SAMSUNG Ads

Programmatic optimization of ad pods for maximizing consumer engagement and revenue

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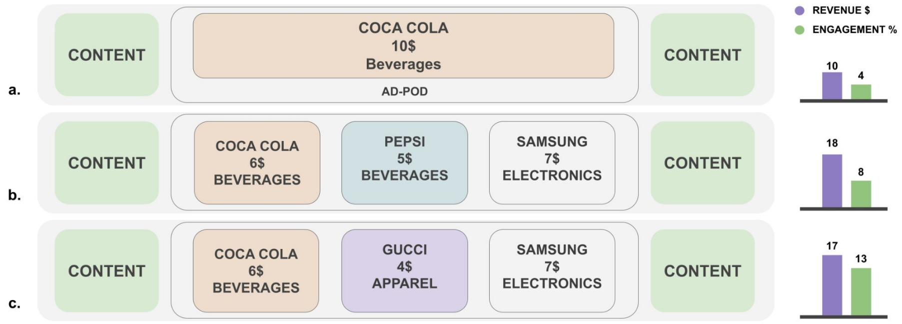
Samsung Ads

- We are the fourth largest advertiser in the world.
- Samsung Ads can reach over 200 million devices across Smart TV, connected TV devices and cross-media solutions.
- There are 30 million Samsung Smart TVs registered in the US, and 73 million globally.
- 75% of audiences in the Samsung Smart TV ecosystem are watching some form of linear TV.

https://www.samsung.com/us/business/samsungads/resources/numbers-you-need-to-know/

Introduction to ad pods in Connected TVs

- Podding is similar to linear ads on TV
- Inserted dynamically into video content on CTV
- Bundling ads together reduces consumer fatigue because of littered ads
- Also increases revenue by increasing impression opportunities
- **Higher revenue can be obtained with some pods with costs in brand conflicts and fatigue**
- **Optimal pods balance consumer engagement and revenue**



Disclaimer: Brand names (unless owned by Samsung) have no affiliation with this work and are used only for representational purposes

Ad-podding RTB auction

- Real-Time Bidding process:
  - Device requests for bid on ad slot
  - Exchange (or SSP) requests bids with device/user info
  - Advertisers (DSPs) submit bids with category and domain information
  - Bids are evaluated and top bidder(s) get to display ads
  - All allocated ads are collated into pods and inserted into video
  - Selection of ads for podding is as per business objectives, formulated as constraints
  - **This is a Multi-Objective Knapsack problem**

$$max \sum_{i=1}^{K} p_i x_i, \; s.t. \sum_{i=1}^{K} d_i x_i \leq D$$

$$where, \; x_i = \begin{cases} 0, if \; b_i \notin S \\ 1, if \; b_i \in S \end{cases}$$

$$\forall b_p, b_q \in S, \; C_p \cap C_q = \phi \; or \; A_p \cap A_q = \phi$$

- a_i : identifier of the linear ad
- p_i : cost to display a_i or it's bidding price.
- d_i : duration of a_i.
- C_i : set of IAB categories of a_i.
- A_i : set of ad domains of a_i.

Possible constraints on pod selection

- **Maximizing sum of bid cpms of constituent ads (revenue maximization)**
- **Low similarity between IAB categories of constituent ads to minimize conflicts**
- **Low similarity between ad domains to minimize over-exposure**
- Capping ad frequency for constituent ads across pods
- Enforcing specific distribution of ads by duration/categories (e.g. shorter ads at end)
- Requests by DSPs to always display the entire pod with their ads or to not pod their ads at all

Approaches to solving MOK problem

Available Approaches

- Exact solutions
  - Dynamic programming
  - Backtracking
- Heuristics
  - ACO
  - Evolutionary
- Learning based solutions
  - Pointer networks
  - Reinforcement learning
- Tailored greedy approaches

Selected Approaches

- Evolutionary algorithms (heuristic)
- Backtracking (exact)
- Dynamic programming (exact)
- Greedy algorithm (heuristic)

