

An Optimisation View of Online Attention Markets

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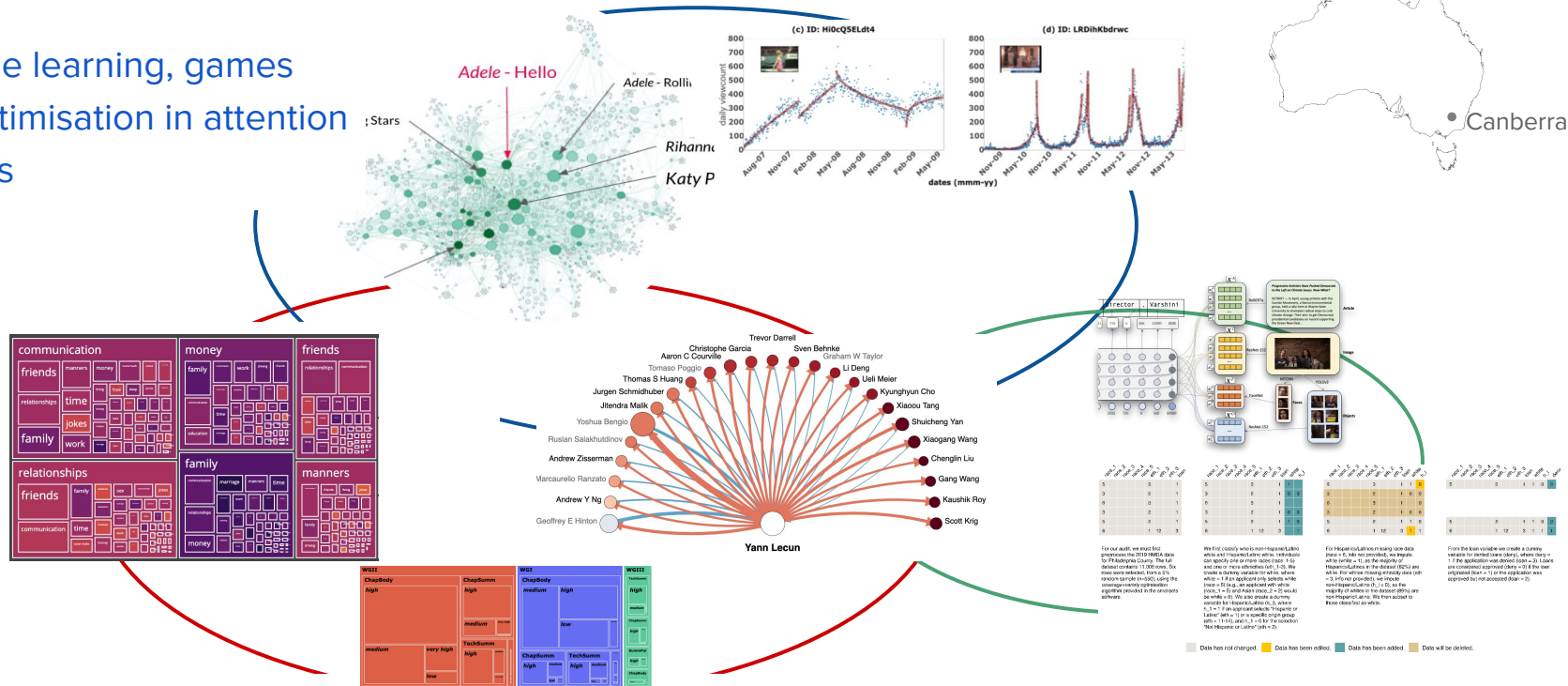
Integrated AI Network <https://ai.anu.edu.au/>
Computational Media Lab <http://cmlab.dev>



computational media lab @ ANU

<http://cmlab.dev>

Machine learning, games
and optimisation in attention
markets



Human-centered AI with a purpose: bridging info gaps in
climate and environment, understanding daily moral
dilemmas

Inter-disciplinary AI, interactive
visualisations, vision and language

Design + teach: {ML, algorithm, games} view of **Network Science**

Attention is a scarce resource



users



platform



digital content



creators

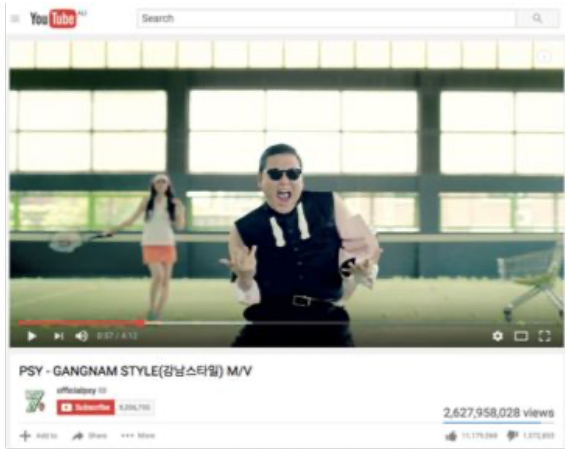


regulator

Abundance of content → scarcity of attention [Simon 1971]

- How do attention evolve, what drives it? (with publicly available data)
- What are the properties of the market system involving content, users, and platforms?

What is item popularity?



J.S. Bach - Brandenburg Concerto No.5 in D BWV1050 - Croatian Baroque Ensemble



1,225,253

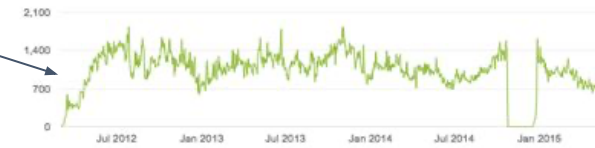
VIEWS

1,225,397

SHARES

3,870

Cumulative Daily ?



