Dynamic Pricing on Online Marketplaces: Strategies and Applications

Description of Projects

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Description of Projects

- Multiple Features (Price, Customer Ratings, Product Condition)
- Multiple Products (Substitution Effects, 2 Products)
- Sale of Perishable Products (Finite Horizon)
- Response Strategies (Price Anticipation, Duopoly)
- Future Projects

A Multiple Features

Project A: Multiple Features

- Customers take different features into account
- Task: Quantify the effect of Multiple Features under Competition
- Include: Customer Ratings
  Feedback Count
  Product Condition/Quality
  Shipping Time
  Amazon Sales Rank
- Compute optimized Prices

Project A: Multiple Features (Demand Estimation)

- Use data from the Amazon Market Place
- Dependent Variable y: sold (1) / not sold (0) within a period of time
- Explanatory Variables $\vec{x}$: Various Functions of the raw data:
  - Our Price a, Competitors' Prices $\vec{p}$
  - Customer Ratings $\vec{v}$, Feedback Count $\vec{f}$
  - Product Quality $\vec{q}$, Shipping Time $\vec{z}$
  - Amazon Sales Rank w
- Use Logistic Regression, $i = 0,1$:

  Find $P(y=i) = \pi(i, \vec{x}(a, \vec{s}))$, where $\vec{s} = (\vec{p}, \vec{q}, \vec{v}, \vec{f}, \vec{z}, w, ...)$

Project A: Multiple Features (Optimization)

- Consider a state $\vec{s}$. Use sales probability $\vec{\pi}(\vec{x}(a,\vec{s}))$. Choose T (e.g., 1000).

- Let $V_T(n,\vec{s}):=0$, let $V_t(0,\vec{s})=0$ (run-out), and compute:

$$V_t(n,\vec{s})=\max_{a\geq 0}\left\{\sum_{i=0,1}\underbrace{\pi(i,x(a,\vec{s}))}_{probability}\cdot\left(\underbrace{\min(n,i)\cdot a}_{today's\ profit}-\underbrace{n\cdot l}_{\substack{holding\\ costs}}+\underbrace{\delta\cdot V_{t+1}\left(\max(0,n-i),\vec{s}\right)}_{disc.\ exp.future\ profits\ (n-i)^+\ items}\right)\right\}$$

- Result: $V_0(n,\vec{s})$, the expected discounted future profits.

- Optimal prices $a^*(n,\vec{s})$, $n=1,\ldots,N$, are given by the arg max of the last step.

Project A: Multiple Features (Simulation)

- Consider an initial state $\vec{s}$. Simulate changes state (from time to time).
- For every period compute optimal price adjustments.
- For every period simulate realized sales (with probability $\pi(\vec{x}(a,\vec{s}))$).
- Visualize accumulated sales over time (e.g., 1000 periods).
- Visualize price paths, inventory level over time.
- Compare different strategies (pricing policies).

B Multiple Products

Project B: Multiple Products

- Typically firms sell different products with mutual dependent demand
- Task: Quantify mutual demand dependencies (Substitution Effects)
- Assume: We sell two types of products under Competition
- Include: Combinations of prices (2 products)
  Substitution Effects
- Compute optimized **Pairs** of Prices

Project B: Multiple Products (Demand Estimation)

- Use simulated data or data from the Amazon Market Place

- Dependent Variables $y^{(j)}$: number of products sold within a period of time

- Explanatory Variables $\vec{x}^{(j)}$: Various Functions of the raw data, $j = 1, 2$:

  - Our Prices $\vec{a}$

  - Competitors' Prices $\vec{p}$

- Use Least Squares or Logistic Regression (for each product $j = 1, 2$):

  Find expected sales $\lambda^{(j)}(\vec{x}^{(j)}(a^{(1)}, a^{(2)}, \vec{p}))$ (OLS)

  or logit probabilities $\vec{\pi}^{(j)}(\vec{x}^{(j)}(\vec{a}, \vec{p}))$ (logistic regression).

Project B: Multiple Products (Optimization)

- Consider state $\vec{s} = \vec{p}$. Use probability, e.g., $\vec{\pi}^{(j)} = Pois(\lambda^{(j)}(\vec{x}^{(j)}(\vec{a}, \vec{p})))$.