Some works have combined multiple approaches to address their problems

Experimental setup

- Two datasets:
  - In-house: 7 days of auction logs with 15 extracted IAB categories, duration, bid value
  - YouTube ad dataset: Public domain dataset without bid information. Modelled with viewership. 5000 ads with metadata.
- Pods constructed from ads in datasets
  - Sampling in heuristics, ordered selection in exact and greedy
- Constraints on IAB categories and revenue (sum of bids in pods)
- Repetition of IAB category is (mild) engagement loss

- Evolutionary algorithms as heuristic approach
  - Linearly increasing generations with pod size
  - Very high penalty for exceeding capacity
  - Moderate-to-high penalty for similarity of constituent ads
- Dynamic programmatic and backtracking as exact solutions
  - Used as benchmarks for profit, engagement and computational complexity
- Our greedy solution

Greedy solution

- We have developed two heuristics for greedy sampling of slots
    - PDR - Price to duration ratio
    - PDRwP - Price to duration ratio with price prioritized
- PDR selects slot with optimum balance of price and duration
- PDRwP gives less preference to very long ads, further preventing fatigue
- PDRwP can be tuned to also remove very small ads

$$PDR_i = \frac{p_i}{d_i} \qquad PDRwP_i = p_i(1 + \frac{1}{d_i})$$

Algorithm 1: Greedy algorithm for solving ad-podding MOK

Result: Optimized ad-pod S and revenue P_{total}
Initialize selected categories (C_{sel}) as an empty set;
Alternatively, initialize selected ad domains (A_{sel}) as an empty set;
Initialize cumulative profit ($P_{total} \leftarrow 0$) and remaining duration ($D_{rem} \leftarrow D$);
sort B w.r.t. heuristic in descending order;
for $b_i \in B$ **do**
  if $D_{rem} - d_i \geq 0$ $and\, C_i \notin C_{sel}$ $and\, A_i \notin A_{sel}$ **then**
    $P_{total} \leftarrow P_{total} + p_i$;
    $D_{rem} \leftarrow D_{rem} - d_i$;
    $C_{sel} \leftarrow C_{sel} \cup C_i$;
    Alternatively, $A_{sel} \leftarrow A_{sel} \cup A_i$;
    $S \leftarrow S \cup b_i$;
  end
end

Estimating performance of algorithms

- Percentage deviation in profit - measure non-optimal profit
- If profit is non-optimal then so is engagement
- Similar to Mean-Absolute Percentage Error (MAPE)
- 1000 iterations for each approach
- EA is farthest from optimal, in spite of tuning, while DP is optimal
- Greedy approaches, in particular PDRwP, perform near-optimal
- Some solutions for PDRwP are non-optimal (rounding error)

$$Dev = \frac{1}{R}\sum_{t=1}^{R}\left(\frac{abs(\alpha_t - \beta_t)}{\beta_t} * 100\right)$$

- α_t is profit from the selected approach
- β_t is profit from optimal approaches
- R is indexing over calculations

In-house

Percentile	DP	EA	G-PDR	G-PDRwP
50^{th}	0.0	47.57	11.84	0.0
95^{th}	0.0	111.97	33.11	14.38
99^{th}	0.0	133.64	41.94	29.05

