Data-Driven Demand Learning and Dynamic Pricing Strategies in Competitive Markets

Pricing Strategies

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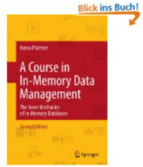
Outline

- Goals of today’s meeting: Pricing Strategies
- How to set offer prices: Simple Approaches
- Summarizing Exercise: From data to Pricing

Pricing Competition



A Course in In-Memory Data Management: The Inner Mechanics of In-Memory Databases (Gebundene Ausgabe)

von Hasso Plattner (Autor)

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Observable Data: Market Situations

seller k	price p_k	quality q_k	rating r_k	feedback f_k	shipping c_k
1	44.90	akzeptabel	100%	4	5 Tage
2	**45.00**	**sehr gut**	**98%**	**28,584**	**6 Tage**
3	65.60	wie neu	89%	439	11 Tage
4	79.56	sehr gut	90%	338	10 Tage
...					
K			...		

Price Adjustments in Market Situations

time	**adjusted price**	rank	market situation				
t	a_t	r_t	$p_{t,1}$	$p_{t,2}$	$p_{t,3}$	$p_{t,4}$	… $p_{t,K}$
0	**19**	3	13	17	20	25	
1	**16**	2	13	17	20	25	
2	**12**	1	13	15	20	/	
3	**10**	1	11	15	20	22	
4	**14**	2	11	15	20	24	
5	**19**	3	11	13	20	24	
…							

Observable Data: Sales within Adjustment Periods

period	sale	price	rank	market situation				
$(t,t+1)$	$y_t^{(1)}$	a_t	r_t	$p_{t,1}$	$p_{t,2}$	$p_{t,3}$	$p_{t,4}$	… $p_{t,K}$
(0,1)	**0**	**19**	3	13	17	20	25	
(1,2)	**0**	**16**	2	13	17	20	25	
(2,3)	**1**	**12**	1	13	15	20	/	
(3,4)	**0**	**10**	1	11	15	20	22	
(4,5)	**1**	**14**	2	11	15	20	24	
(5,6)	**0**	**19**	3	11	13	20	24	
…								

Extension: Multiple Sales

period	**sales**	**price**	rank	competitor's prices	for product i (ISBN)			
$(t,t+1)$	$y_t^{(1)}$	a_t	r_t	$p_{t,1}$	$p_{t,2}$	$p_{t,3}$	$p_{t,4}$	… $p_{t,K}$
(0,1)	**3**	**19**	3	13	17	20	25	
(1,2)	**15**	**16**	2	13	17	20	25	
(2,3)	**23**	**12**	1	13	15	20	/	
(3,4)	**19**	**10**	1	13	15	20	22	
(4,5)	**21**	**14**	2	11	15	20	24	
(5,6)	**9**	**19**	3	11	13	20	24	
…								

Simple Approach: Least Squares Regression

- Idea: explain the „dependent variable“ by „explanatory variables“
- „Dependent variable“: number of sales y (of our firm)
- „Explanatory variables“: price rank r

  price difference to best competitor’s price

  time (day time, weekday, month etc.)

  ratings, shipping time, . . .

- Remember: Derive the β^* – coefficients for every explanatory variable by minimizing **sum of squared deviations** (over all observations)

Example: Expected Sales as Function of Price Rank

- Explanatory variable: $x_i^{(1)}(a,\vec{p}) = 1$, price rank $x_i^{(2)}(a,\vec{p}) = r_i(a,\vec{p})$
- Regression result: Intercept β_1^*, price rank impact β_2^*
- Expected sales: $\hat{y}(a,\vec{p}) = \beta_1^* + \beta_2^* \cdot r(a,\vec{p})$
- Impact analysis: Each better rank boosts the expected number of sales by β_2^* units!
- We can estimate expected sales for all prices a and situations $\vec{p}$!

Let's be creative: Multi Linear Regression

- Invent multiple explanatory variables from the raw data!

- Use transformed variables, e.g., $x^{(3)} = r^2$

  $$x^{(4)} = \ln(r)$$

- Use and combine multiple features (customer ratings, shipping time, etc.).

- Same Model: $$y(a, \vec{p}, \ldots) \approx \sum_{m=1}^{M} \beta_m \cdot x^{(m)}(a, \vec{p}, \ldots) = \vec{\beta}'\vec{x} = \hat{y}(\vec{\beta}, \vec{x}(a, \vec{s}))$$

- LS Minimization: $$\min_{\beta_1, \ldots, \beta_M \in \mathbb{R}} \left\{ \sum_{i=1}^{N} \left(y_i - \hat{y}_i(\vec{\beta}, \vec{x}_i) \right)^2 \right\}$$

What is a Good Model?