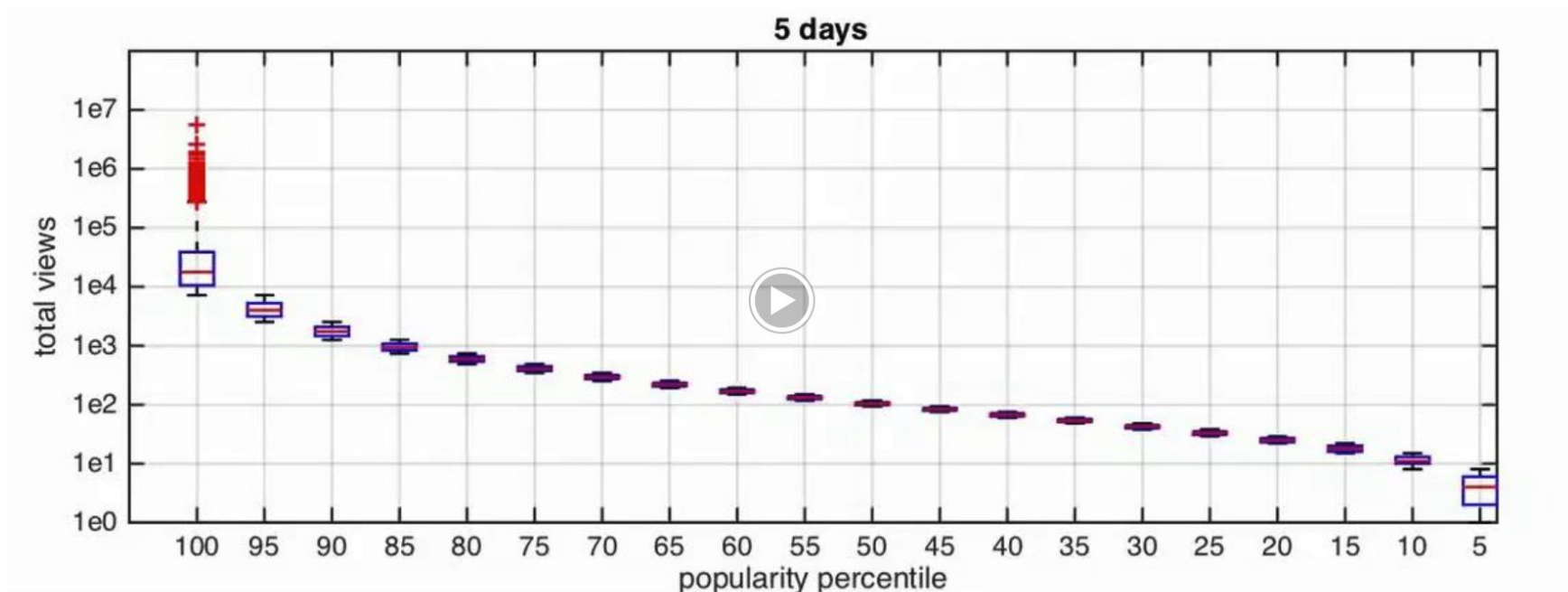
Video statistics Through Aug 16, 2016

VIEWS	SUBSCRIPTIONS DRIVEN	SHARES
2,626,900,489	1,332,717	2,907,575



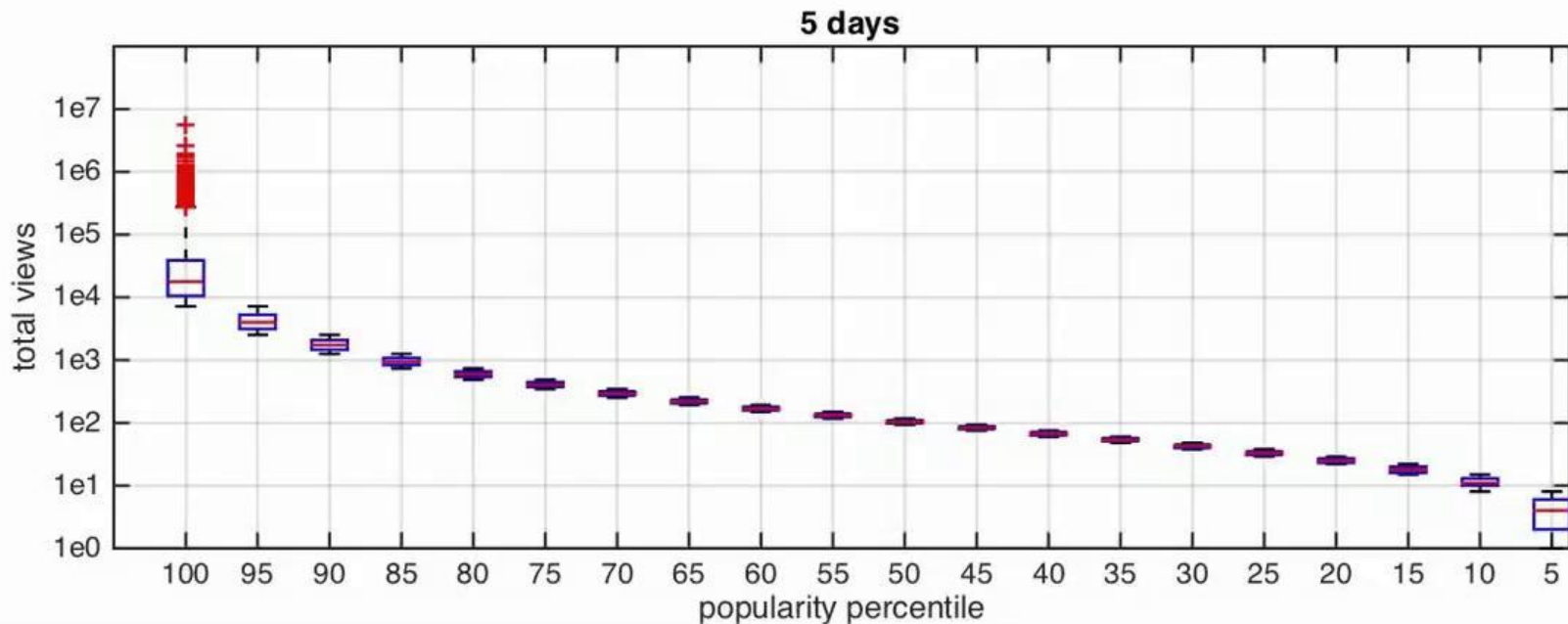
daily # of views

Popularity scale over time



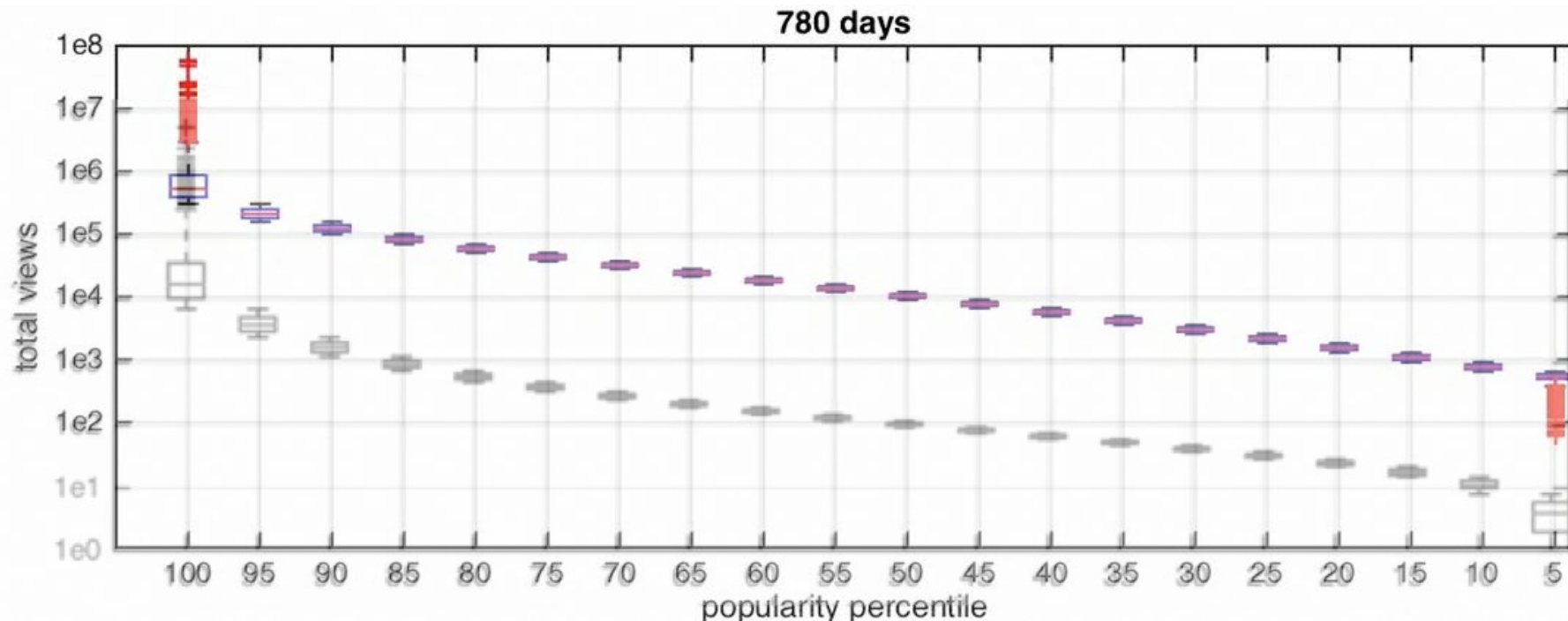
- 172K+ videos, >8K in each 5% *popularity bin*;
- videos in the middle bins are within 1.3x of each other's view-count.
- < 1% videos has 1M views after 2 years

