

A Business Model Analysis of Mobile Data Rewards

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I. Background

- Explain what are mobile data rewards.

Mobile Data Rewards

- Conventionally, users pay subscription fees to the network operators to gain mobile data.
 - e.g., Orange Mobile: €17/month for a 5GB monthly plan.
- Recently, some network operators offer mobile data rewards: users can complete certain tasks (e.g., watch ads, take surveys, and download apps) to earn free mobile data.

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Example of Ad-Sponsored Data Rewards

Steps to gain data rewards:



Download the
dedicated app
(e.g., watching ads)

Select tasks
(e.g., watching ads)

Watch ads to
accumulate "credits"

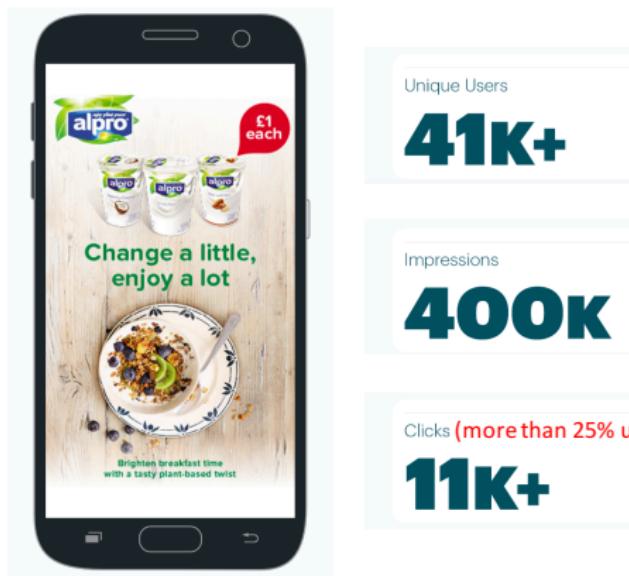
Gain mobile data from
operator based on "credits"

Example of Ad-Sponsored Data Rewards

Rewarding users for watching ads can improve ad effectiveness.

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Rewarding users for watching ads can improve ad effectiveness.



Effectiveness of *Alpro Yoghurt's* ad
(displayed on the app shown in the last slide)

Win-Win-Win Outcome

Data rewards lead to a win-win-win outcome for **network operators**, **users**, and **advertisers**.



Key Market Players



Operators implementing data rewards

Key Market Players



Operators implementing data rewards

Key Market Players



Operators implementing data rewards *Companies providing technical support
(e.g., connecting with advertisers)*

Background
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Problem Description
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Model
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Key Results
○○

Conclusion
○○

II. Problem Description

Problem Description

- Key Question: Who are eligible to receive data rewards?
 - Scheme 1: Only the data plan's subscribers.
 - Incentivize more subscriptions → more subscription revenue.

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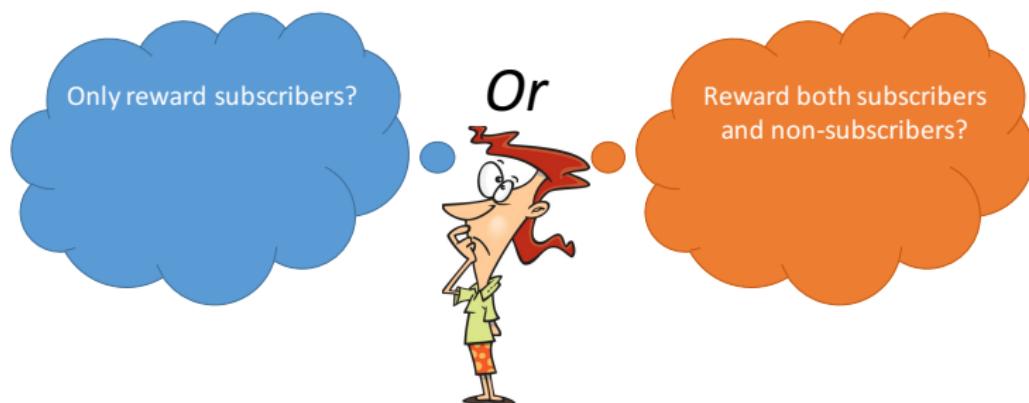
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Network Operator