- Compare “Goodness of Fit” measures

- OLS: R^2 (share of explained variance in *y*)

- Model fit: $\hat{y}_i = \beta_1^* + \beta_2^* \cdot x_i^{(2)} + \beta_3^* \cdot x_i^{(3)} + \; . . . \; \approx y_i$

- New variance: $VAR_{new} = \frac{1}{N} \cdot \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad \leq \; VAR = \frac{1}{N} \cdot \sum_{i=1}^{N} (y_i - \underbrace{\overline{y}}_{1/N \cdot \sum_i y_i})^2$

- Goodness of fit: $R^2 := 1 - \frac{VAR_{new}}{VAR} \; \in [0,1]$ (large is good)

From Forecasts to Sales Probabilities

- We have **estimations** to sell $\hat{y}^{(h)}(a,\vec{s})$ items at price a within a period of length h which starts with situation $\vec{s}$

- We look for a **probability distribution** $\tilde{P}^{(h)}(i,a,\vec{s})$ to sell i items at price a within a period of length h which starts with situation $\vec{s}$

- Simple Approach: **Poisson Probabilities** with mean $\hat{y}^{(h)}(a,\vec{s})$

$$\tilde{P}(i,a,\vec{s}) = \tilde{P}(i,a,\vec{p},...) = Pois\left(\hat{y}\left(\vec{\beta},\vec{x}(a,\vec{s})\right)\right) = \frac{\hat{y}^i}{i!} \cdot e^{-\hat{y}}, \quad i = 0,1,2,...$$

Summary: Demand Estimation

- Explain dependent variable $y_t^{(1)}$ by customized explanatory variables $\vec{x}_t(\vec{s})$
- *Various* Regression/ML techniques can be used
- Result: Probability $\tilde{P}^{(h)}(i,a,\vec{s})$ to sell *i* items at price *a*
  within a period of length *h* which starts with situation $\vec{s}$
- Measure the Goodness of fit of your model/result
- Compare your estimated probabilities $\tilde{P}^{(h)}(i,a,\vec{s})$ with true ones $P^{(h)}(i,a,\vec{s})$

What Do We Have Learned?

- We can model: Customer Choice
- We can analyze: Sales data & market situations
- We can estimate: Sales probabilities for time intervals
- We can verify the: Quality of our estimations
- We want to: *Compute optimized prices*

Price Reaction Strategies (Rule-Based)

- Idea: (1) Observe market situation + (2) Adjust price

- Examples:

$$a(\vec{s}) = a^{(1)}(\vec{p}) := \max\left(c, \min_{k=1,..,K} p_k - \varepsilon\right)$$

$$a(\vec{s}) = a^{(n)}(\vec{p}) := \max_{a \in A : rank(a,\vec{p}) = n} a$$

$$a(\vec{s}) = a^{(random)}(\vec{p}) := if\ U(0,1) < 0.5\ \ then\ a^{(1)}(\vec{p})\ \ else\ a^{(2)}(\vec{p})$$

$$a(\vec{s}) = a^{(gas)}(\vec{p}) := \begin{cases} a^{(1)}(\vec{p}) & , p^{\min} \leq \min_{k=1,..,K} p_k \leq p^{\max} \\ p^{\max} & , else \end{cases}$$

Price Reaction Strategies (Data-Driven)

- Idea: (1) Observe market situation + (2) Adjust price

  (3) Use expected sales probabilities

- Use: Probability $\tilde{P}^{(h)}(i,a,\vec{s})$ to sell i items at price a

  within a period of length h which starts with market situation $\vec{s}$

- Examples: Maximize short-term profit via

$$a^{(*)}(\vec{s}) := \arg\max_{a \in A} \sum_{i=0,1,\ldots} i \cdot (a-c) \cdot \tilde{P}^{(h)}(i,a,\vec{s})$$

Mandatory Exercise – Combine all Components

(1) **Create** random market situations with multiple sellers

Choose randomized prices for our firm (exploration phase)

(2) Choose a specific Buying Behavior, e.g., Approach II (with 0.6, 0.3, 0.1)

Simulate our firm's sales for all market situations

(3) **Estimate** sales probabilities, e.g., Logit model or Poisson via least squares

Use different combinations of explanatory variables

Mandatory Exercise – Combine all Components

(4) **Measure** the goodness of fit of your models, i.e.,

Compare original and estimated sales probabilities

(5) **Create** new random market situations with multiple sellers

Evaluate your estimated sales probabilities for potential offer prices

Compute prices that maximize expected short-term profits

(6) **Simulate** sales for all new market situations and your optimized prices

Compare realized profit for rule-based strategies & the optimized prices

Overview

2	April 25	Customer Behavior
3	May 2	Demand Estimation
4	May 9	Pricing Strategies I
5	May 16	no Meeting
6	**May 23**	**Pricing Strategies II (Optimal Solution of the Duopoly Game)**
7	May 30	Dynamic Pricing Challenge & Price Wars Platform
8	June 6	Workshop / Group Meetings
9	June 13	Presentations (First Results)
10	June 20	Workshop / Group Meetings
11	June 27	no Meeting
12	July 4	Workshop / Group Meetings
13	July 11	Workshop / Group Meetings
14	**July 18**	**Presentations (Final Results), Feedback, Documentation (Aug/Sep)**