Popularity scale over time



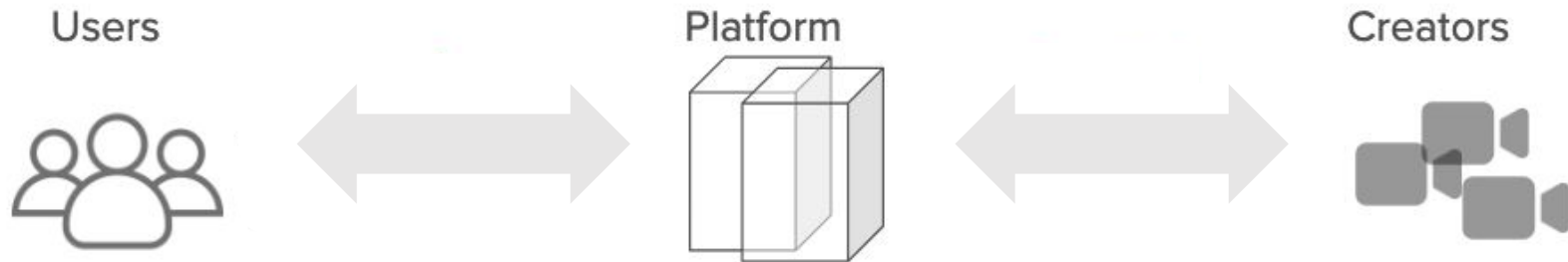
- 172K+ videos, >8K in each 5% *popularity bin*;
- videos in the middle bins are within 1.3x of each other's view-count.
- only 1% videos has 1M views after 2 years

“Rich-get-richer” as videos age



Videos (of the same popularity percentile) has ~100x in views over 2 years

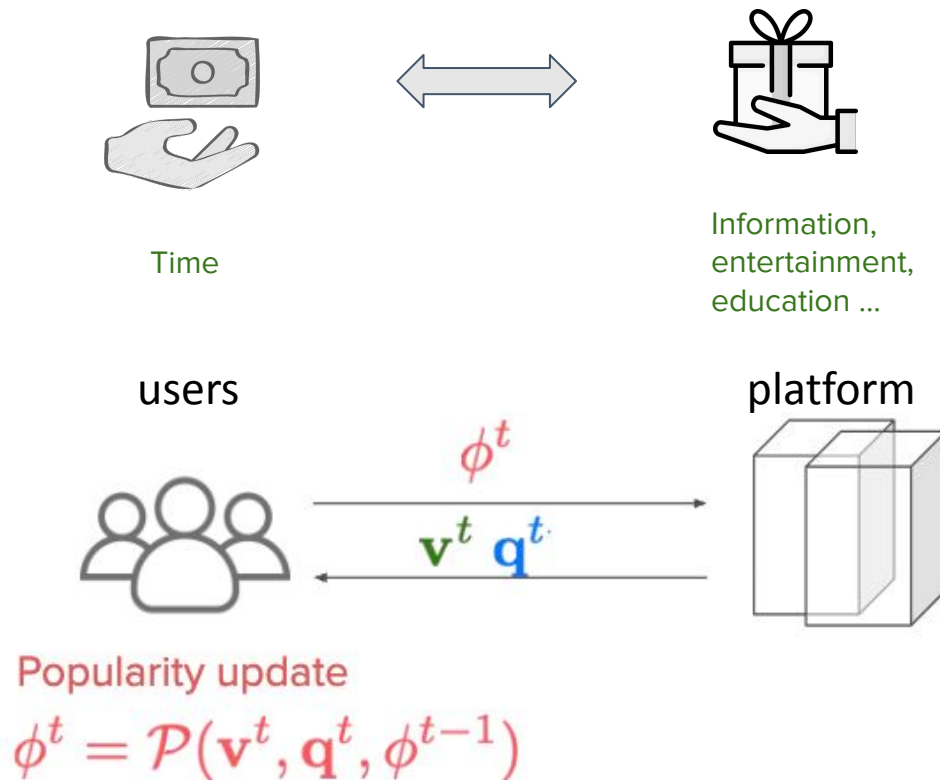
Talk outline



- How to describe **Attention as a marketplace?**
- Are there implicit potential (Lyapunov) functions for the underlying dynamics?
- Do the distributed interactions have equilibria – are they reachable?
Are they good?
- Can we incentivize or influence quality of production?

Aside: morals, LLMs, influence flowers

Attention as a marketplace



Markets	“Traditional” e.g. Arrow-Debreu	Attention
Supply	limited	∞
Price	modulate supply-demand	constant (per unit time)
Scarcity	\$	attention/time
Market maker	minimal power	recsys/reward

