A Unified Online-Offline Framework for Co-Branding Campaign Recommendations

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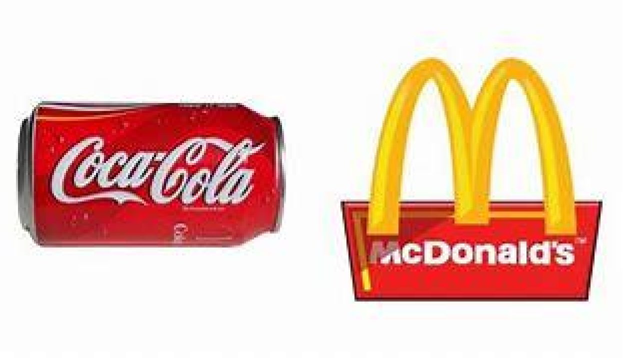
Introduction

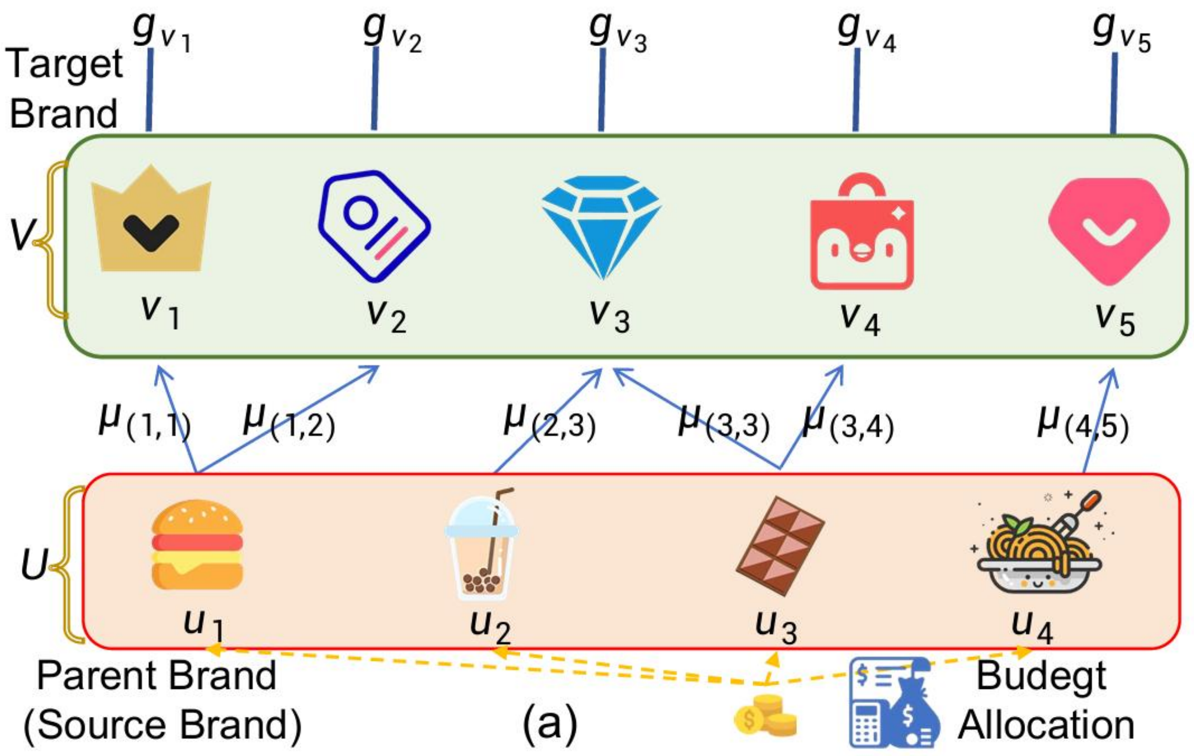
- Cobranding represents a powerful marketing strategy.
- Involve two brands collaborating to create a unique product or campaign.
- Enhance market reach, brand equity, and appeal to diverse demographics.
- Example:
  - Making luxury accessible (Versace + H&M),
  - Elevating premium design (BlackBerry + Porsche Design),
  - Or targeting niche lifestyles (Nike + Apple)
- Cobranding drives innovation and strengthens consumer connections.

