The Role of Luck in the Success of Social Media Influencers

Student Project for Applied Network Science

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The Role of Luck in the Success of Social Media Influencers

- Source: Ionescu, S., Hannák, A. & Pagan, N. The role of luck in the success of social media influencers. Appl Netw Sci 8, 46 (2023).

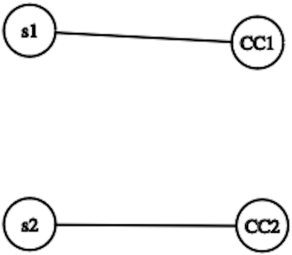
- The paper examines how the recommendation process of a social media platform influences the fairness for the content creators (CCs).
- It introduces a parameter for the recommendation process to reflect the level of popularity bias in the visibility of CCs.
- Fairness metrics for CCs and a measure for user (dis-)satisfaction are formally defined.
- Simulations show how popularity biases and time constraints influence the fairness of CCs and the satisfaction of seekers.

Model

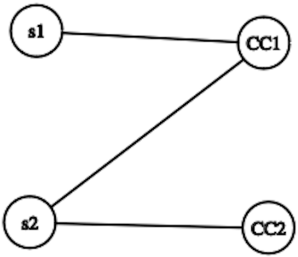
- A bipartite graph with m regular users/seekers and n content creators (CCs).
- The network at time t is denoted by $A^t \in \{0, 1\}^{m \times n}$.
- As an entry in A^t, $a^t_{s,c}$ is 1 if seeker $s \in [m]$ follows CC $c \in [n]$ at time t, and 0 otherwise.
- Network formation:
  1. The follower network is initially empty;
  2. Recommendation phase: each seeker is recommended a CC;
  3. Decision phase: seekers decide to follow the recommended CC or not.
     - Seekers follow a recommended CC only if the CC is higher ranked by quality than any of their current followees.

Visualization

- CC_1 is of higher quality than CC_2.
- Suppose at time $t+1$, CC_2 is recommended to s_1 and CC_1 is recommended to s_2.



Network at time t



Network at time $t+1$

Recommendation Process

- The recommendation process maps a follower network A^t to a recommendation function $R^t : [m] \to [n]$.
- The parameter α:
  - $\alpha = 0$ corresponds to uniform random(UR) recommendations;
  - $\alpha > 0$ corresponds to preferential attachment(PA);
  - $\alpha < 0$ corresponds to anti-preferential attachment(antiPA);
  - $\alpha = \pm\infty$ corresponds to extreme cases where only CCs with the most(least) number of followers being recommended.
- The visibility of each CC is determined by

$$\mathbb{P}(R^t_\alpha(s) = i) = \frac{(1 + a^t_{\cdot,i})^\alpha}{\sum_{j \in [n]} (1 + a^t_{\cdot,j})^\alpha},$$

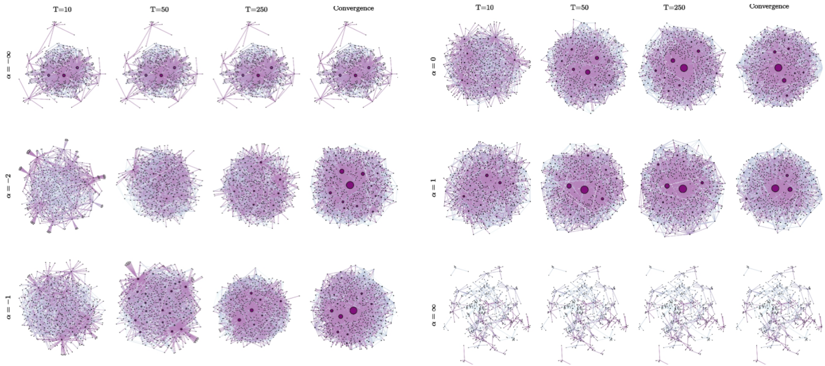
where $a_{\cdot,i} := \sum_{s \in [m]} a_{s,i}$ is the number of followers of CC_i.