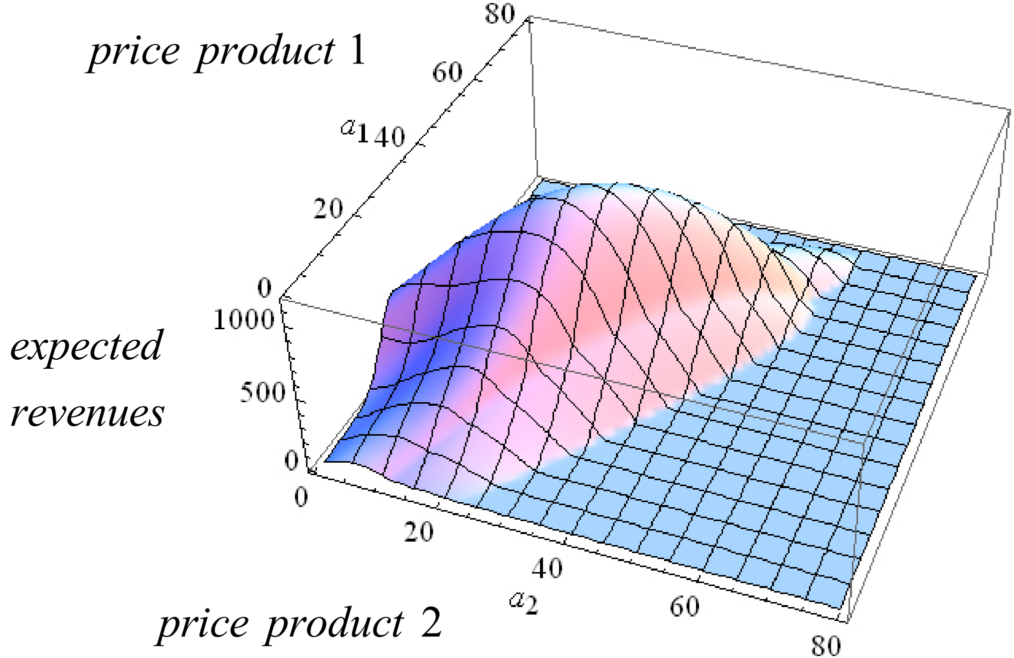
- Choose T, let $V_T(n^{(1)}, n^{(2)}, \vec{s}) := 0$, let $V_t(0, 0, \vec{s}) = 0$, and compute:

$$V_t(\vec{n}, \vec{s}) = \max_{\vec{a} \geq 0} \left\{ \sum_{i_1} \underbrace{\pi^{(1)}(i_1, \vec{x}^{(1)}(\vec{a}, \vec{s}))}_{probability\ \ product\ \ 1} \cdot \sum_{i_2} \underbrace{\pi^{(2)}(i_2, \vec{x}^{(2)}(\vec{a}, \vec{s}))}_{probability\ \ product\ \ 2} \right.$$
$$\left. \cdot \left(\sum_{j=1,2} \left(\underbrace{\min(n^{(j)}, i_j) \cdot a^{(j)}}_{today's\ \ profit} - \underbrace{n^{(j)} \cdot l^{(j)}}_{\substack{holding \\ costs}} \right) + \underbrace{\delta \cdot V_{t+1}\left((\vec{n} - \vec{i})^+, \vec{s} \right)}_{disc.\ exp.\ future\ \ profits\ \ (\vec{n}-\vec{i})^+\ \ items} \right) \right\}$$

- Result: $V_0(\vec{n}, \vec{s})$, the expected discounted future profits.

- Optimal pairs of prices $\vec{a}^*(\vec{n}, \vec{s})$ are given by the arg max of the last step.

Project B: Multiple Products (Illustration)



Project B: Multiple Products (Simulation)

- Consider an initial state $\vec{s}$. Simulate changes state (from time to time).
- For every period compute optimal price pair adjustments.
- For every period simulate realized sales (with probabilities $\vec{\pi}^{(j)}(\vec{x}(\vec{a},\vec{s}))$).
- Visualize accumulated sales over time (e.g., 1000 periods).
- Visualize price paths, inventory levels over time.
- Compare different strategies (pricing policies).

C Perishable Products

Project C: Perishable Products

- Many Products are Perishable, i.e. the Time Horizon is Finite
- Examples: Groceries, Airline / Hotel / Event Tickets, . . .)
- Task: Quantify Time-Dependent Demand under Competition
- Include: Time-Dependence (cf. time-to-go)

  Salvage Value z
- Compute optimized Prices for every period of time

Project C: Perishable Products (Demand Estimation)

- Use simulated data (the time horizon is T)
- Dependent Variable y: number of items sold within a period of time
- Explanatory Variables $\vec{x}$: Various Functions of the raw data:

  Time t

  Our Price a, Competitors' Prices $\vec{p}$

- Use Least Squares or Logistic Regression, where $t = 0, 1, \ldots, T$:

  Find expected sales $\lambda_t(\vec{x}_t(a, \vec{p}))$ (OLS)

  or logit probabilities $\vec{\pi}_t(\vec{x}_t(a, \vec{p}))$ (logistic regression).

Project C: Perishable Products (Optimization)

- Consider state $\vec{s} = \vec{p}$. Use probability, e.g., $\vec{\pi} = Pois(\lambda_t(\vec{x}_t(a, \vec{p})))$.

