Content Promotion for Online Content Platforms with the Diffusion Effect

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1. Introduction

Content promotion is prominent in online content platforms, such as Facebook, Instagram, and TikTok. Because of the **abundant volume**, users rely heavily on the external sources for what to consume.

User consumption behavior

- Platform promotion
- Friends sharing (usually ignored)

“Users may receive the same content piece both via platform promotion and friend sharing.”

We study the **diffusion-based promotion strategy**.

2. Diffusion Model

Bass diffusion model

√ Natural diffusion process.
× Platform cannot affect the process.

$$\boxed{a_t} = \boxed{p}\,(\boxed{m} - A_{t-1}) + \boxed{\tfrac{q}{m}}\,A_{t-1}\,(m - \boxed{A_{t-1}})$$

Innovative coefficient (p); Imitative coefficient ($\frac{q}{m}$); New adopters (a_t); Market size (m); Cumulative adopters (A_{t-1})

Promotion Bass diffusion model

√ Platform can control the process by choosing promotion decisions.

Promotion fraction $x_t \le 1 - \frac{A_{t-1}}{m}$ cannot exceed the remaining unadopted fraction

$$a_t = pm\boxed{x_t} + \frac{q}{m}A_{t-1}(m - A_{t-1})$$

Promotion effect | Diffusion effect

3. Promotion Optimization

Maximize total adoptions for L periods within promotion constraints

$$\max_{U\subseteq\mathcal{V}:|U|\le K}\ \max_{\boldsymbol{x},\boldsymbol{A}}\ \sum_{v\in\mathcal{V}} A_{v,L}$$

$$\text{s.t. } A_{v,t} = A_{v,t-1} + p_v m x_{v,t} + \frac{q}{m}A_{v,t-1}(m - A_{v,t-1}),\ \forall v,t$$

$$x_{v,t} \le \left(1 - \frac{A_{v,t}}{m}\right)\mathbb{1}\{v\in U\},\ \forall v,t$$

$$m\sum_{v\in U}\sum_{t=1}^{L} x_{v,t} \le C.$$

NP-hard

Nonconvex

Convex equivalence

Submodular objective

Accelerated Greedy Algorithm

- (1-1/e) approximation
- Polynomial runtime

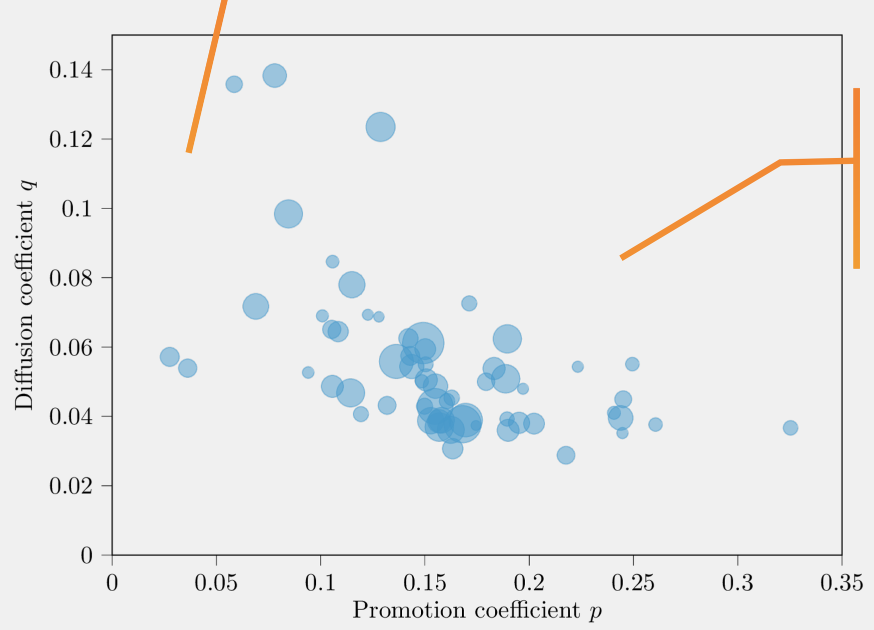
4. Experiments Results from a Large-scale Video Sharing Platform

One of the largest video-sharing platforms in China.
46,444 short videos;
518,646 users;
20 days (7/1-7/20/2020)

Heterogeneity among different categories

Negative correlation between p and q

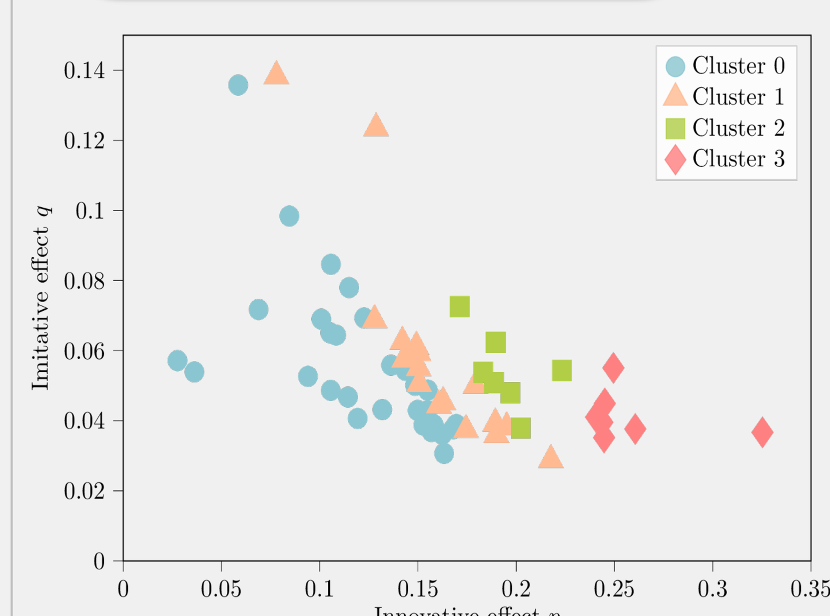
Complexity of the promotion optimization



