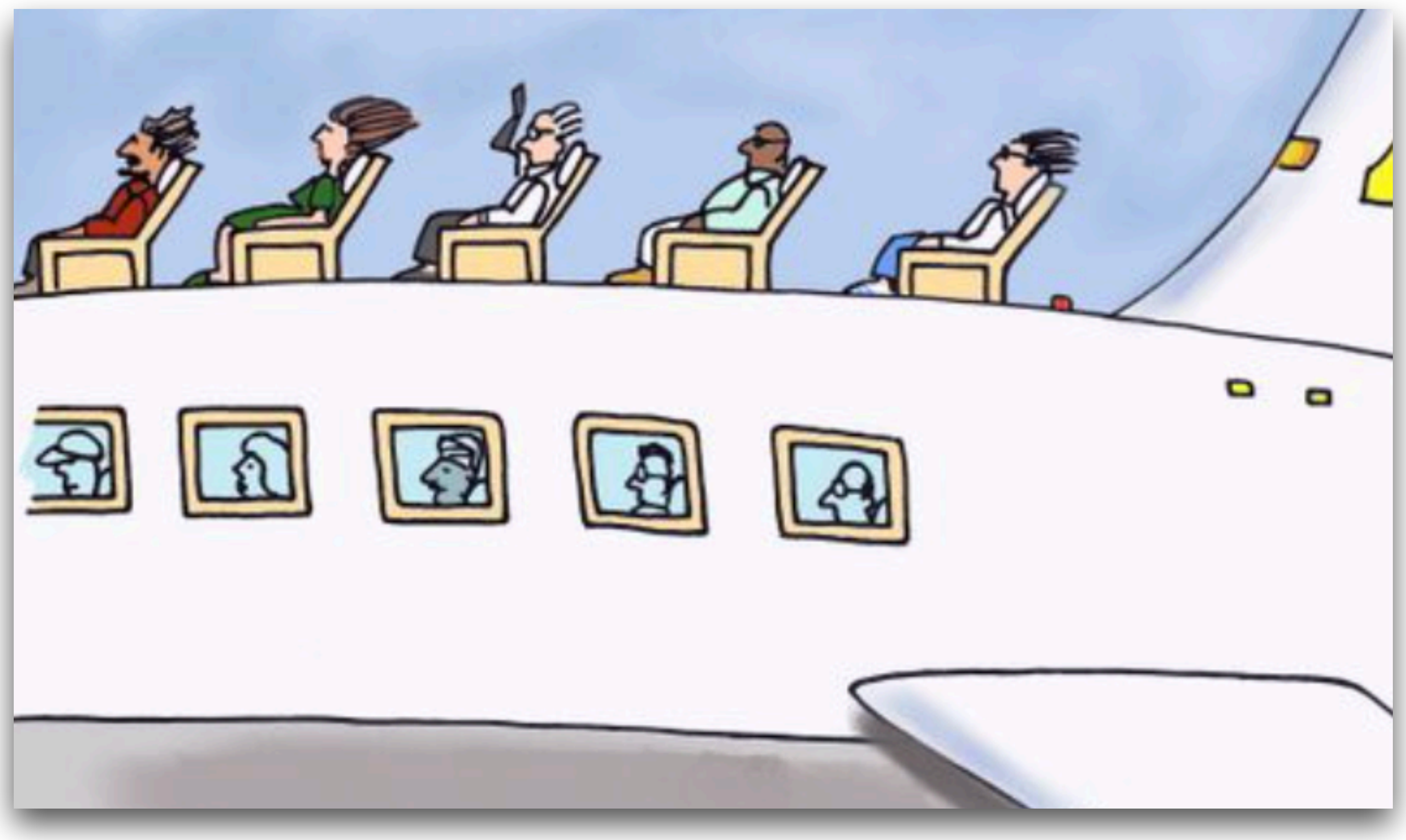

Adaptive Learning to Prevent Spiral-Down in Branded-Fare Revenue Management

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Airline Background

1 Branded Fare Structure

In full-service airlines, a **product** refers to a seat bundled with a specific set of ancillary services. To support brand differentiation and drive upselling, airlines typically offer multiple such products simultaneously, giving customers a choice among tiers of service that vary in price and benefits.