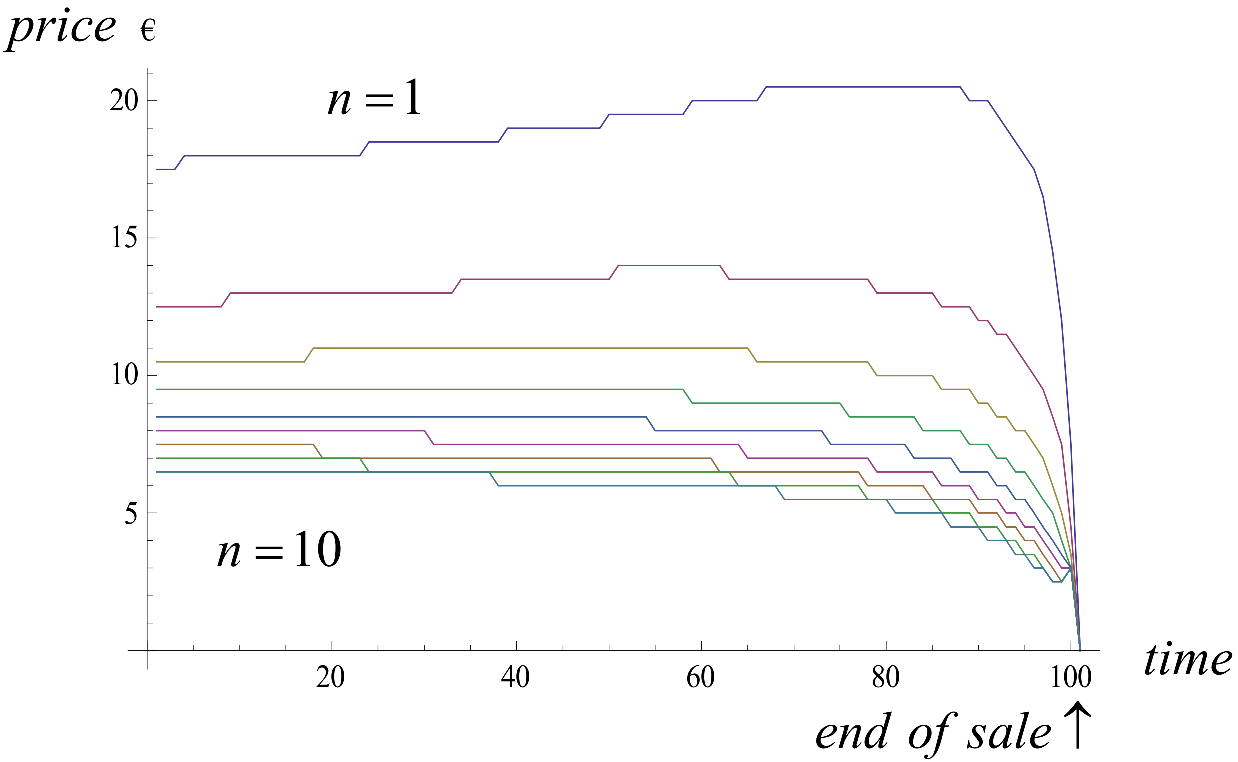
- Choose T, let $V_T(n, \vec{s}) := z \cdot n$ (salvage), let $V_t(0, \vec{s}) = 0$, and compute:

$$V_t(n,\vec{s}) = \max_{a \geq 0} \left\{ \sum_i \underbrace{\pi(i, \vec{x}(a,\vec{s}))}_{probability} \cdot \left(\underbrace{\min(n,i) \cdot a}_{today's\ profit} - \underbrace{n \cdot l}_{\substack{holding \\ costs}} + \underbrace{\delta \cdot V_{t+1}\left((n-i)^+, \vec{s}\right)}_{disc.\ exp.future\ profits\ (n-i)^+\ items} \right) \right\}$$

- Result: $V_t(n, \vec{s})$, the expected discounted future profits **from time *t* on**.

- Optimal prices $a_t^*(n, \vec{s})$, $n = 1, ..., N$, are given by the arg max of **each** step.