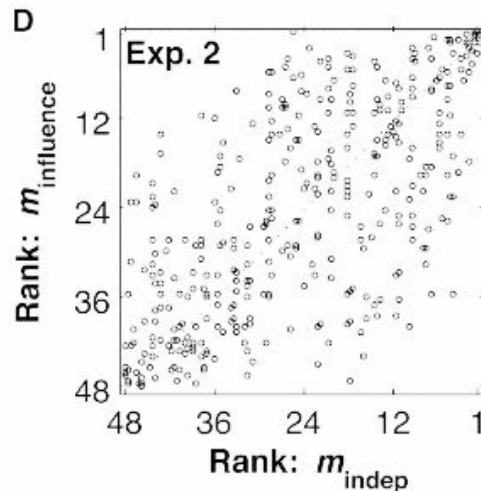
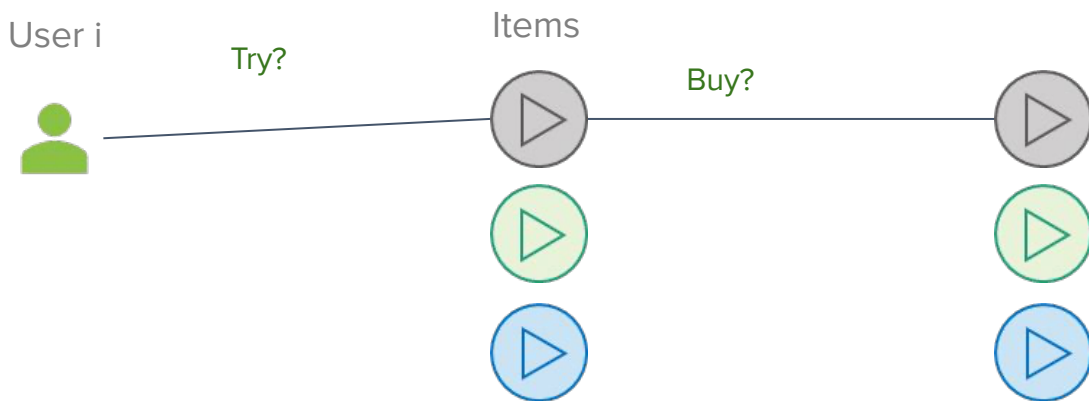
The Musiclab Experiment

["Experimental study of inequality and unpredictability in an artificial cultural market."](#) Salganik, Dodds, and Watts. *Science*, 311:854-856, 2006.

14.3K participants, 48 unknown songs from unknown bands; $8 \times 2 + 1$ “worlds”

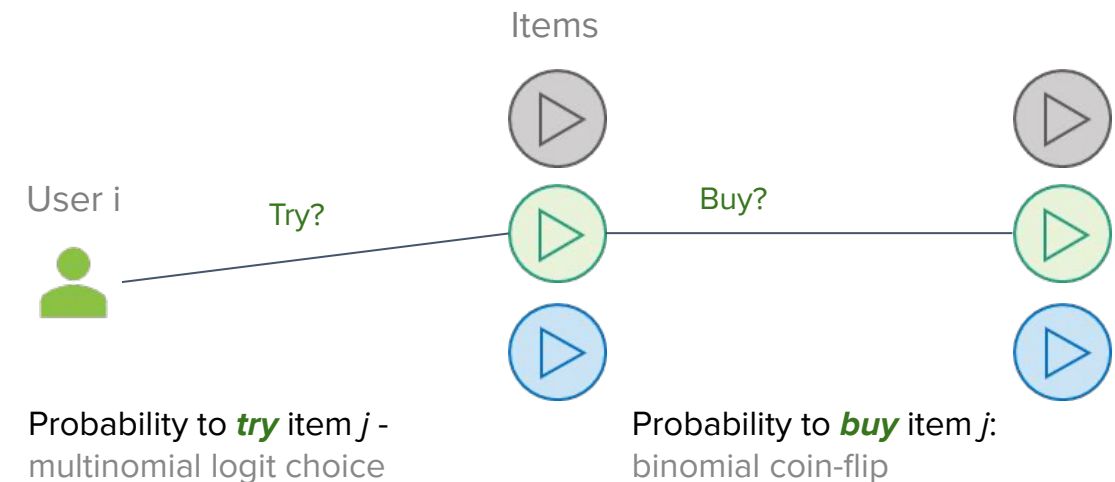
- popularity signal and ranking each plays a role
- unpredictable market shares observed across 8 separate “worlds”

“Success was also only partly determined by quality: The best songs rarely did poorly, and the worst rarely did well, but any other result was possible.”



Musiclab as a Trial-offer Market

[Salganik et al. 2006, Krumme et al 2012, Maldonado et al. 2018]



$$\propto v_{ij}(\phi_j^t)^r$$

Visibility (platform controls this)

$$\phi^t$$

Market share (after round t)
 $\phi \in \Delta$ n -dim simplex

$$q_{ij} \in [0, 1]$$

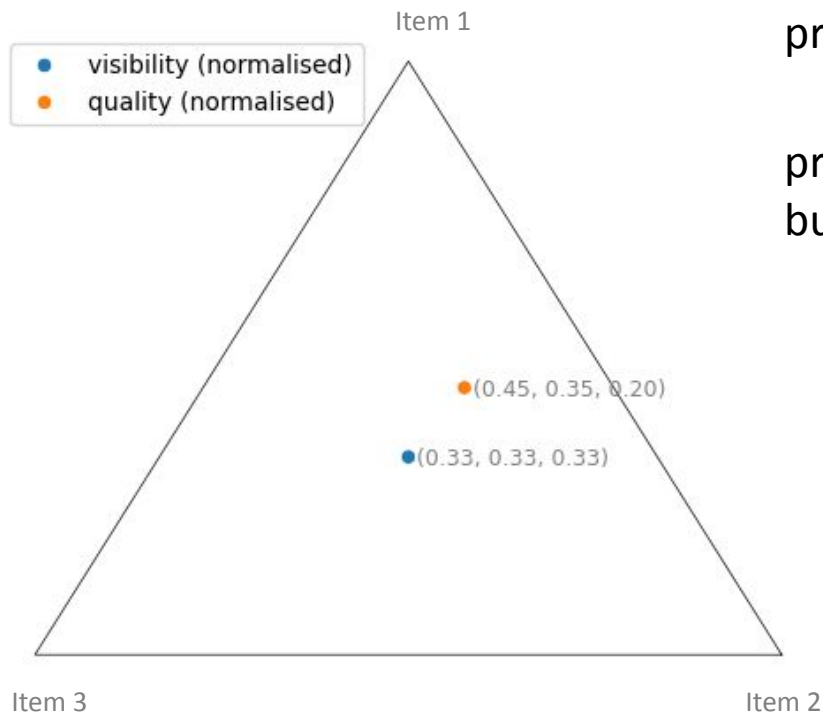
$$\phi^{t+1}$$

Quality (intrinsic of each item)

- Trial-offer market with choice model describes the musiclab experiment.
- There is at least one fixed point in market share.

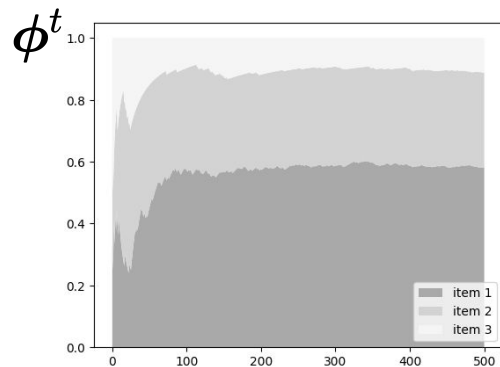
What is the dynamic and interactions between visibility, market share and quality?