Introduction



- **Partner Selection**: Mismatched collaborations can reduce profits or harm reputation.
- **Market Uncertainty**: Unpredictable factors like the **Matthew Effect**, consumer fatigue, and shifting preferences create risks.
- **Partner Willingness**: Target brands' participation is uncertain due to **brand positioning** and **financial commitment**.
- **Exploration Exploitation**: Balancing known partnerships with new ones is tricky, given **high costs** and **early risks**.
- **Budget Constraints**: Managing **multiple subbrands** requires holistic budget allocation for maximum **collective benefits**.

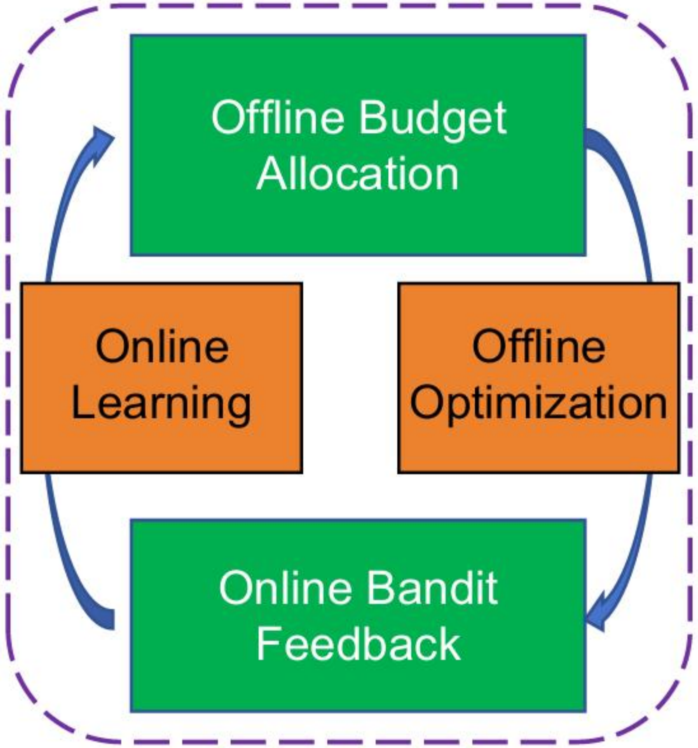
Model



CoBranding Bipartite Graph Model

- $\mathcal{G} = (\mathcal{U}, \mathcal{V}, \mathcal{E})$ models cobranding opportunities between a parent brand and potential partner brands.
- $\mathcal{U}$: Subbrands $|\mathcal{U}| = U$ from parent brand system.
- $\mathcal{V}$: Target partner brands $|\mathcal{V}| = V$.
- Edges $e := (u, v) \in \mathcal{E}$: Represent cobranding pairs.
- Weight vector $\boldsymbol{\mu} = \{\mu_e\}_{e \in \mathcal{E}}$: Probability of success, influenced by alignment and budget.
- Market gain vector $\boldsymbol{g} = \{g_v\}_{v \in \mathcal{V}}$: Revenue from target brand v to entire parent brand company $\mathcal{U}$.
- Visual: See Figure right *U=4, V=5*.

Problem Formulation



Unified Problem Formulation

- **α-approximate regret:**

$$Reg(T) = \alpha T \cdot r_{\mathcal{G}}(\boldsymbol{b}^*) - \mathbb{E}\left[\sum_{t=1}^{T} r_{\mathcal{G}}(\boldsymbol{b}_t^A)\right], \qquad (4)$$

- Objective: Minimize $Reg(T)$ for optimal longterm strategy.