2 Price Ladder & Bid Price

Given the customer demand, ticket inventory, and the remaining selling time periods, the **bid price** is the minimum amount of money the company believes the next seat should earn. From K to Y, the price increases monotonically. The company consistently offers customers *the lowest price for each fare type* that exceeds the bid price.

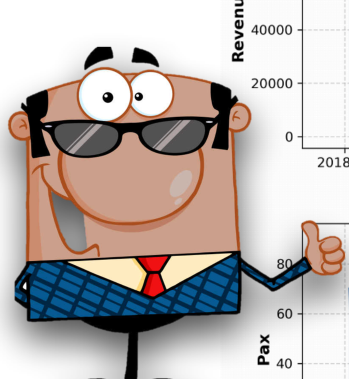
Lite		Value			Standard			Flexi	
K	V	N	Q	W	H	M	E	B	Y
100	150	200	250	300	350	400	450	500	550

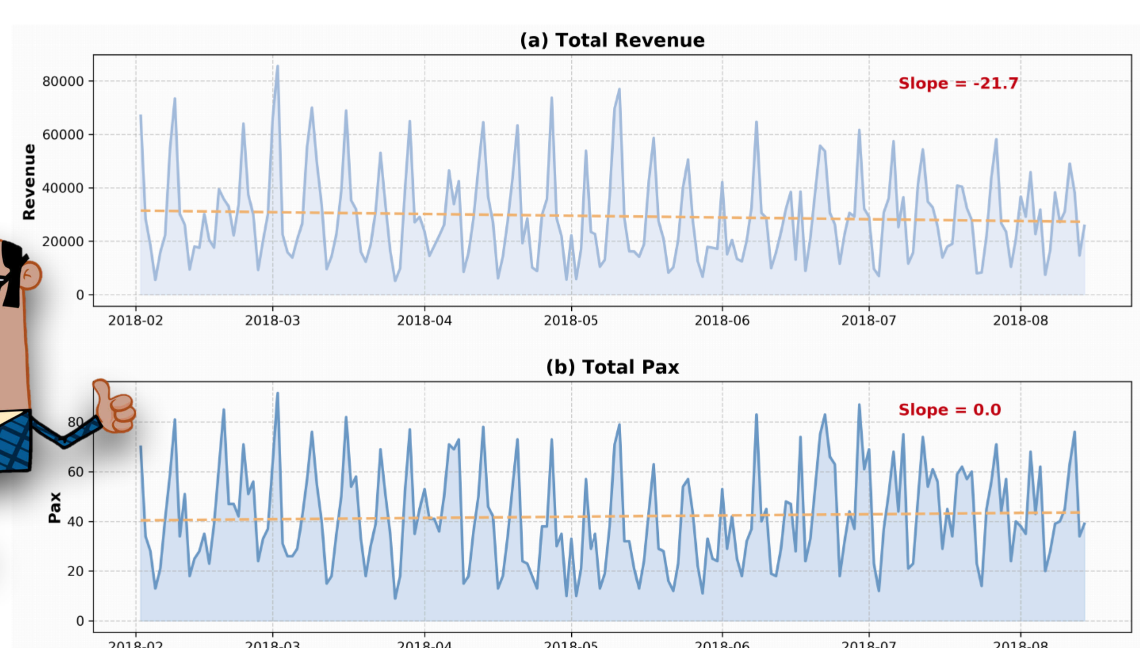
- Nested Structure
- Decreasing Purchase Probability