Toy example: attention market with 3 items

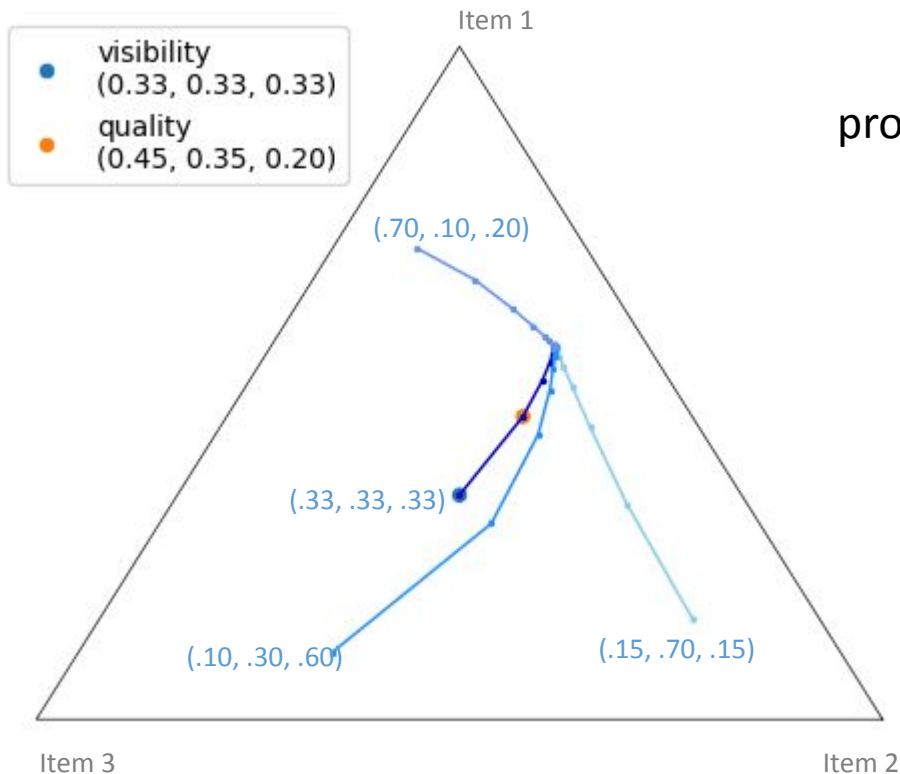


prob. to try item j $\propto v_j(\phi_j^t)^r$

prob. to try and then buy item j $\phi_j^{t+1} \propto q_j v_j(\phi_j^t)^r$



Toy example: how does quality affect market share?



prob. to buy item j

$$\phi_j^{t+1} \propto q_j v_j(\phi_j^t)^r$$

set $r = 0.5$

Does this dynamical system have an objective function?

Will this stochastic process converge?

Two potential functions

let $\bar{q}_j = v_j q_j$

Trial-offer update

$$\phi_j^{t+1} \propto \bar{q}_j (\phi_j^t)^r$$

Total utility

$$\max \sum_{j=1}^{|I|} \bar{q}_j \phi_j^r,$$

subject to $\phi \in \Delta$.

Log utility regularised by entropy

$$\max \Psi(\phi) := \sum_{j=1}^{|I|} (\phi_j \log \bar{q}_j - (1-r) \phi_j \log \phi_j),$$

subject to $\phi \in \Delta$.

Does it naturally
get to the
optimal?

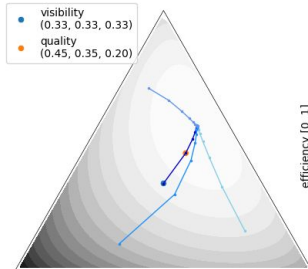
Mirror descent update with KL div

$$\phi \in \Delta \rightarrow \left\{ \sum_{j=1}^{|I|} \left(-\log \bar{q}_j + (1-r)(1 + \log \phi_j^{t-1}) \right) \cdot \phi_j + \left(\phi_j \log \frac{\phi_j}{\phi_j^{t-1}} - \phi_j \right) \right\}$$

stationary point for the argmin

Unique equilibrium

$$\phi_j^* \propto (\bar{q}_j)^{1/(1-r)}$$



Attention market with personal preferences

Change of variable $\phi_{ij}^t \leftarrow \text{normalize}(b_{ij}^t)$ $b_j^t = \sum_i b_{ij}^t$

$$b_{ij}^t = w_i q_{ij} \frac{v_{ij}(\phi_j^{t-1})^{r_i}}{\sum_k v_{ik}(\phi_k^{t-1})^{r_i}} = w_i q_{ij} \frac{v_{ij}(b_j^{t-1})^{r_i}}{\sum_k v_{ik}(b_k^{t-1})^{r_i}}$$

↑
Fraction of the
population w
preference q_{ij}

Positive feedback loop:
higher market share
begets more attention

Attention market with personal preferences

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Positive feedback loop:
higher market share
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Proportional response in
Fisher Markets

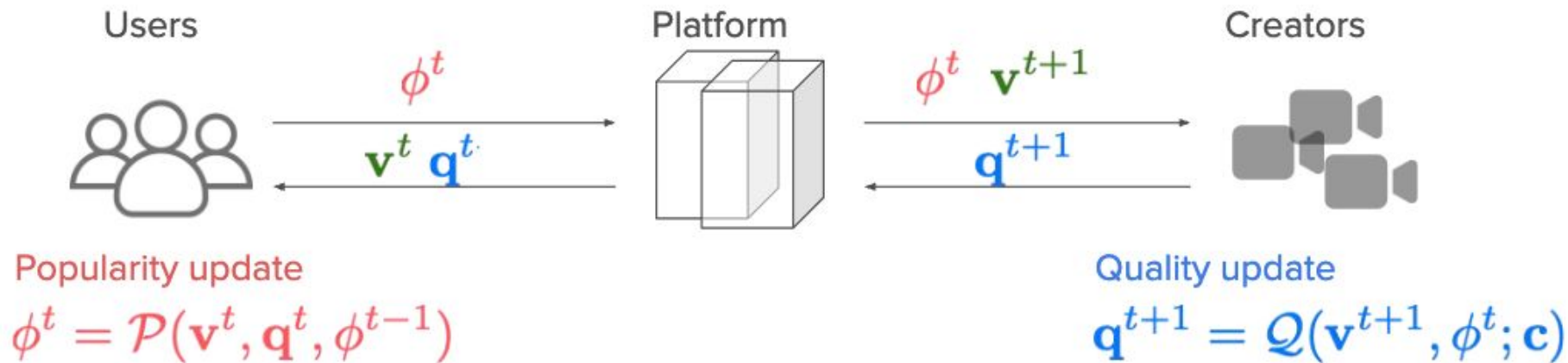
[Zhang2007,Birbaum2011, Cheung2018]

$$b_{ij}^t = w_i \frac{v_{ij}(b_{ij}^{t-1}/b_j^{t-1})^{r_i}}{\sum_{k=1} v_{ik}(b_{ik}^{t-1}/b_k^{t-1})^{r_i}}$$