Metric of Fairness, Simulation Setup

- Assumption: CCs are ranked by their quality with $CC_1 \succeq CC_2 \succeq \cdots \succeq CC_n$ and all users prefer higher ranked CCs.
- Individual fairness for CCs: An outcome A is fair for CC_i if CC_i is one of the top i most popular CCs, i.e. if $|\{j : a_{\cdot,j} > a_{\cdot,i}\}| < i$.
- We define the dissatisfaction of seeker s as $\min\{i : a_{s,i} = 1\}$.

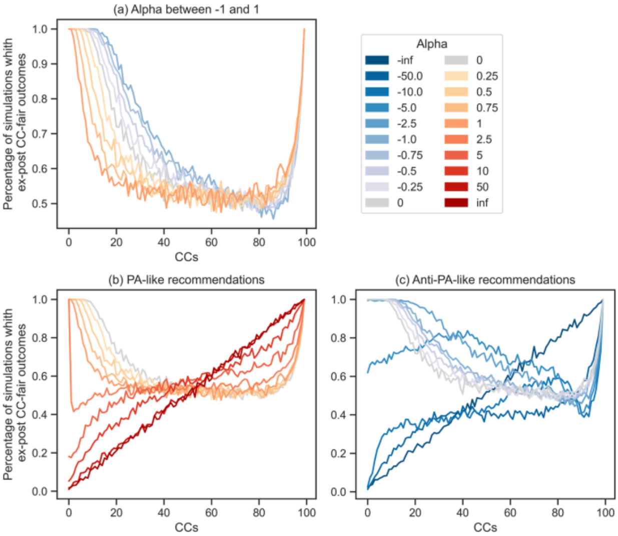
- Simulation Set-Up:
  - 100 Content Creators
  - 10000 Users
  - Repeat 1000 times

Sparsity and convergence rate depend on the recommendation process



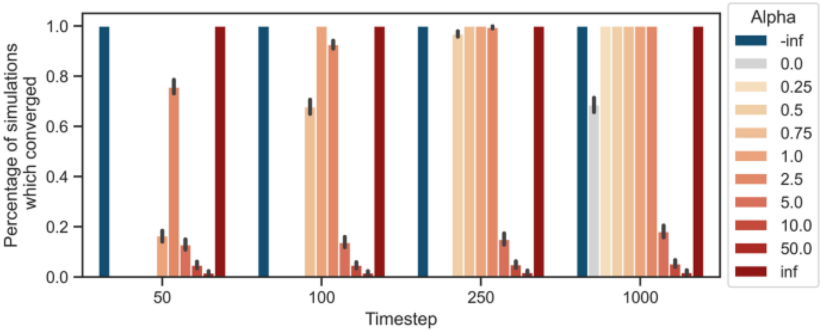
Evolution of the network under different $\alpha \in \{-\infty, -2, -1, 0, 1, \infty\}$ at timesteps $T = 10$, 50, 250 and at convergence.

Increases in the visibility of low-popularity CCs improves fairness



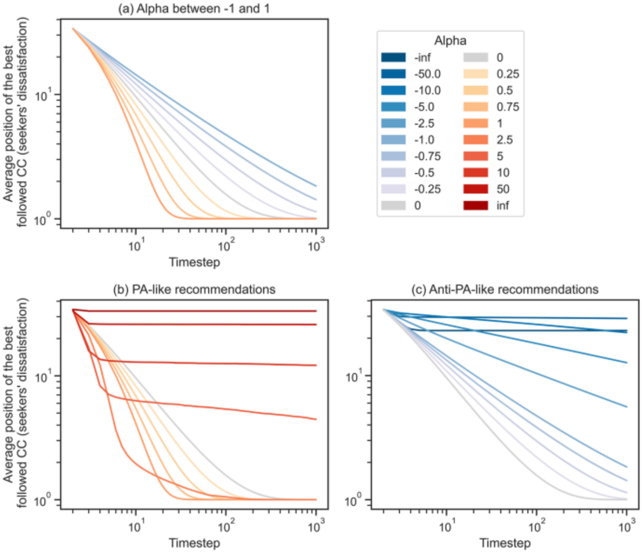
CC_i-fairness after 1000 timesteps with different recommendation processes