Project C: Perishable Products (Simulation)



Project C: Perishable Products (Simulation)

- Consider an initial state $\vec{s}$. Simulate changes state (from time to time).
- For every period compute optimal price adjustments.
- For every period simulate realized sales (with probability $\pi_t(\vec{x}(a,\vec{s}))$).
- Visualize accumulated sales over time (e.g., 1000 periods up to T)
- Visualize price paths, inventory level over time.
- Compare different strategies (pricing policies)

D Response Strategies

Project D: Response Strategies

- Often competitors' strategies are known & prices can be anticipated.
- Typically there are many passive and a few active competitors.
- Task: Compute optimal response strategies.
- Include: Competitor's Reaction Strategy $F(a, p)$

  Price Anticipations

  Reaction Frequencies
- Compute optimized Price Reaction Strategies

Project D: Response Strategies (Demand Estimation)

- Use simulated data or data from the Amazon Market Place
- Dependent Variable y: number of items sold within a period of time
- Explanatory Variables $\vec{x}$: Various Functions of the raw data:

  Our price a

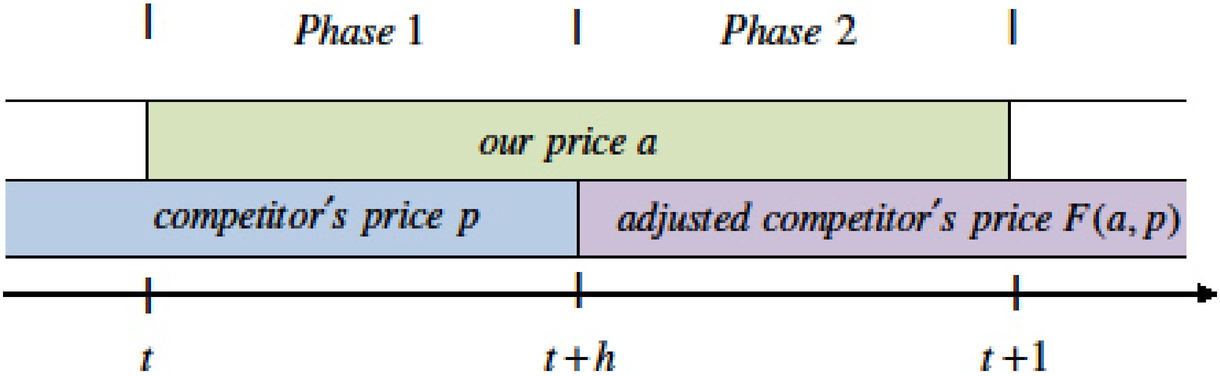
  Competitors' Prices p (duopoly case)

- Use Least Squares or Logistic Regression:

  Find expected sales $\lambda(\vec{x}(a,p))$ (OLS)

  or logit probabilities $\vec{\pi}(\vec{x}(a,p))$ (logistic regression).

Project D: Response Strategies (Price Adjustments)



- Sequence of price reactions in case of a duopoly, h=0.5

Project D: Response Strategies (Optimization)

- Consider state $\vec{s} = p$. Use sales probabilities $\vec{\pi}(\vec{x}(a,\vec{s}))$. Choose T.
- Let $V_T(n,\vec{s}) := 0$, let $V_t(0,\vec{s}) = 0$ (run-out), and compute, $0 < h < 1$:

$$V_t(n,p) = \max_{a \geq 0} \left\{ \sum_{i_1} \underbrace{\pi^{(h)}(i_1, \vec{x}(a,p))}_{probability\ \ phase\ 1\ (t,t+h)} \cdot \sum_{i_2} \underbrace{\pi^{(1-h)}(i_2, \vec{x}(a, F(a,p)))}_{probability\ \ phase\ 2\ (t+h,t+1)} \cdot \left(\underbrace{\min(n, i_1 + i_2) \cdot a}_{today's\ \ profit} - \underbrace{n \cdot l}_{\substack{holding \\ costs}} + \underbrace{\delta \cdot V_{t+1}\left((n - i_1 - i_2)^+, F(a,p)\right)}_{disc.\ \ exp. future\ \ profits} \right) \right\}$$

- Result: $V_0(n,p)$, the expected discounted future profits.
- Optimal Prices $a^*(n,p)$, $n = 1,\ldots,N$, are given by the arg max of the last step.

Project D: Response Strategies (Simulation)

- Consider an initial state $\vec{s}$. Simulate changes state (from time to time).
- For every period compute both firms' price adjustments.
- For every period simulate realized sales (with probability $\pi(\vec{x}(a,p))$).
- Visualize accumulated sales over time (e.g., 1000 periods)
- Visualize price paths, inventory level over time.
- Compare different strategies (pricing policies)

Future Projects

- Identification of Competitors' Strategies
- Personalized Pricing
- Risk Aversion
- Strategic Customers
- Multiple Decisions (Advertising, Ordering, . . .)
- . . .

Overview

2	April 19	Demand Estimation
3	April 26	Optimization Techniques
4	May 3	Extensions / Projects A-D
5	**May 10**	**Assign Projects to Teams**
6	May 17	no Meeting
7	May 24	Workshop / Group Meetings
8	May 31	Workshop / Group Meetings
9	June 7	Presentations (First Results)
10	June 14	Workshop / Group Meetings
11	June 21	Workshop / Group Meetings
12	June 28	Workshop / Group Meetings
13	July 5	no Meeting
14	**July 12**	**Presentations (Final Results), Discussions, Feedback**