Negative feedback
loop: higher price
drives down
consumption

- Overall objective function is similar to Nash social welfare
- The probabilistic response dynamic is stochastic **mirror descent**

Attention Markets are Two-sided

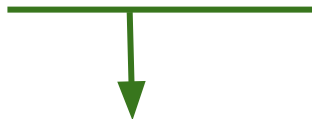


$$\phi_j^{t+1} \propto q_j v_j (\phi_j^t)^r$$

“Best response” by creators

Creators act by adjusting their q to maximize their own utilities.

$$\text{maximize } u^t(q_j) = q_j \cdot \frac{v_j^{t+1}(\phi_j^t)^r}{\sum_i v_i^{t+1}(\phi_i^t)^r} - c_j(q_j).$$

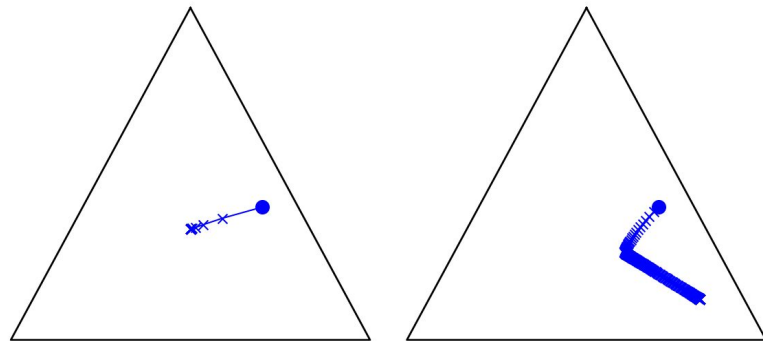
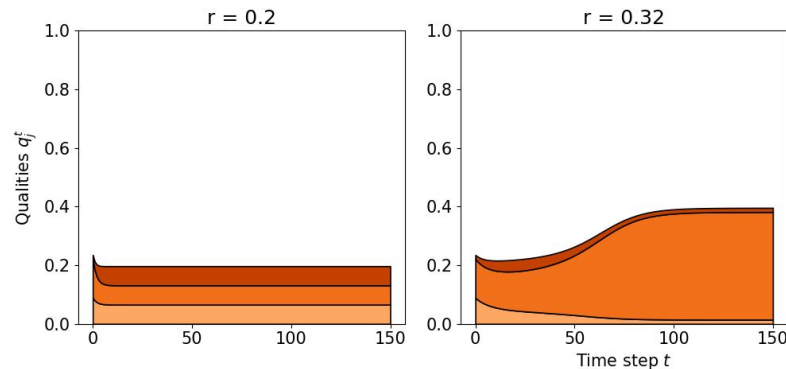


$$c'_j(q_j) = s_j^t : \text{Exposure - prob. of item } j \\ \text{being shown at time } t$$

“Best response” by creators

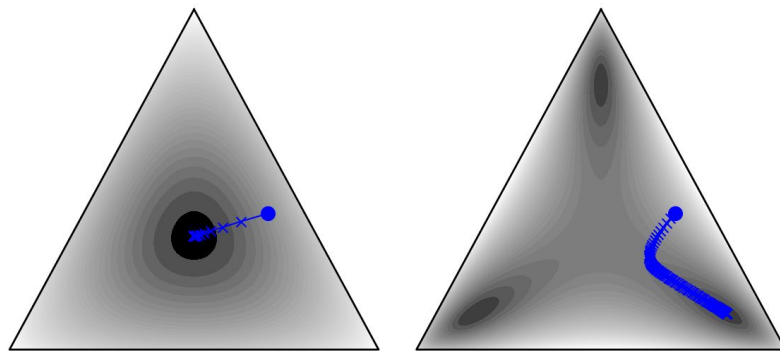
Larger r

- stronger feedback from market share.
- Can stimulate creators to improve quality and hence be more competitive.
- Subject to randomness in initial q



Initialisation: $s^0 = [0.4, 0.5, 0.1]$

Potential function



Initialisation: $s^0 = [0.4, 0.5, 0.1]$

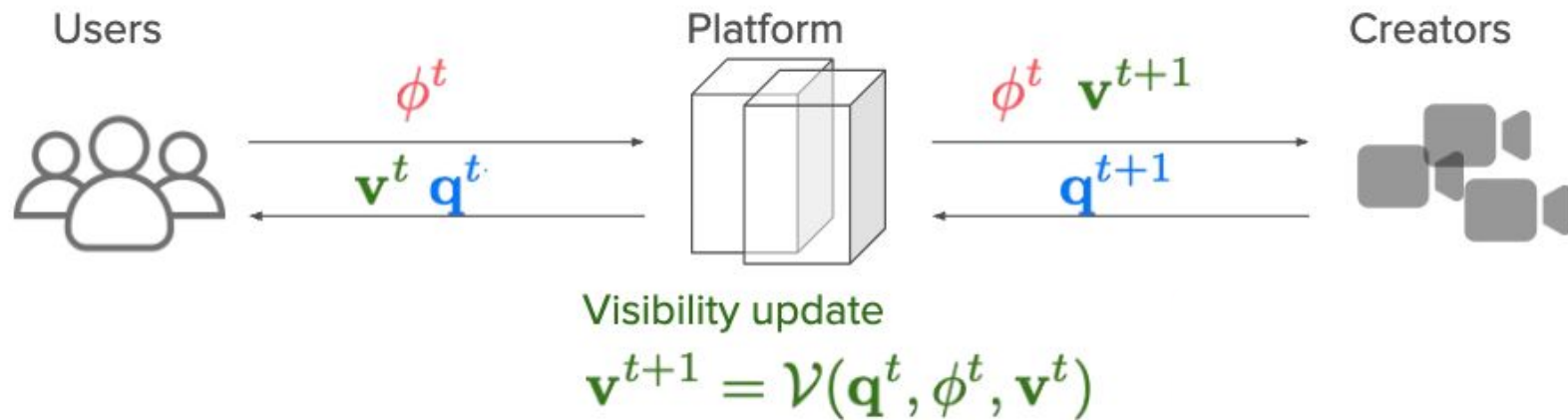
$$\max \sum_j \left(\underbrace{s_j \log v_j}_{\text{Alignment between exposure and recsys}} + \underbrace{(r-1)s_j \log s_j}_{\text{Entropy}} + r \underbrace{\int_0^{s_j} \log(c'_j)^{-1}(z) dz}_{\text{Production cost}} \right)$$

Alignment between
exposure and recsys

Entropy

Production cost

What can the platform do?