3 Company Task & Challenges

Challenge I. Customer Buy-down Behavior

Challenge II. Distribution Shift





***Company task**: Choose the optimal strategy at different time periods in the ticket-selling process.*

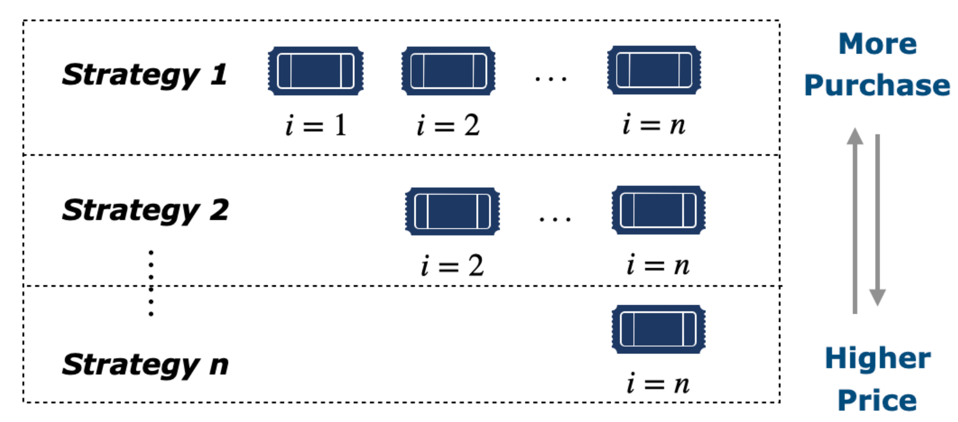
Model & *Methodology*

Product i

- Each product, denoted by $i \in \{1,2,\dots,n\}$, is assigned a price f_i. We have $f_1 \le f_2 \le \dots \le f_n$.
- B: the total number of available seats

Strategy j

- We have n strategies, labeled as $j = 1,2,\dots,n$
- Each strategy j is linked to a distinct assortment, F_j, where $F_j = \{i \mid i \ge j, i \in 1,2,\dots,n\}$.



Customer Demand

Customers have stable joint WTP distribution W(·) and arrival rate λ. Invariably, the customer selects the product that provides the highest nonnegative utility from the available options. At each time period, the DM will select a strategy and wait to see if a purchase happen.

Reshaping the Problem

Cannot Distinguish: Non-arrival / Non-purchase = Cannot Separately Estimate: λ / W_i

- Probability of ticket i purchase under strategy j

While applying a given strategy j at time period t, the probability of selling a type i ticket (where $i \in F_j$) is denoted as p_{ji}.

$$p_{ji} := \lambda Pr(w_i^t - f_i > 0, i = \arg\max_{i' \in F_j}\{w_{i'}^t - f_{i'}\})$$

(Fiig et al. 2010)

Adjusted Fare	$r_j := \sum_{i \in F_j} p_{ji} f_i$

It can also be considered as expected revenue per strategy.

The relaxed fluid LP (Exploitation Phase)

$$\max \sum_{j\in[n]} \Big(\sum_{i\in F_j} f_i \hat{p}_{ji}\Big) x_j \quad \cdots\cdots \text{Adjusted fare: } r_j$$

$$\text{s.t.} \sum_{j\in[n]} \Big(\sum_{i\in F_j} \hat{p}_{ji}\Big) x_j \le b, \quad \cdots\cdots \text{Budget constraint}$$

$$\sum_{j\in[n]} x_j \le t \quad \cdots\cdots \text{Time constraint}$$

$$\mathbf{x} \ge 0.$$

Decision Variable:

1. The number of times we plan to apply strategy j
2. A score indicating if the strategy should be applied at t

Estimate $\hat{P}^t$: Empirical purchase probability

Solve $P[B_t, \hat{P}^t, t]$: Retrieve x^t

Bayes Selector

Apply strategy j where $x_j^t = \max\{x_1^t, x_2^t, \dots, x_n^t\}$

THEOREM 1. ***(Customer Buy-down Setting without Known WTP)*** *Suppose that* $C \ge \frac{18}{\epsilon^2}$. *Then the expected regret of the Mixed-fare Bayes Selector with Learning (Algorithm 1) is upper bounded by* $\frac{(n+1)f_{max}}{\min\{\delta_p/(8n), \delta_r/(8f_{max}n)\}^2} logT + 4n^2 f_{max}$, *where* f_{max} *is the maximum fare.*

- Remark 1: The bound is determined by the time horizon T, the number of strategies n, the smallest gap in strategy purchase probability δ_p, and the smallest gap in strategy adjusted fare δ_r.
- Remark 2: With regard to the time horizon T, we obtain a regret level of logT, half of which arises from accurately ordering the estimated purchase probabilities for strategies, and the other half from locally optimizing the selected strategies.
- Remark 3: Although the derived bound becomes very large as the smallest strategy purchase probability gap or the smallest strategy adjusted fare gap approaches zero, in practice, we can avoid two very similar strategies.
- Remark 4: The same bound can be extended to known shape arrival curve and observable multiple customer groups.

