Revenue Management under Reviews and Online Ratings[1]

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[1]This work is in collaboration with dr. D.M. Roijers

M

Mark
🇬🇧 United Kingdom
1 property review

10 **"Excellent value for money in a great location"**

◀ Leisure trip   ◀ Couple   ◀ King Studio   ◀ Stayed 3 nights

⊖ Lifts a little slow at times.

⊕ Great location, right next to subway and downtown sights. Staff helpful and friendly. Room the usual small NY standard, but well appointed and laid out. Felt modern and clean. Bed very comfortable. Breakfast was as expected and always well stocked. Gym was small and more for running / cross training etc (a few dumbbells) but perfectly adequate.

[Helpful]

C

Chris
🇬🇧 United Kingdom
20 property reviews
2 destination reviews
1 helpful vote

9.2 **"Very clean and modern hotel. Friendly. Near WTC"**

◀ Leisure trip   ◀ Solo traveler   ◀ King Studio   ◀ Stayed 2 nights

⊖ Nothing really. Financial district not really where I want to stay but very near subway. I stayed during memorial weekend and was woken by noise in the corridor (just a group getting back) at 5am. Once they were in their rooms (I think they had two rooms next to each other), I couldn't hear a thing but it all woke me with a start. When there is room (and the rooms here nice and large), I don't know why designers don't put in an internal hall, creating an inner hallway. Hotels that do this are great and it blocks off all the noise from the hallway, people coming in/out, discussing what time for breakfast, knocking on friends doors etc. Anyway not the hotel's fault I stayed during memorial w/e or that I happened to stay next to two rooms who went out partying :-)

Trade-off: Revenue vs Rating

- 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

Goal: Maximize long-term revenue

- Optimizing revenue might lead to worse ratings and suboptimal revenue

- 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 ($P_j(\mathcal{R}, S)$)
- A purchase leads to:
    - revenue r_j
    - positive review probability q_j^p
    - negative review probability q_j^n
- purchased products can be cancelled
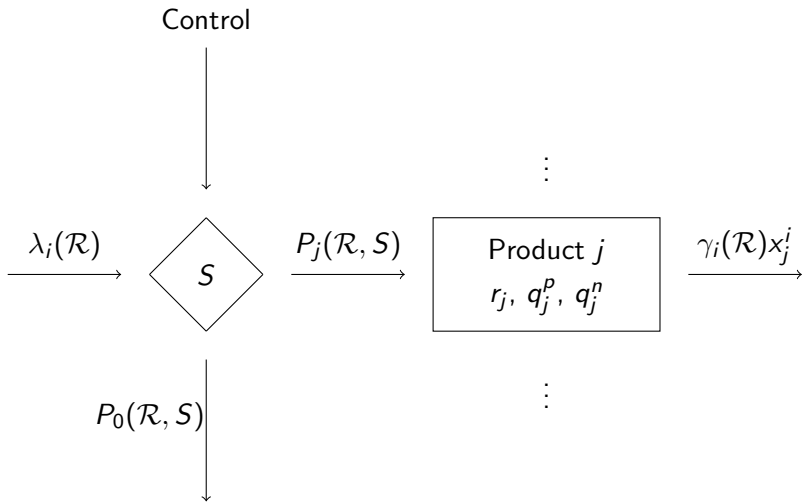
Modelling demand and cancellations as a function of reviews

- $Q_i^p = \#$ 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:

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

Modelling demand and cancellations as a function of reviews

- 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

rating	0.5	0.5	0.5	0.6	0.6	0.6

arrival day 1 | S_3^1 | S_2^1 | S_1^1 | $*$ | | |

arrival day 2 | | S_3^2 | S_2^2 | S_1^2 | $*$ | |

arrival day 3 | | | S_3^3 | S_2^3 | S_1^3 | |

Day 0   Day 1   Day 2   Day 3   Day 4   Day 5
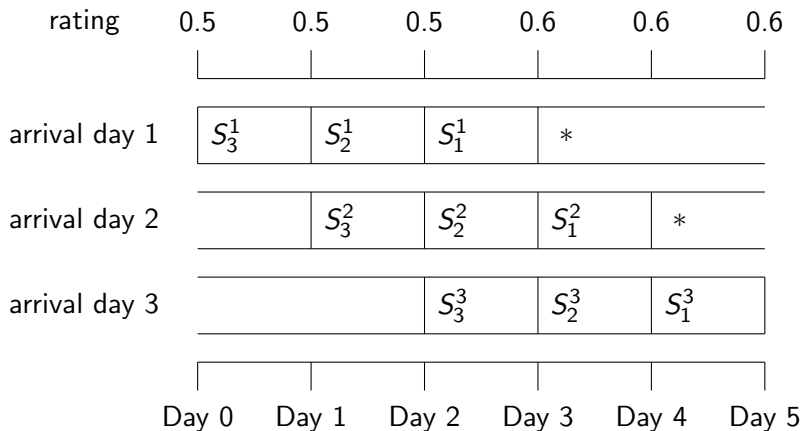
- $R^i(S^1, \ldots, S^i)$ revenue from arrival day i
- $S^i = \{S_T, \ldots, S_1\}$ strategy for arrival day i
- Objectives:

$$\phi^I(S) = \sum_{i=1}^{I} R^i(S^1, \ldots, S^i),$$

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

Problem

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

Solution: Equilibrium Solutions

- Keep expected rating constant, equal to a **target rating** ρ^*
- Now R^i depends solely on S^i
- Each arrival day can be solved separately

One arrival day Bellman equation

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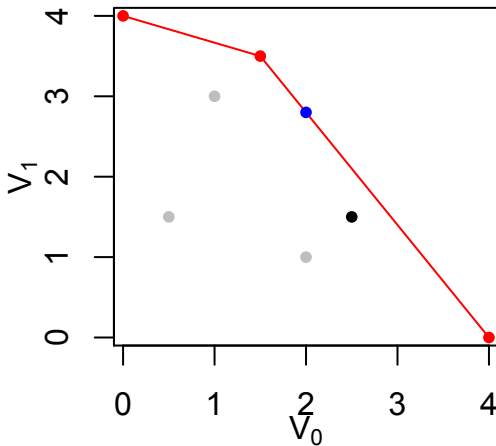\end{aligned}
$$

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

- Policy $\pi \in CCS$ corresponds to value vector V^π
- Hyperplane where rating $= \rho$:

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

- Target-rating policy:

$$\pi(\rho) = \arg\max_{\pi \in \text{CCS}} \left\{ V_1^\pi \,\middle|\, \mathbf{V}^\pi \in \text{CCS}' \cap \mathcal{H} \right\}$$

- Optimal target-rating and corresponding policy:

$$\pi(\rho^*) = \arg\max_{\pi(\rho)} V_1^{\pi(\rho)}$$

One instance: policy analysis

Revenue	Positive reviews	Negative reviews	Rating ρ
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

Observations

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

Scenarios

1. Large effects of demand and review probabilities
2. Large effect of demand, small effect of review probabilities
3. Small effect of demand, large effect of review probabilities
4. small effects of demand and review probabilities
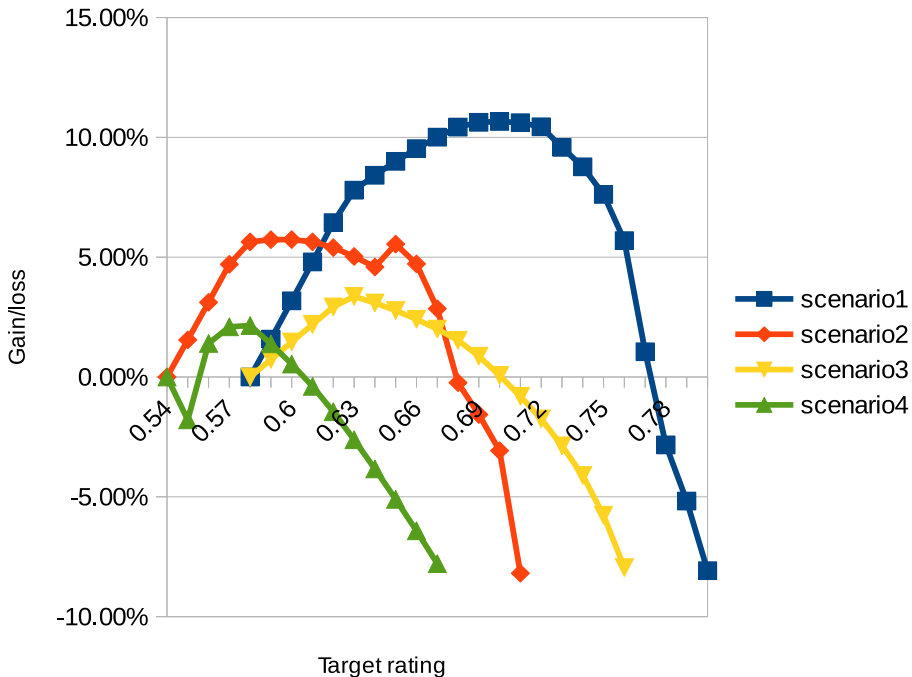
Observations

1. All scenarios show structural increase in revenue, of up to 11%
2. 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
- Multiple night stay