292	0.321	0.874
	XQ	0.818	0.358	0.100	0.956	0.364	0.343	0.850
	FS	0.857	0.249	0.126	0.772	0.299	0.328	0.856
	CP	0.837	0.123	0.130	0.672	0.314	0.392	0.844
ML	Pop	0.381	0.629	0.381	0.000	0.000	0.007	0.993
	Base (ALS)	0.738	0.261	0.243	0.634	0.391	0.425	0.851
	XQ	0.656	0.378	0.167	0.989	0.442	0.412	0.848
	FS	0.697	0.237	0.202	0.839	0.397	0.432	0.835
	CP	0.720	0.101	0.223	0.676	0.408	0.477	0.821

- Define set of metrics
- Get datasets
- Testing against other algorithms
- Make sure the chosen strategy works well enough for later live testing

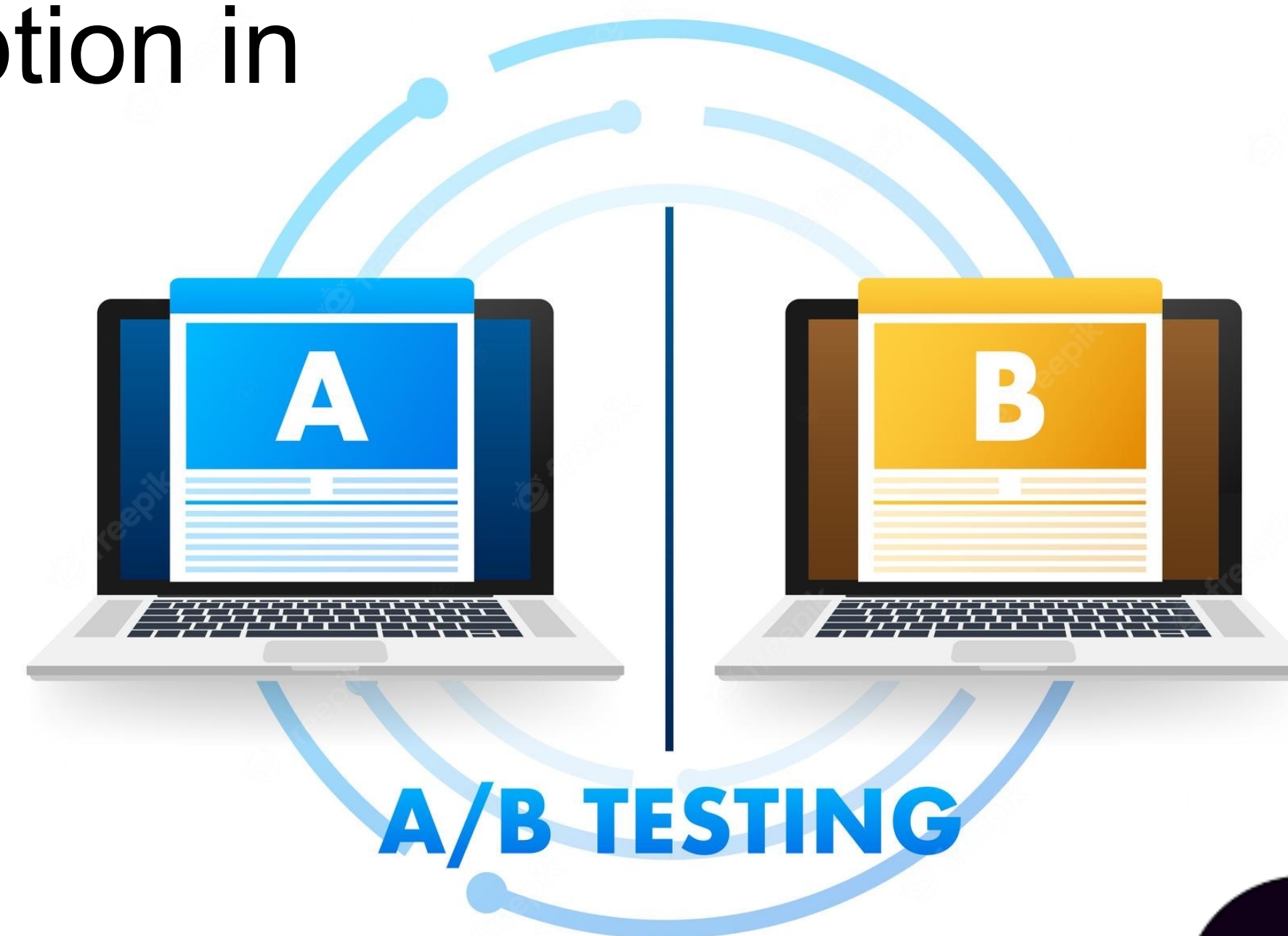
Online A/B Testing

Assess user satisfaction and perception in real life scenario:

- Less biased setting
- Much greater user pool

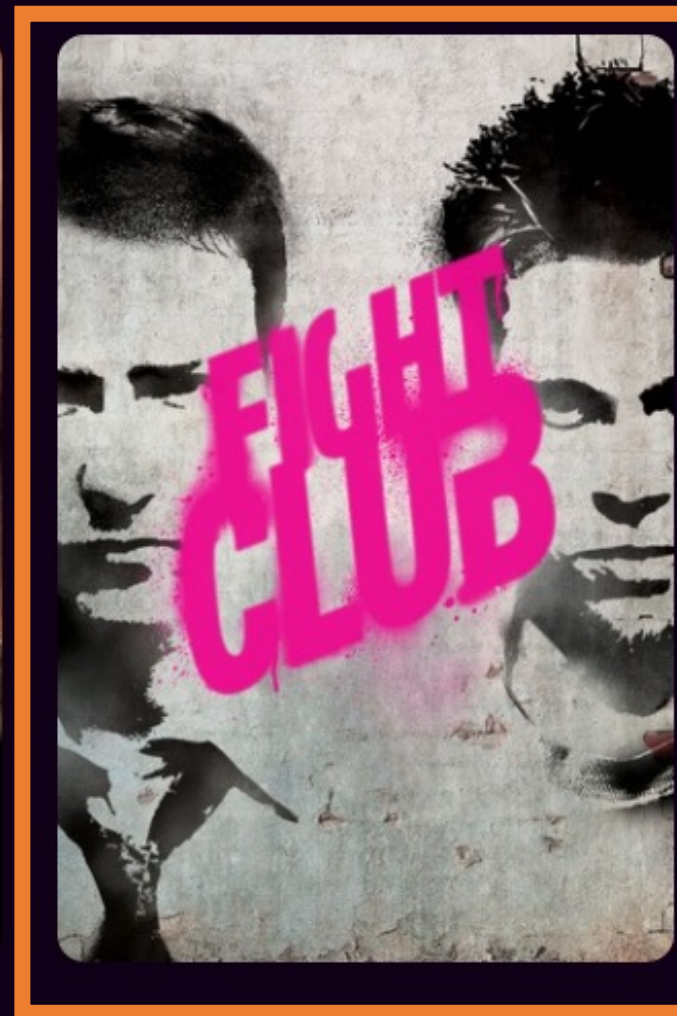


Academic  Industry:
Scalability is important



Movie recs

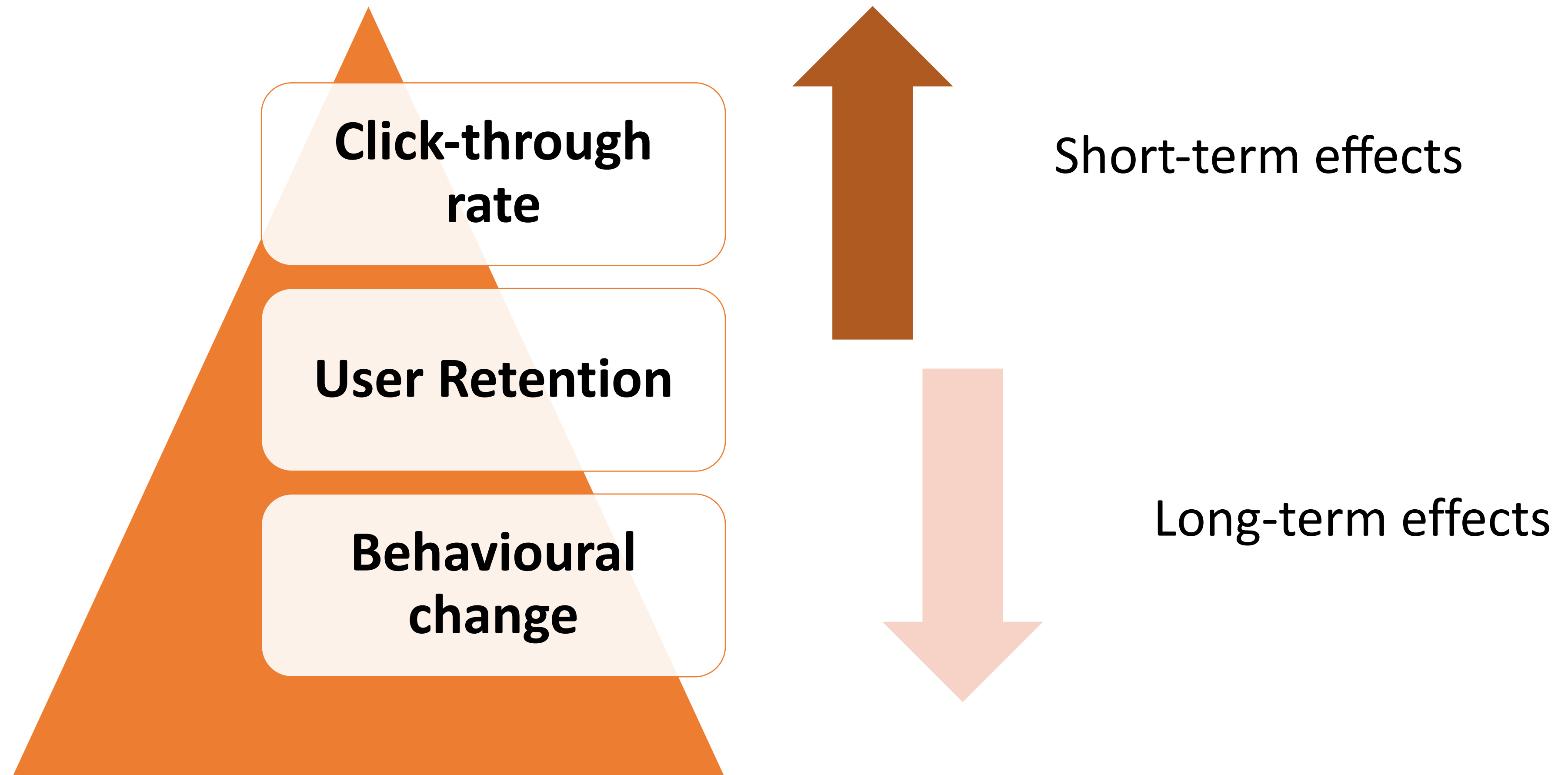
Se alle