Numerical Results and Use Case

We first consider a simple 2-product experiment with 3 customer types: 2 independent demand customer types and one buy-down customer.

Benchmarks

Algos	Our Algorithm (BSOL)	Bench-mark 1 (BLC)	Bench-mark 2 (BP)	Bench-mark 3 (AAA)	Benchmark 4. Fluid LP
Demand Model	Buy-down Model	Independent Demand Model	Independent Demand Model	Independent Demand Model	$\max \ (f_1\cdot(p_1+p_3))x_1 + (f_1\cdot p_1 + f_2\cdot(p_2+p_3))x_2$ s.t. $(p_1+p_3)x_1 + (p_1+p_2+p_3)x_2 \le B$, $x_1+x_2 \le T$, $x_j \ge 1, \ j=1,2.$
Control Policy	Bayes Selector	Booking Limit Control	Bid Price Control	Adaptive Allocation Control	
Algorithm Type	Resolving	Static	Dynamic	Resolving	
Learning or not	✓	✗	✗	✓	with known probability

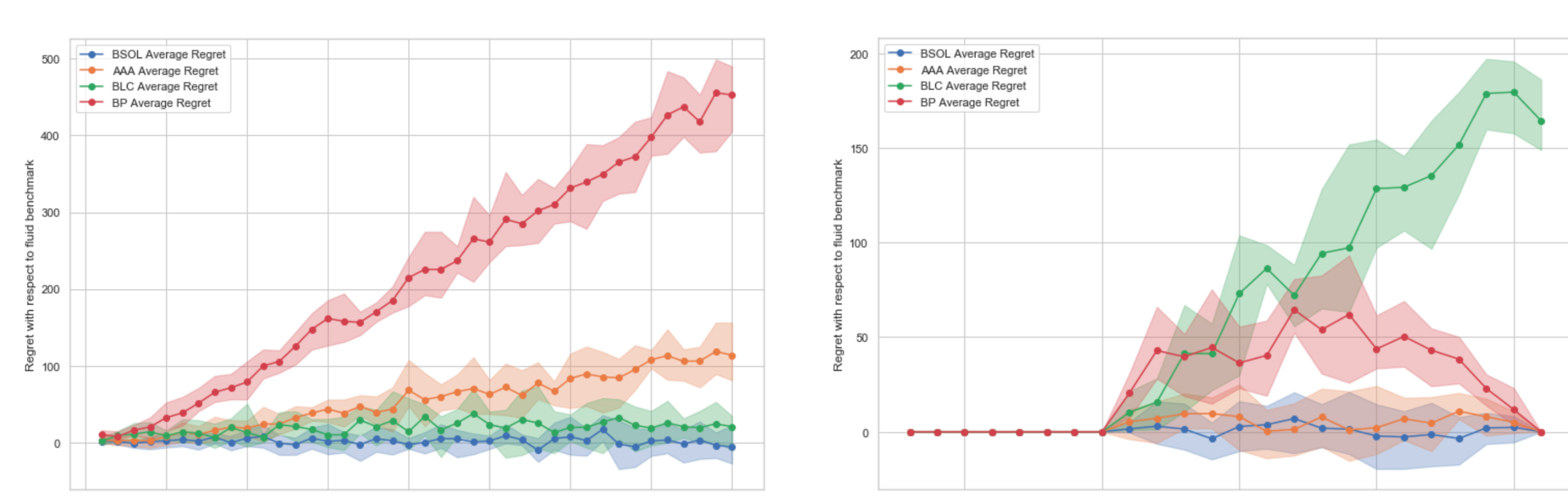


Figure 7 Comparison of regret between our algorithm (blue) and benchmarks (AAA, BLC, BP) across various time horizons (left) and different ticket allocations (right). The shaded areas represent the range between the 10th and 90th percentiles over 20 trials.