Online Feedback Mechanism

- T round (co-branding season) online learning process.
- Budget allocation: $\boldsymbol{b}_t = (b_{t,1}, \ldots, b_{t,U})$ per season.
- Action: $S_t^{\boldsymbol{b}_t} \subseteq \mathcal{E}$ for cobranding pairings.
- Feedback: $X_{t,S_t} = (X_{t,1}, \ldots, X_{t,|S_t|}) \in [0,1]^{|S_t|}$ (success propensity) and $Y_{t,\mathcal{V}}$ (market gain) observed.
- Reward: $$R_{\mathcal{G}}(\boldsymbol{b}_t) = \sum_{v \in \mathcal{V}} \mathbb{I}\{\exists\, e = (u,v) \in S_t \text{ s.t. } X_{t,e,b_u} = 1\} Y_{t,v}, \qquad (1)$$
- Goal: Learn **probability of successful co-branding** and **brand market gain** to maximize cumulative reward.

Offline Strategic Budget Allocation

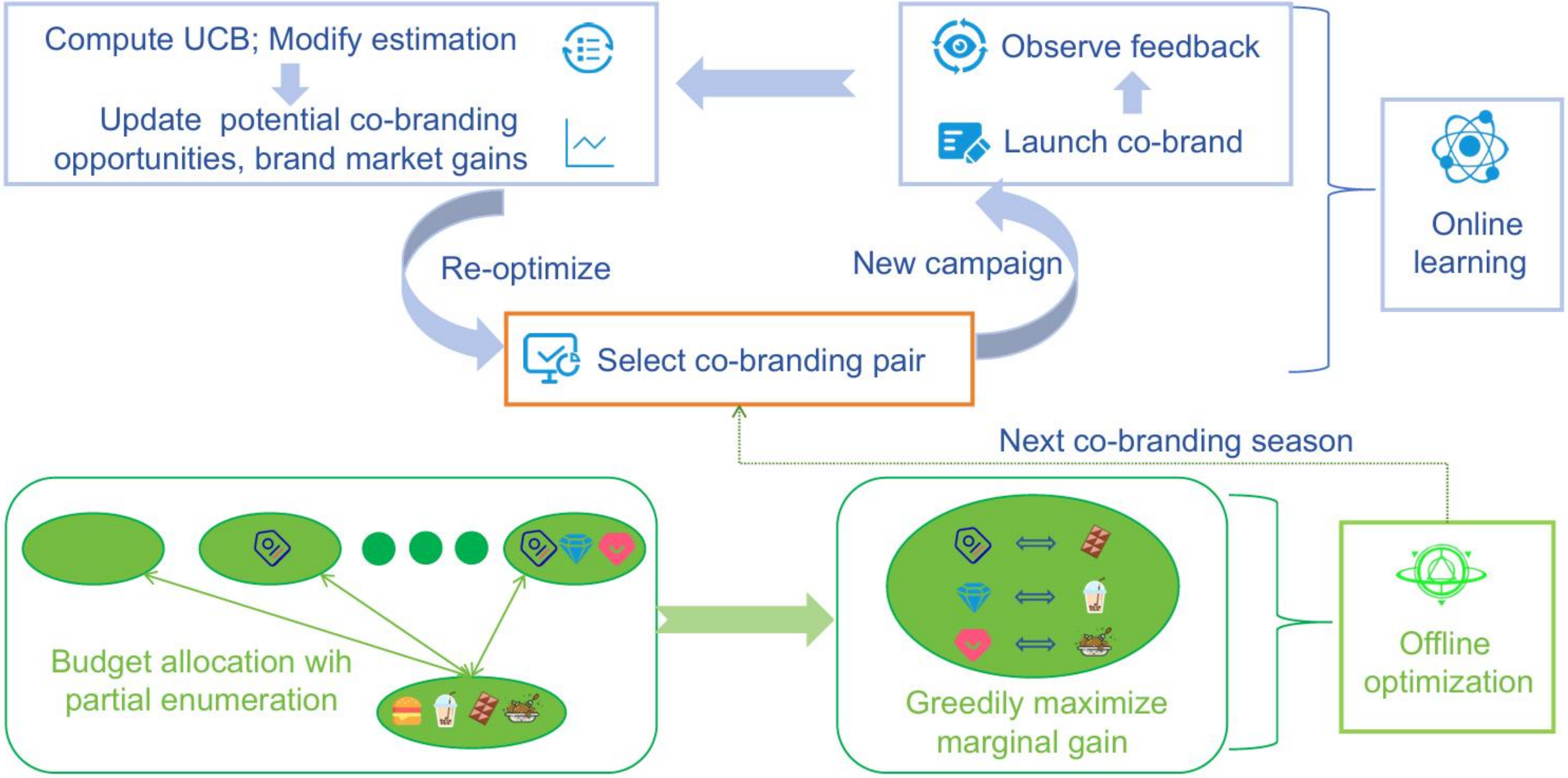
- Total budget B allocated as $\boldsymbol{b} = (b_1, \ldots, b_U)$.
- Constraints: Each subbrand is assigned a predetermined budget cap.
- Expected reward: $$r_{\mathcal{G}}(\boldsymbol{b}) = \sum_{v \in \mathcal{V}} g_v \left(1 - \prod_{e=(u,v) \in S} (1 - \mu_{e,b_u})\right). \qquad (2)$$
- Optimization: Maximize expected reward under constraints, **NP-hard**, solved via **α-approximation**.
- Goal: Prioritize highpotential subbrands within budget limits.