Time to convergence



Percentage of simulations that converge within 1000 timesteps

Seekers are most satisfied with α around 1



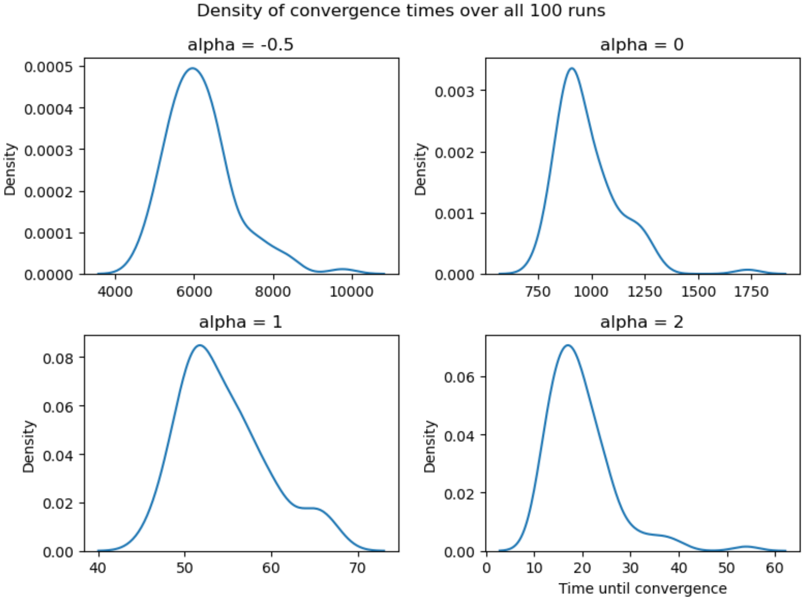
Average quality-position (over users and simulations) of the best followed CC over time

Our Project: So what parameters should I use?

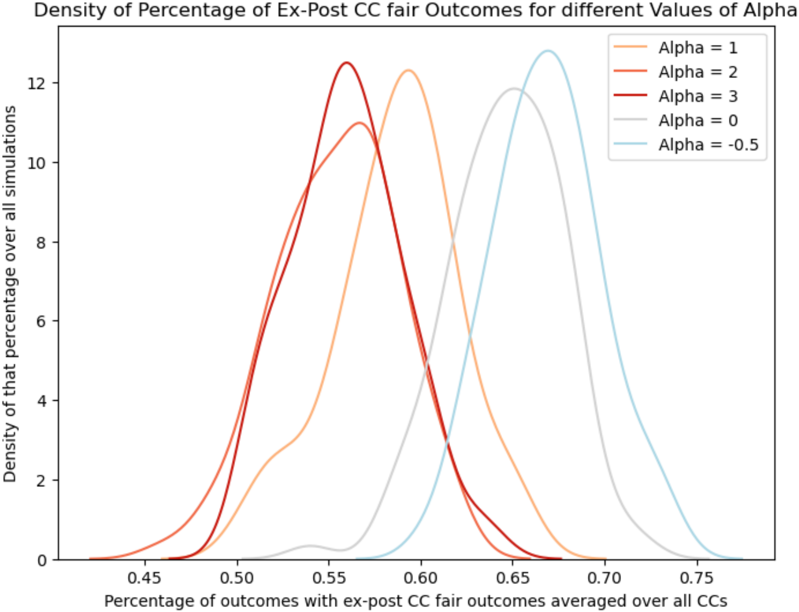
- The paper explained: PA leads to many users being treated unfairly
- And that antiPA is better for CC fairness than PA

- We try to answer: If I want to use PA or antiPA in practice, what should I do? We do this in two steps.
- First step: Perform further, more fine-grained analysis.
- Second step: Devise a modification of the algorithm with better properties for practical use cases.