Mixed recommendation: to balance among quality q , popularity ϕ , signal from any other data μ

$$\frac{\mu_j (q_j^t)^\alpha (\phi_j^t)^r}{\sum_i \mu_i (q_i^t)^\alpha (\phi_i^t)^r}$$

r : market signal strength
 α : quality signal strength

Potential functions – generalised

Mixed recommendation strategy - a, b , are constants defined by α, r and learning rate.

$$\max \sum_j \left(s_j \log v_j + (b) s_j \log s_j + a \int_0^{s_j} \log(c'_j)^{-1}(z) dz \right)$$

Constant recommendation

$$\max \sum_j \left(s_j \log v_j + (r - 1) s_j \log s_j + r \int_0^{s_j} \log(c'_j)^{-1}(z) dz \right)$$

Alignment between
exposure and recsys

Entropy

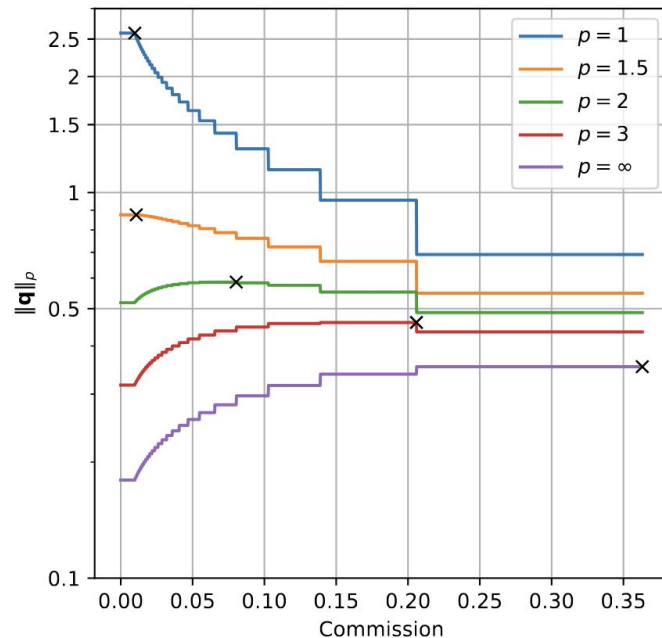
Production cost

Entry fees vs quality

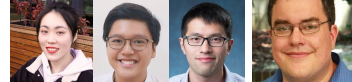
Can one discourage or prevent production of low-quality content?

- “Structural” ... existing participants prevents new participants with worse cost functions from entering
- Strategic: Platform charge a commission and redistribute the income to creators

Different reward strategies for two-sided markets is worth further investigation.



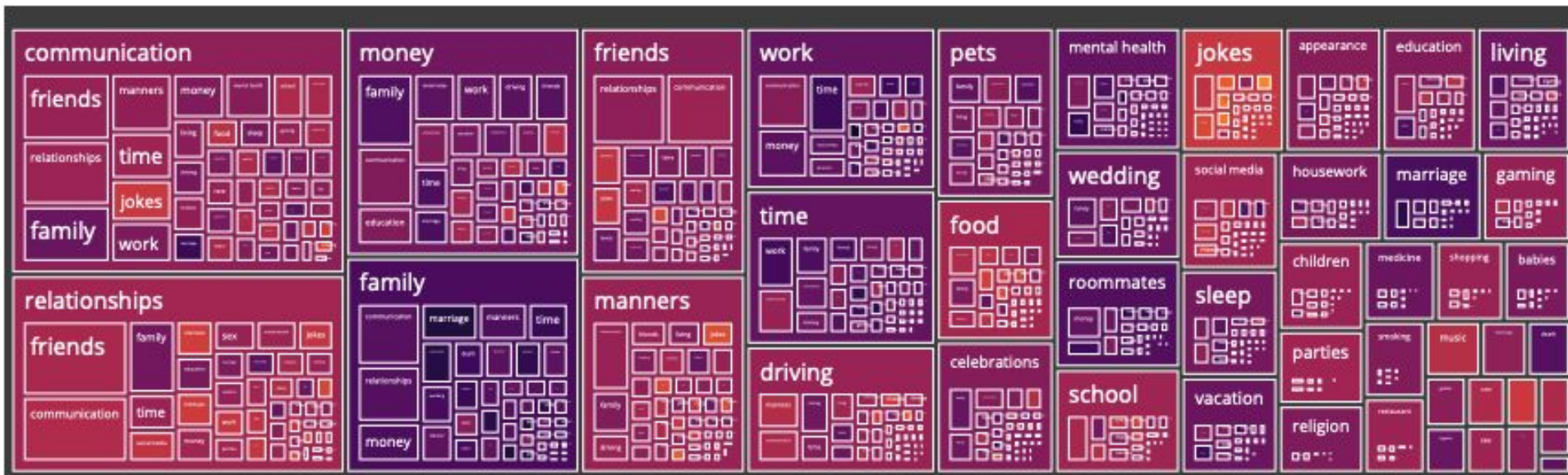
Q: What can we say about other people's work on creator incentives? In fact, we should have a related work slide, what should it say?



[Nguyen, Chen et al,
ICWSM 2022, 2024, in
submission]]

Aside 1 of 3 - Mapping 100,000 real-life moral dilemmas

- /r/AmlTheAsshoe - what moral issues do people grapple with?
- 47 topics found, people perceive them in pairs
- Empirical philosophy meets moral psychology - judgements are malleable
- NLP method: prompting right is the key to labeling moral+value relevance



Aside 2 of 3 - What is an influence flower?

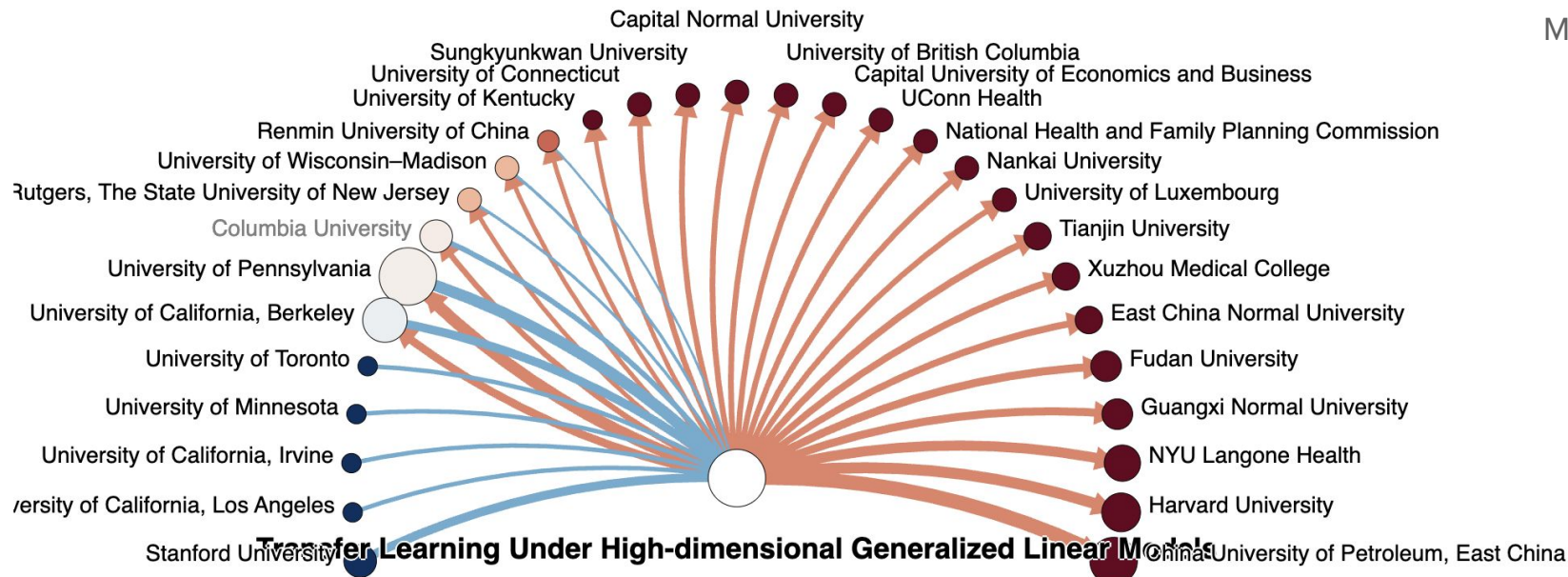
See arxiv.org/2105.14328

[this flower](#)