Algorithm

Algorithmic Workflow

Hybrid online-offline: Integrate online and offline processes for co-branding optimization.

① Estimate co-branding bipartite graph $\mathcal{G}$.
② Allocate budget to select optimal co-branding pairs.
③ Execute initial campaigns and collect market feedback.
④ Refine graph estimates with feedback.
⑤ Re-optimize for subsequent campaigns.



Overview: Combines dynamic learning with strategic planning for maximum market impact.

Algorithm

Graph Learning via Online Feedback

Exploration-Exploitation Trade-off:

✦ Co-branding bipartite information often partially or unknown.

✦ Naive best-partner selection risks local optima.

✦ Solution: Confidence-based Multi-Armed Bandit (MAB) strategy.

Enhancements:

✦ Bernstein-type bound tightens confidence radius using variance.

✦ Non-decreasing UCBs reflect realistic spending trends.

✦ Historical data initializes but excludes from radius for short-term focus.

Algorithm 1 Confidence-Based Online Learning for Co-Branding (CBOL)

Require: Set of co-branding initiators $\mathcal{U}$, set of target brands $\mathcal{V}$.

Initialize $T_{t,e,s}$, $\hat{\mu}_{e,s}$ for each $(e,s) \in \mathcal{A}$, and T'_v, $\hat{g}_v$ for each $v \in \mathcal{A}'$ using historical dataset $\mathcal{D}$.

for season $t = 0, 1, 2, ..., T$ **do**

  For $(e,s) \in \mathcal{A}$, $\rho_{e,s} \leftarrow Eq.\ (5)$, $\tilde{\mu}_{e,s} \leftarrow \hat{\mu}_{e,s} + \rho_{e,s}$, $\bar{\mu}_{e,s} \leftarrow \max_{j \in \mathcal{N}_u, j \le s} \tilde{\mu}_{e,j}$.

  For $v \in \mathcal{A}'$, $\rho'_v \leftarrow \sqrt{\frac{6\hat{V}_v \log t}{T_{t,v}}} + \frac{9 \log t}{T_{t,v}}$, $\hat{g}_v \leftarrow \hat{g}_v + \rho'_v$.

  Budget allocation $\boldsymbol{b} \leftarrow$ GPE (Algorithm 2).

  Observe co-branding intention feedback $\boldsymbol{X}_{t,S_t}$ under budget allocation $\boldsymbol{b}$.

  For each (e,s) that receives feedback $X_{e,s}$, update $T_{t,e,s} \leftarrow T_{t,e,s} + 1$, $\hat{\mu}_{e,s} \leftarrow \hat{\mu}_{e,s} + (X_{e,s} - \hat{\mu}_{e,s})/T_{t,e,s}$, $\hat{V}_{e,s} \leftarrow \frac{T_{t,e,s}-1}{T_{t,e,s}} \left(\hat{V}_{e,s} + \frac{1}{T_{t,e,s}} \left(\hat{\mu}_{e,s} - X_{t,e,s}\right)^2\right)$.