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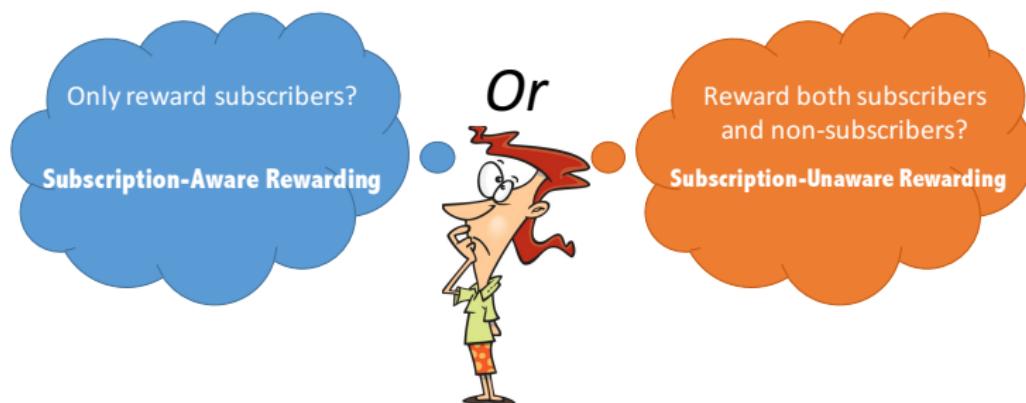
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 - Scheme 1: Only the data plan's subscribers.
 - Incentivize more subscriptions → more subscription revenue.
 - Scheme 2: Both subscribers and non-subscribers.
 - More people watch ads → more ad revenue.



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Network Operator

Related Work

- **Mobile data rewards:** [Bangera *et al.* 2017] and [Sen *et al.* 2017] conducted surveys and experiments to evaluate the effectiveness of rewarding users for watching ads.
 - Our work conducts the first [analytical analysis](#) of ecosystem.

III. Model

- Model the strategies and payoffs of the **users**, **advertisers**, and **network operator**.

Model: Heterogeneous Users

- We consider a continuum of users, with a total mass of N .
- Each user's type θ captures its valuation for mobile service.
 $\theta \in [0, \theta_{\max}]$ follows a general distribution with PDF $g(\cdot)$.
- Each user decides:
 - $r \in \{0, 1\}$: whether to subscribe to (monthly) data plan.
 - $x \geq 0$: total numbers of ads to watch per month.
- A type- θ user's payoff is

$$\Pi^{\text{user}}(\theta, r, x, \omega) = \theta u \underbrace{\left(\underbrace{Qr + \omega x}_{\text{total data}} \right)}_{\text{utility}} - \underbrace{Fr}_{\text{payment}} - \underbrace{\Phi x}_{\text{ads disutility}} .$$

- $u(\cdot)$: a general utility function, e.g., logarithmic function.

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Model: Heterogeneous Users

- We consider a continuum of users, with a total mass of N .
- Each user's type θ captures its valuation for wireless service.
 $\theta \in [0, \theta_{\max}]$ follows a **general** distribution with PDF $h(\cdot)$.
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- $Q > 0$: data amount associated with subscription.
- $F > 0$: data plan subscription fee.
- $\omega \geq 0$: amount of data rewarded for watching one ad (ω will be optimized by operator).
- $\Phi > 0$: disutility of watching one ad.