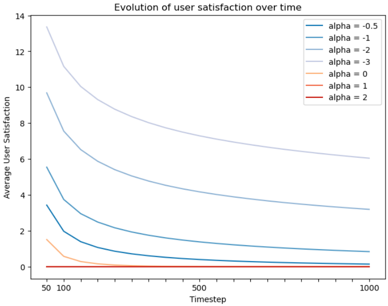
antiPA leads to exorbitant convergence times



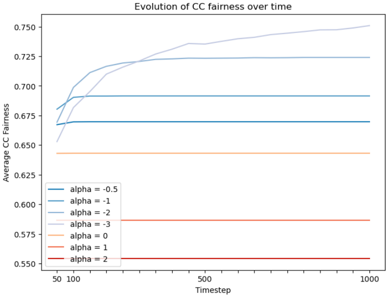
Reminder: antiPA leads to more CC fairness



The Trade-off: CC fairness vs. user dissatisfaction



Evolution of User (Dis-)satisfaction



Evolution of CC Fairness

A new approach and better solution: (α, β)-PA

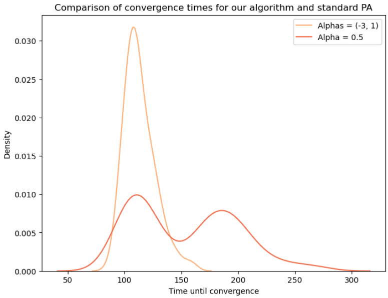
- To improve upon this trade-off, we developed a new modification of PA, called (α, β)-PA.
- The idea: Why not use both PA and negPA?
- negPA ensures fairness, while PA ensures fast convergence

We thus do the following. Given a parameter $\alpha \geq 0$ (PA parameter), and a parameter $\beta < 0$ (negPA parameter), at each timestep perform the following 2-step procedure:

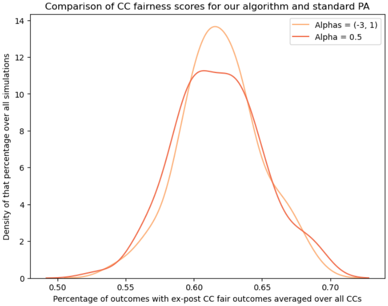
1. Flip an unbiased coin; if it shows head, choose α, otherwise choose β
2. Perform a (neg-)PA step with the parameter chosen in step 1.

(α, β)-PA: empirical results (1)

- In order to get a average convergence time of ≤ 200, for standard PA we need to choose $\alpha \geq 0.5$
- But when using $(-3, 1)$-PA, the average convergence time is only half that of 0.5-PA, while being just as fair.



Convergence times



CC fairness

(α, β)-PA: empirical results (2)

- By using biased coins, we can even achieve a 15-times speed-up of -0.5-PA while achieving the same CC-fairness!
- As a further bonus: the results are of less variance
- Downside: If convergence time needs to be ≤ 100 steps, we do not achieve significantly better results.

Conclusion

- There is an inherent trade-off between CC fairness and user dissatisfaction / convergence times in a PA-type recommendation scheme
- Using (α, β)-PA, we can slightly mitigate it and gain in both metrics.
- Based on the - admittedly naive - model we worked with, we believe that $(-3, 1)$-PA is a very decent parameter choice.

Summary

- The paper introduced a recommendation procedure called α-PA.
- It further introduced metrics of CC fairness and user dissatisfaction.
- It then shows empirically that one can expect that such a recommendation procedure leads to many content creators being treated unfairly.
- It further shows that using a negPA scheme, the CC fairness can be expected to be much better than with standard PA.

- Upon further analysis, we show that negPA's extremely long convergence times are unsuitable for possible practical use cases.
- But PA with positive exponent yields very bad content creator fairness.
- We thus introduce a new scheme called (α, β)-PA which tries to get the best of both worlds.