  For any successful co-branding pair $e \in S_t$ with $X_{t,e,s} = 1$, observe market gain $Y_{t,\mathcal{V}}$ and update $T'_{t,v} \leftarrow T'_{t,v} + 1$, $\hat{g}_v \leftarrow \hat{g}_v + (Y_v - \hat{g}_v)/T'_{t,v}$, $\hat{V}'_v \leftarrow \frac{T'_{t,v}-1}{T'_{t,v}} \left(\hat{V}'_v + \frac{1}{T'_{t,v}} \left(\hat{g}_v - Y_{t,v}\right)^2\right)$.

end for

Algorithm

Budget Optimization via Offline Planning

Submodular Property Basis:

✦ Reward exhibits **diminishing marginal returns**.

✦ **Total** marginal gain decreases as budget shifts to one sub-brand.

Refining Approximation Ratio:

✦ Improves on ***α*** with **partial enumeration**.

✦ Focuses on **quality over time complexity** due to high co-branding costs.

Integration with Online Learning:

✦ Use **learned bipartite graph** for campaign execution.

✦ Balance budget planning **across multiple partners** or proportionally.

✦ Feedback **updates estimates** for future seasons.

Algorithm 2 Greedy Partial Enumeration for Budget Optimization (GPE)

Require: Co-Branding graph $\mathcal{G}$, total budget B, budget cap c_u, tentative spending plans $\mathcal{N}_u, u \in \mathcal{U}$, operational constraint K.

Initialize $\boldsymbol{b}_{max} \leftarrow \boldsymbol{0}$.
$\mathcal{B} \leftarrow \{\boldsymbol{b} = (b_1, ..., b_U) | 0 \le b_u \le c_u, b_u \in \mathcal{N}_u, \sum_{u \in \mathcal{U}} b_u \le B, \sum_{u \in \mathcal{U}} \mathbb{I}\{b_u > 0\} \le K\}$.
for $\boldsymbol{b} \in \mathcal{B}$ **do**
  $B' \leftarrow B - \sum_{u \in \mathcal{U}} b_u$.
  Let $Q \leftarrow \{(u, s_u) \mid u \in \mathcal{U}, s_u \in \mathcal{N}_u, 1 \le s_u \le c_u - b_u\}$.
  while $B' > 0$ and $Q \neq \emptyset$ **do**
    $(u^*, s^*) \leftarrow \arg\max_{(u,s) \in Q} \delta(u, s, \boldsymbol{b})/s$.
    if $s^* \le B'$ **then**
      $s_{u^*} \leftarrow s_{u^*} + s^*$, $B' \leftarrow B' - s^*$.
      Adjust all pairs $(u^*, s) \in Q$ to $(u^*, s - s^*)$.
      Remove all pairs $(u^*, s) \in Q$ such that $s \le 0$.
    else
      Remove (u^*, s^*) from Q.
    end if
  end while
  if $r_{\mathcal{G}}(\boldsymbol{b}) > r_{\mathcal{G}}(\boldsymbol{b}_{max})$, **then** $\boldsymbol{b}_{max} \leftarrow \boldsymbol{b}$.
end for

Theoretical Analysis

Online Learning

- **Regret Bound (Theorem 1):** Algorithm 1 achieves $O(V\sqrt{(NU+1)T\log T} + \log(UVT + VT)\log \mathrm{T})$ sub-linear regret.
- **Remark 1:**

✦ Expand base arms from $\mathcal{A}$ to $\mathcal{A} \bigcup \mathcal{A}'$ for unknown market gains.

✦ Redefine the definition of the set of triggered armsin previous works, improving the leading term by $O((U+1)/(NU+1))$.

✦ Use historical data average to bound regret with a constant.

Offline Optimization

- **Approximation (Theorem 2):** Algorithm 2 achieves $(1-1/e)$-approximate solution (i.e., $\alpha = 1-1/e$).