A qualitative visualisation and webapp to profile the incoming and outgoing intellectual influence among academic entities.

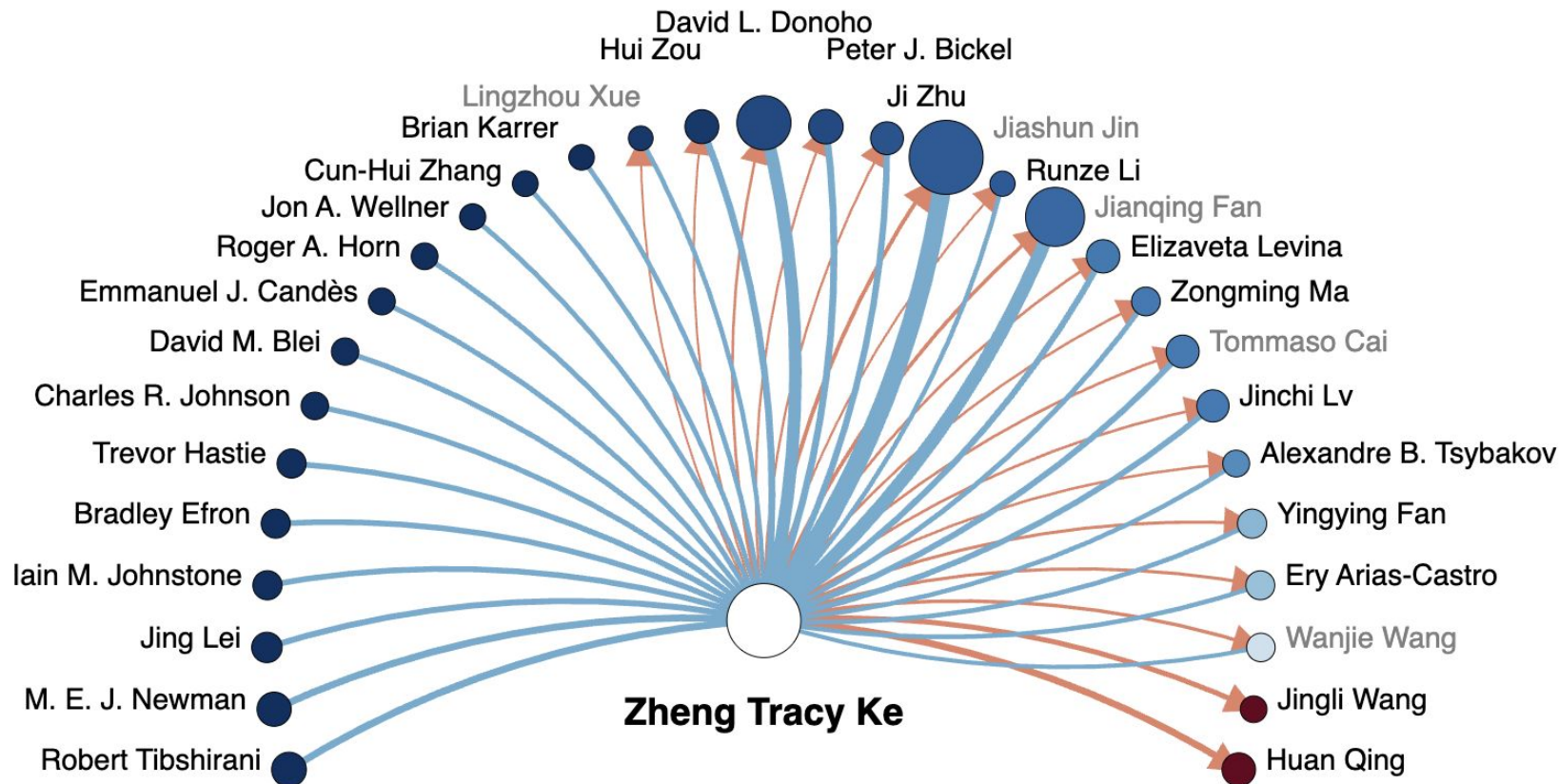


Minjeong Shin

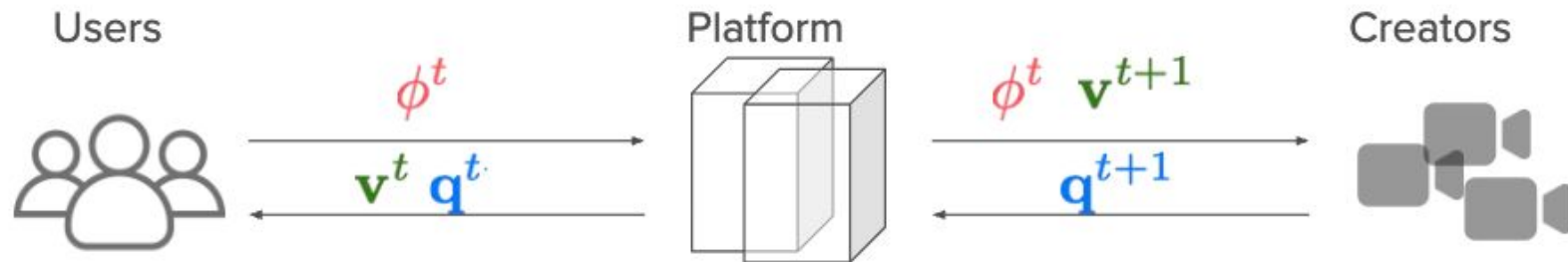


Blue arcs denote *incoming* influence from the authors to the paper, with their thickness proportional to the number of *references* made.
Red arcs denote *outgoing* influence from the paper to the authors, with their thickness proportional to the number of *citations* received.

Aside 2 of 3 - Influence Flower for Academic Entities



Summary and outlook



- Distributed interactions among Users, creators, platform is a market with positive feedback loop
- We uncover a series of underlying potential functions
- Natural interaction dynamics correspond to mirror descent on this landscape
- Structural and strategic barriers can incentivize creators

Ongoing work: fairness of the attention ecosystem, attention market in science