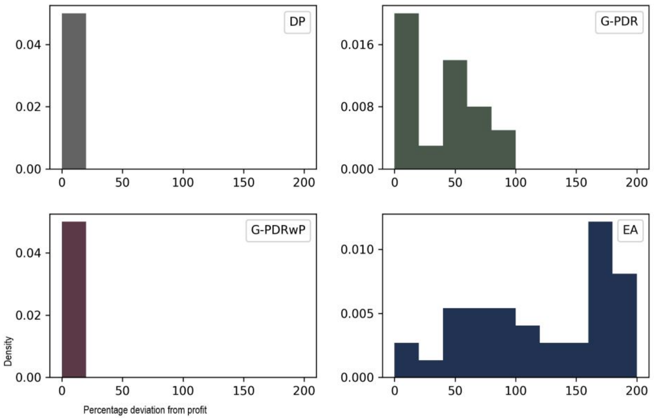
YouTube

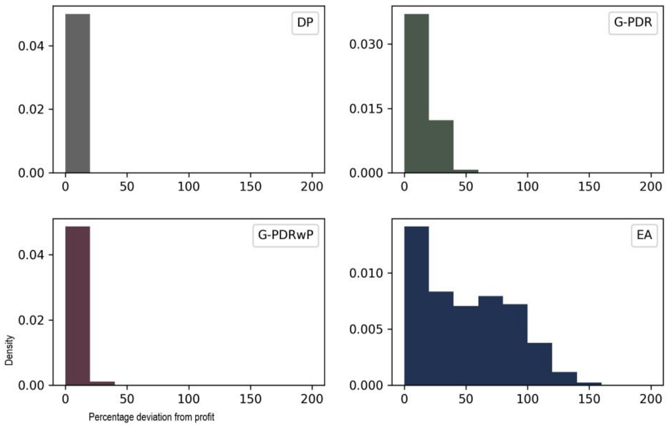
Percentile	DP	EA	G-PDR	G-PDRwP
50^{th}	0.0	152.73	15.26	0.0
95^{th}	0.0	294.80	79.95	0.0
99^{th}	0.0	405.45	87.62	0.0

Distribution of errors

- Density of percentage deviation will give a holistic overview of performance
- If spread away from 0 is high - poor performance
- Greedy approaches are near-optimal

In-house





YouTube

Computational complexity in RTB context

Bids in pod	Dataset	Backtracking	DP	EA	G-PDR	G-PDRwP
5	In-house	0.108 ± 0.0	0.256 ± 0.0	46.7 ± 0.235	0.019 ± 0.0	0.020 ± 0.0
	YT	0.143 ± 0.0	0.409 ± 0.001	48.2 ± 0.18	0.027 ± 0.0	0.028 ± 0.0
10	In-house	1.53 ± 0.004	0.914 ± 0.0	95.4 ± 0.512	0.045 ± 0.0	0.045 ± 0.0
	YT	1.05 ± 0.003	0.730 ± 0.003	98.8 ± 0.421	0.038 ± 0.0	0.038 ± 0.0
15	In-house	3.63 ± 0.013	1.17 ± 0.002	172 ± 0.308	0.055 ± 00	0.055 ± 0.0
	YT	9.35 ± 0.015	1.48 ± 0.038	140 ± 0.488	0.049 ± 0.0	0.051 ± 0.0
20	In-house	22.9 ± 0.061	2.13 ± 0.013	203 ± 0.786	0.067 ± 0.0	0.067 ± 0.0
	YT	23 ± 0.153	2.33 ± 0.01	195 ± 0.407	0.076 ± 0.0	0.074 ± 0.001
25	In-house	89 ± 0.290	2.12 ± 0.005	261 ± 2.17	0.083 ± 0.0	0.082 ± 0.0
	YT	86.2 ± 1.09	2.27 ± 0.046	248 ± 1.17	0.080 ± 0.0	0.081 ± 0.0
30	In-house	191 ± 1.11	3.54 ± 0.015	329 ± 1.74	0.104 ± 0.0	0.104 ± 0.0
	YT	126 ± 0.281	3.68 ± 0.032	305 ± 1.94	0.091 ± 0.0	0.093 ± 0.0
40	In-house	1000 ± 3.21	4.54 ± 0.011	462 ± 6.88	0.111 ± 0.0	0.123 ± 0.0
	YT	928 ± 4.07	4.95 ± 0.014	440 ± 4.45	0.113 ± 0.001	0.116 ± 0.0
50	In-house	3540 ± 18.1	5.96 ± 0.022	611 ± 1.05	0.125 ± 0.0	0.160 ± 0.0
	YT	3350 ± 11.8	8.3 ± 0.044	581 ± 4.34	0.155 ± 0.0	0.162 ± 0.001

Running times of the algorithms for varying pod sizes. Both in-house and YouTube dataset are listed. Time units are milliseconds.

Conclusions

- Optimal podded ads offer a balance between revenue and consumer engagement
- Optimizing ads pods can be modelled as a multi-objective knapsack problem
- Four families of algorithms can be used to solve MOKs - exact, heuristic, greedy and learning-based
- We have compared greedy, heuristic and exact approaches
- Greedy approaches are nearly as accurate as exact ones
- The efficiency of greedy approaches makes them ideal for RTB deployment

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Thank you!