- **Remark 2:**

✦ Combines partial enumeration and greedy methods.

✦ Best polynomial-time solution unless P=NP.

✦ Time complexity: $O(BN^2UV^2)$ of any partial enumeration, scales linearly with U, quadratically with V.

✦ Practical efficiency with finite allocation plans (e.g., 3 tiers: low, medium, high).

✦ K=3 balance time and performance.

Experiment

Research Questions

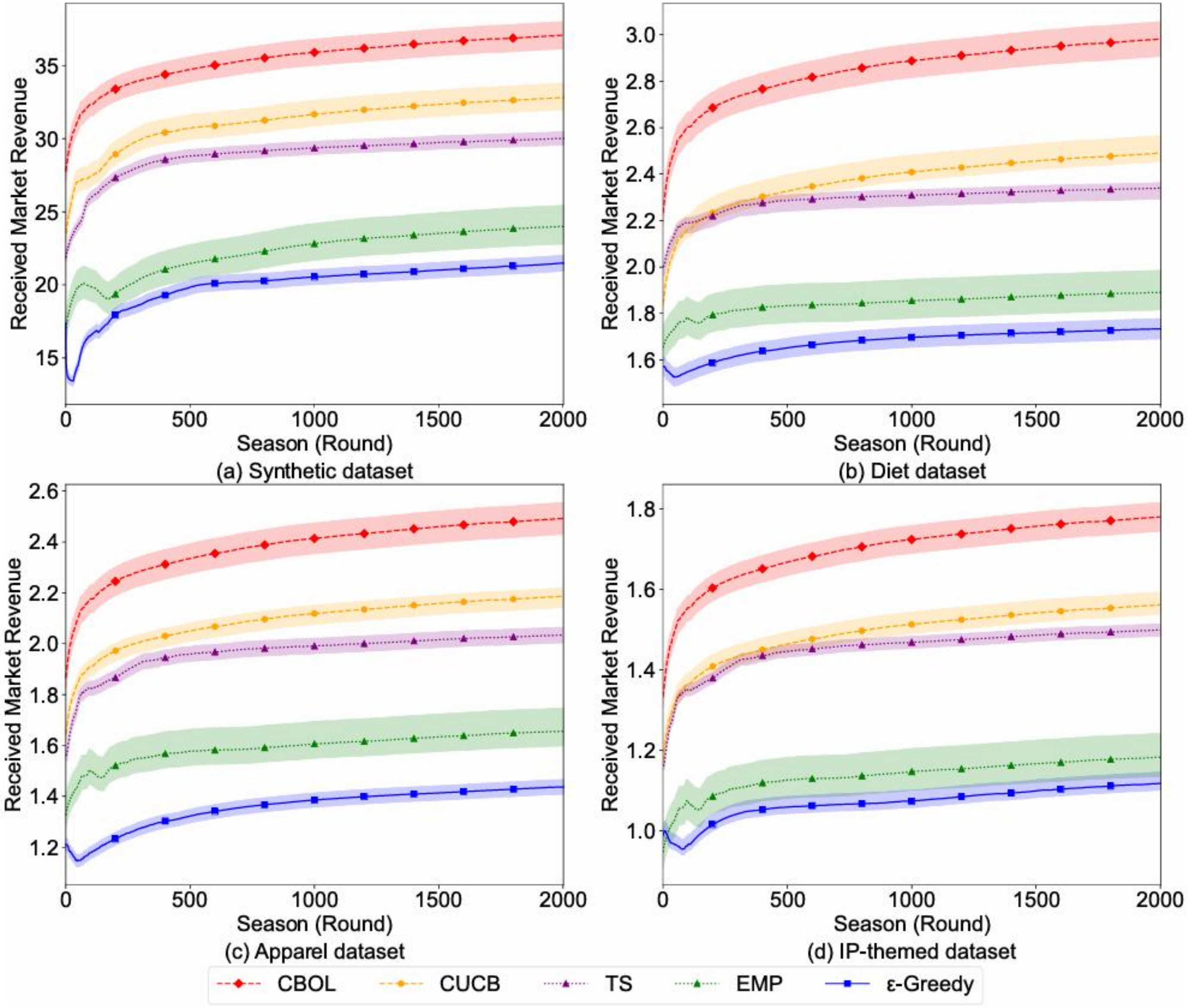
- **RQ1:** Can online learning algorithm outperform in high-uncertainty co-branding for shortand long-term revenue?
- **RQ2:** Does offline budget strategy enhance revenue across multiple sub-brands?
- **RQ3:** Is framework stable across varying budgets, seasons, and plans?

