Revenue Management under Reviews and Online Ratings^I

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Revenue Management under Reviews and Online Ratings



- Customers are highly influenced by (negative) information
- (Negative) reviews influence customers purchasing products
- (Negative) price/quality perception influences customers writing reviews

Trade-off: Revenue vs Rating





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Goal: Maximize long-term revenue

• Optimizing revenue might lead to worse ratings and suboptimal revenue

Model

- Clients consider the hotel, depending on the reviews \mathcal{R} $(\lambda_i(\mathcal{R}))$
- Depending on the products S that are offered, clients make a purchase (P_j(R, S))
- A purchase leads to:
 - revenue r_j
 - positive review probability q_i^p
 - negative review probability q_i^n
- purchased products can be cancelled



Modelling demand and cancellations as a function of reviews

- $Q_i^p = \#$ positive reviews from day *i*
- $Q_i^n = \#$ negative reviews from day *i*
- $\alpha \in (0,1)$ discounting parameters
- M = # past arrival days
- Adjusted reviews:

$$\tilde{Q}_k^p := \sum_{i=k-M}^{k-1} \alpha^{k-i-1} Q_i^p, \qquad \tilde{Q}_k^n := \sum_{i=k-M}^{k-1} \alpha^{k-i-1} Q_i^n.$$

• Rating:

$$\rho := \frac{\tilde{Q}_k^p}{\tilde{Q}_k^p + \tilde{Q}_k^n}$$

• Demand and cancellation parameters:

$$\lambda_i(\mathcal{R}) := \bar{\lambda}_i \exp\left(\beta_p^{\lambda} \rho + \beta_n^{\lambda} (1-\rho)\right),\\ \gamma_i(\mathcal{R}) := \bar{\gamma}_i \exp\left(\beta_p^{\gamma} \rho + \beta_n^{\gamma} (1-\rho)\right).$$

Multiple arrival day example



- $R^i(S^1, \ldots, S^i)$ revenue from arrival day *i*
- $S^i = \{S_T, \dots, S_1\}$ strategy for arrival day i
- Objectives:

$$\phi^{\prime}(S) = \sum_{i=1}^{\ell} R^{i}(S^{1}, \dots, S^{i}),$$
$$\phi^{\infty}(S) = \sum_{i=1}^{\infty} a^{i-1} R^{i}(S^{1}, \dots, S^{i}).$$

Problem

- State space size: N¹
- Action space size: N^T
- Intractable due to curse of dimensionality

Solution: Equilibrium Solutions

- Keep expected rating constant, equal to a target rating ho^*
- Now Rⁱ depends solely on Sⁱ
- Each arrival day can be solved separately

One arrival day Bellman equation

$$V_{i,t}^{\pi}(x) = \sum_{S \subset N} \pi(x, t, S) \Biggl\{ \lambda \sum_{j \in S} P_j(S) [r_j^i - \Delta H_j^i(t) + V_{i,t-1}^{\pi}(x+1)] + \gamma x V_{i,t-1}^{\pi}(x-1) + \left(1 - \lambda \sum_{j \in S} P_j(S) - \gamma x \right) V_{i,t-1}^{\pi}(x) \Biggr\}.$$

Three objectives:

$$\mathbf{V}^{\pi} = (V_1^{\pi}, V_2^{\pi}, V_3^{\pi})$$

Scalarization:

$$V_{\mathbf{w}}^{\pi} = f(\mathbf{V}^{\pi}, \mathbf{w}) = w_1 V_1^{\pi} + w_2 V_2^{\pi} + w_3 V_3^{\pi}$$

Convex Coverage Set (CCS)

Every weight w has a corresponding optimal policy π and value function V^{π}



Finding equilibrium solution

- Policy $\pi \in \mathit{CCS}$ corresponds to value vector V^π
- Hyperplane where rating = ρ :

$$\mathcal{H} = \left\{ x \in \mathbb{R}^3 \left| \frac{x_2}{x_2 - x_3} = \rho \right\} = \left\{ x \in \mathbb{R}^3 \right| x_2(\rho - 1) - \rho x_3 = 0 \right\}.$$

Target-rating policy:

$$\pi(\rho) = \operatorname*{arg\,max}_{\pi \in \mathsf{CCS}} \left\{ V_1^{\pi} \left| \mathbf{V}^{\pi} \in \mathsf{CCS}' \cap \mathcal{H} \right. \right\}$$

• Optimal target-rating and corresponding policy:

$$\pi(
ho^*) = rg\max_{\pi(
ho)} V_1^{\pi(
ho)}$$

One instance: policy analysis

Revenue	Positive reviews	Negative reviews	Rating $ ho$
0	0	0	-
7493.76	33.01	3.75	0.90
12513.99	42.88	9.28	0.82
12595.63	41.42	6.30	0.87
14252.80	42.48	9.77	0.81
15137.33	41.09	7.57	0.84
16021.48	41.67	10.38	0.80
17983.01	40.40	11.16	0.78
18693.24	39.78	10.61	0.79
19985.47	38.61	9.99	0.79
21719.66	36.79	11.74	0.76
23528.79	33.55	12.81	0.72
24686.86	26.26	12.34	0.68
25194.50	29.93	13.87	0.68
26943.83	25.33	15.07	0.63
27098.09	21.11	15.62	0.57

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Observations

- By sacrificing revenue the rating can be increased
- Sacrificing revenue not always increases rating
- When revenue increases, positive reviews increase and negative reviews decrease
- However, increases are not strict due to the trade-off

Scenarios

- Large effects of demand and review probabilities
- 2 Large effect of demand, small effect of review probabilities
- Small effect of demand, large effect of review probabilities
- small effects of demand and review probabilities



Gain/loss

Observations

- ${\small 0}\,$ All scenarios show structural increase in revenue, of up to 11%
- 11.1% increase in rating leads to 5.7% increase in revenue (similar to Ye et alii (2011)

Implications

- Tractable solution methods
- Improving hotel facilities
- $\bullet\,$ Multiple night stays \rightarrow constant target rating challenging