Popularity bias experiment

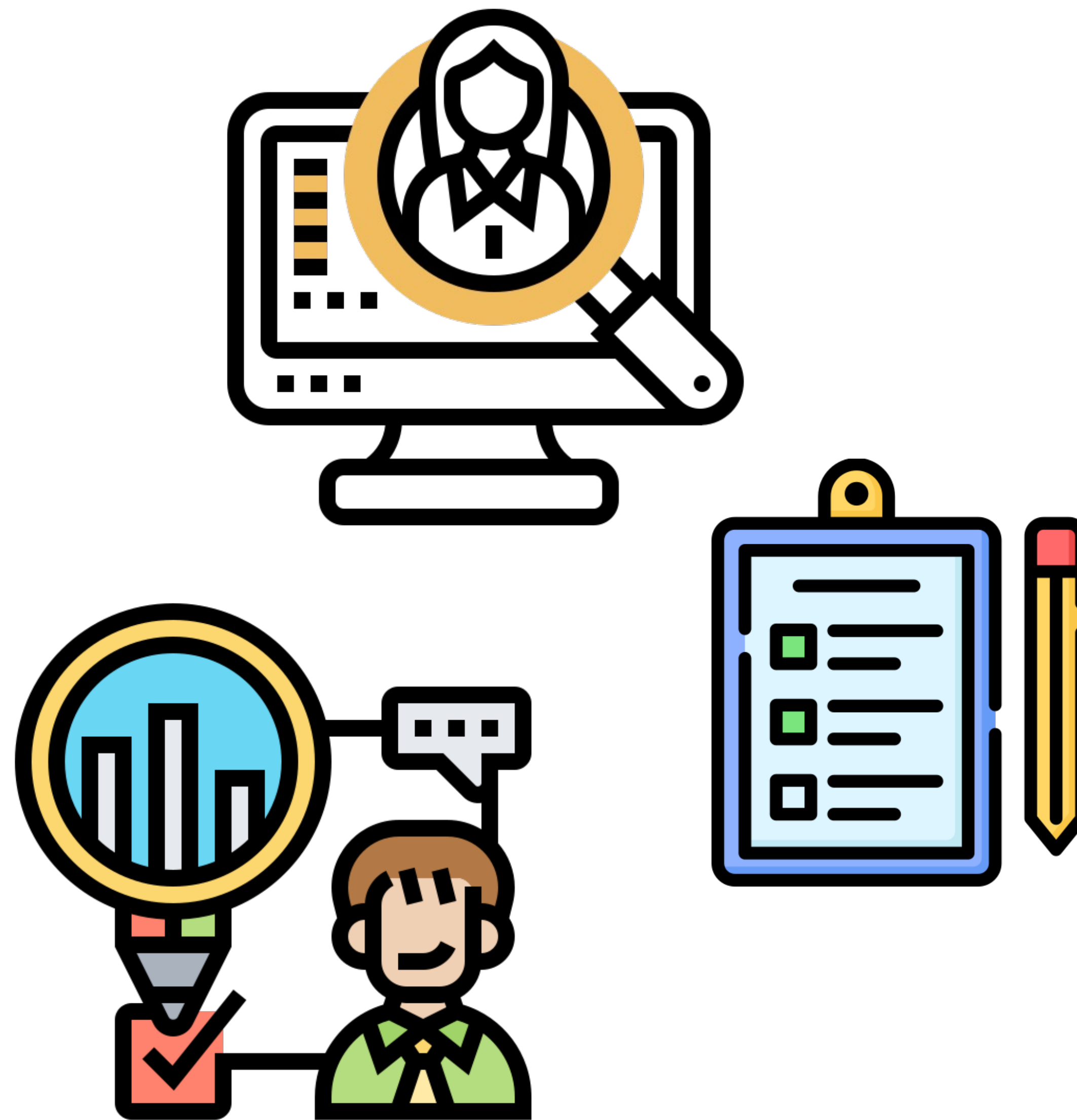


Online A/B Testing



Future Work

- More tests and experiments
- Qualitative analysis: user studies, questionnaires
- Algorithm modifications and improvements



Media Futures ●

Thank you!

Contact information:

Anastasiia Klimashevskaja anastasiia.klimashevskaja@uib.no

sf = **Research Centre for Responsible
Media Technology and Innovation**

Project number 309339