Real-world Datasets.

- 3,500 cases from SocialBeta and dataworld:
- Datasets: Diet (269 U, 608V, Apparel (192 U, 471 V, IP-themed (161 U, 405 V).

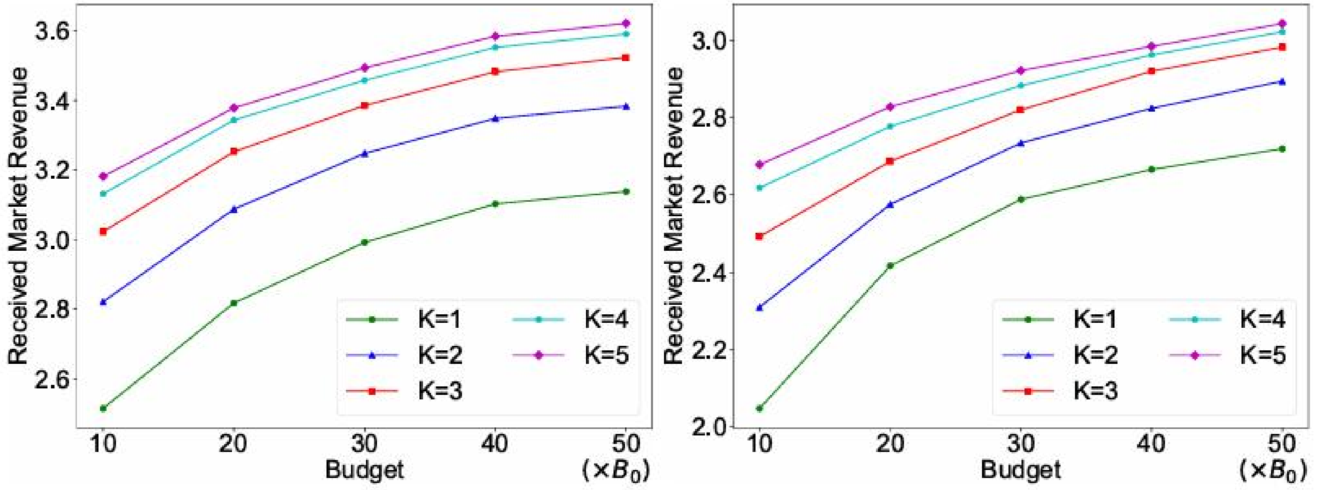
Evaluation Results

➢ **Co-branding Online Performance (RQ1):** Outperforms baselines by 12%-73%, fastest convergence on market revenue.