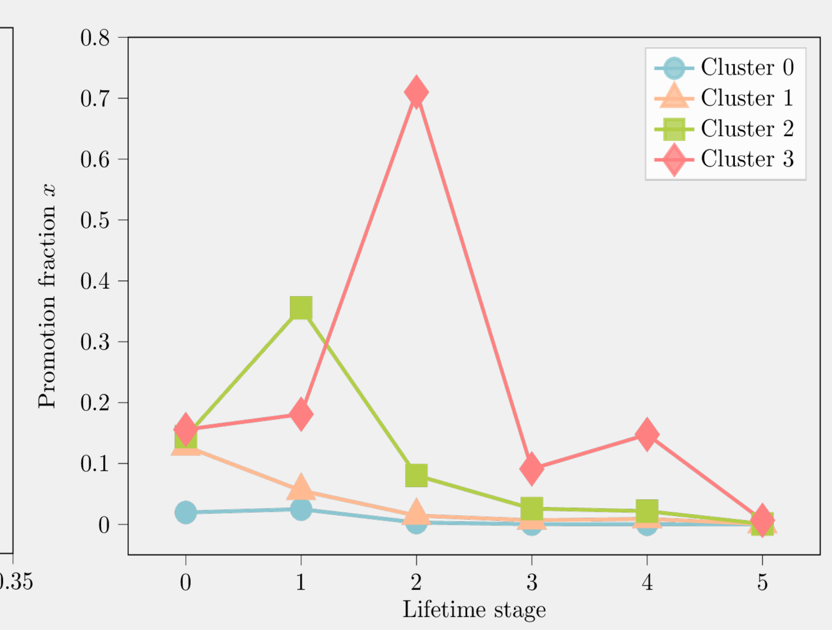
Distribution of p and q

Videos can be clustered into **4 groups** by their different promotion policies.

- **small p & large q**: receive promotion at the beginning.
- **small q & large p**: receive more promotion in later stages.

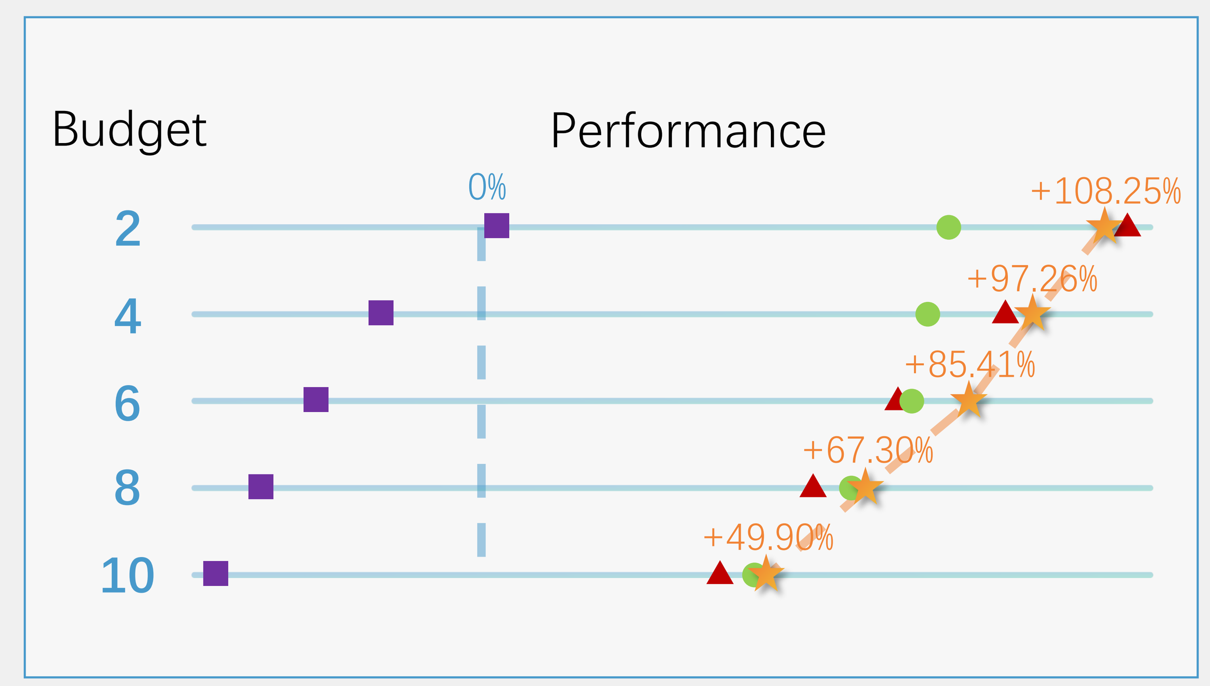


Video clusters



Average promotion policy

Performance of **Accelerated Greedy Algorithm** compared with benchmark policies mostly used in industry



Baseline NoD: ignore diffusion effect

- AGA: accelerated greedy algorithm
- ATT: select videos with the largest promotion potential
- TIM: select videos that are most recently added
- POT: select videos with the most new adopters

5. Conclusion

1. **The proposed model** well characterizes online content promotion procedure with the diffusion effect.
2. For a better **promotion policy**, content with a large diffusion effect should be promoted at the beginning while content with a large promotion effect can be continuously promoted.
3. **The proposed promotion policy** can achieve considerable improvement when compared with the benchmark policies currently used in the industry.