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Model: Homogeneous Advertisers

- We consider K advertisers, and each advertiser decides $m \geq 0$: the total number of ads displayed by the operator per month.
- An advertiser's payoff is

$$\Pi^{\text{ad}}(m, \omega, p) = \mathbb{E}_{\theta} \left[\underbrace{Bg(m, x^*(\theta, \omega)) - Ag(m, x^*(\theta, \omega))^2}_{\text{ads' effectiveness on a type-}\theta\text{ user}} \right] N - \underbrace{mp}_{\text{payment}} .$$

expected ads' effectiveness on all users

- Ad effectiveness on a user is quadratic in $g(m, x^*(\theta, \omega))$.
- $g(m, x^*(\theta, \omega))$: the number of **this advertiser's** ads seen by a type- θ user. It increases with both m and $x^*(\theta, \omega)$.
 - $g(m, x^*(\theta, \omega))$ can be computed under concrete ad displaying rules. Our work considers *random sampling w/o replacement*.
- B, A : parameters describing shape of the quadratic function.
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Model: Operator

- The operator decides
 - Unit data reward $\omega \geq 0$: the amount of data that a user receives for watching one ad.
 - Ad price $p > 0$: the price for displaying one ad.
- The operator solves the following problem:

$$\max_{\omega \geq 0, p > 0} \underbrace{NF \int_0^{\theta_{\max}} r^*(\theta, \omega) h(\theta) d\theta}_{\text{revenue from subscription}} + \underbrace{K m^*(\omega, p)p}_{\text{revenue from advertising}}$$
$$\text{s.t. } \underbrace{N \int_0^{\theta_{\max}} (Qr^*(\theta, \omega) + \omega x^*(\theta, \omega)) h(\theta) d\theta}_{\text{total data demand}} \leq \underbrace{C}_{\text{network capacity}},$$
$$\underbrace{K m^*(\omega, p)}_{\text{total number of displayed ads}} \leq \underbrace{N \mathbb{E}_\theta [x^*(\theta, \omega)]}_{\text{total number of ads users will watch}}.$$

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Two-Stage Game

Stage I

Operator decides unit data reward ω and ad price p .



Stage II

Users make subscription decisions r , ad watching decisions x .
Advertisers decide number of displayed ads m .

We compare two data rewarding schemes:

- Subscription-Aware Rewarding: $x > 0$ only if $r = 1$.
- Subscription-Unaware Rewarding: $x \geq 0$, regardless of r .

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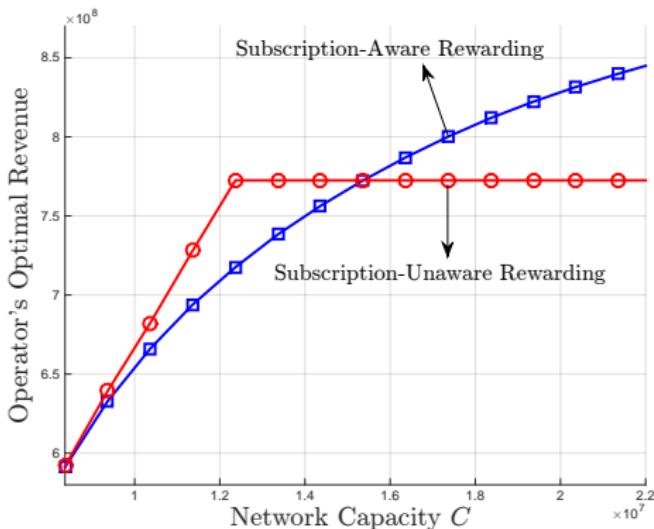
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IV. Key Results

- Comparison between two rewarding schemes.

Comparison Between SAR and SUR Schemes

When users have logarithmic utility $u(\cdot)$, we have



- **Observation:** When network capacity C exceeds a threshold, operator should only reward subscribers; otherwise, operator should reward both subscribers and non-subscribers.

Conclusion

- Conclusion: We study the data rewarding ecosystem, and analyze the operator's optimal choice of rewarding scheme.
- Future directions
 - Consider competition between operators;
 - Consider targeted advertising (increasing ad effectiveness and reducing users' disutility).

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Problem Description
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Model
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Key Results
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THANK YOU