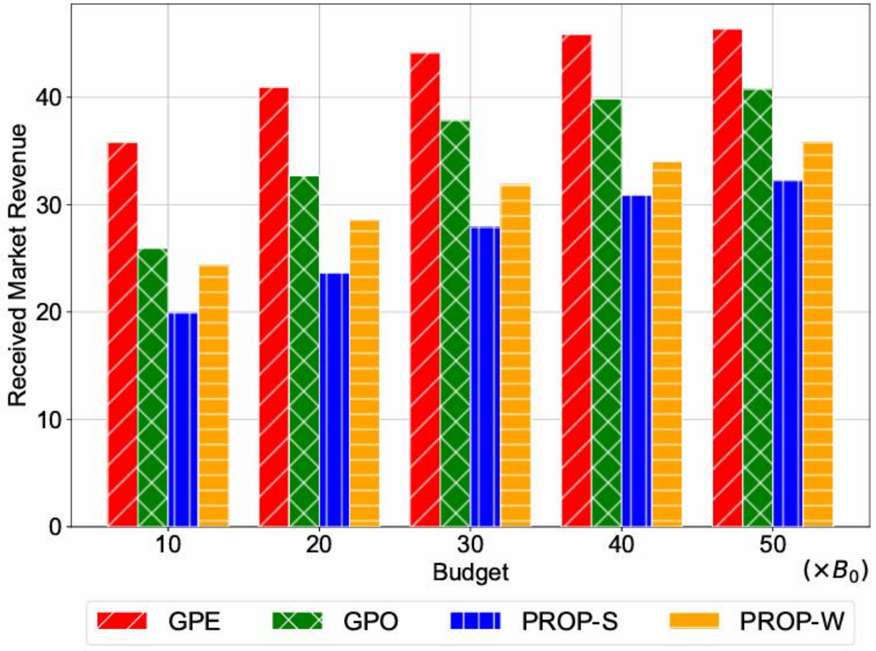


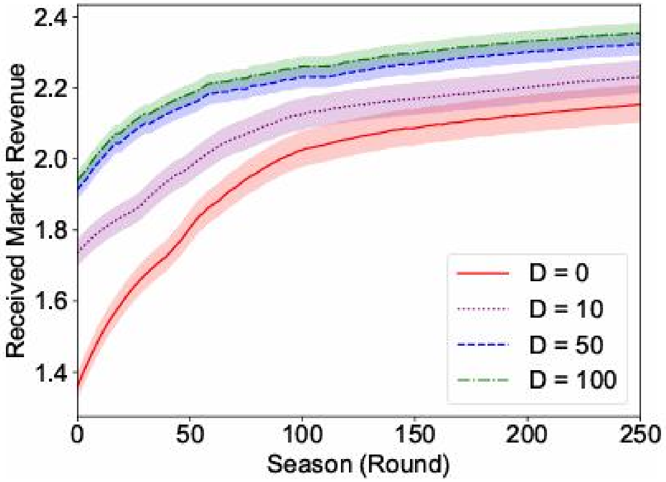
Experiment

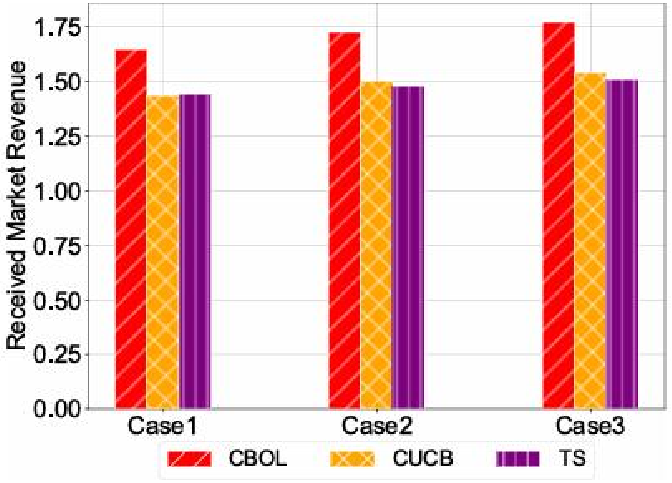
- **Offline Budget Allocation (RQ2):** Improve revenue from holistic parent brand perspective.
- **Performance-Cost Tradeoff (RQ2 & RQ3):** Revenue rises with K=1 to 3, marginal beyond 4; Running time: K=4,5 significantly increase.
- **Impact of Historical Dataset (RQ1):** Boost early performance, mitigate uncessary exploration loss.
- **Ablation Study (RQ3):** Consistently best.



Value of K	1	2	3	4	5
Average running time (s)	0.1304	0.3214	0.8921	1.9052	3.5116
Average reward	2.9126	3.1772	3.3329	3.4148	3.4515
Increase of running time	0	146.1%	584.0%	1361.6%	2592.7%







Thank You :)