

# Dynamic Pricing & Revenue Management in Service Industries

**Kannapha Amaruchkul**

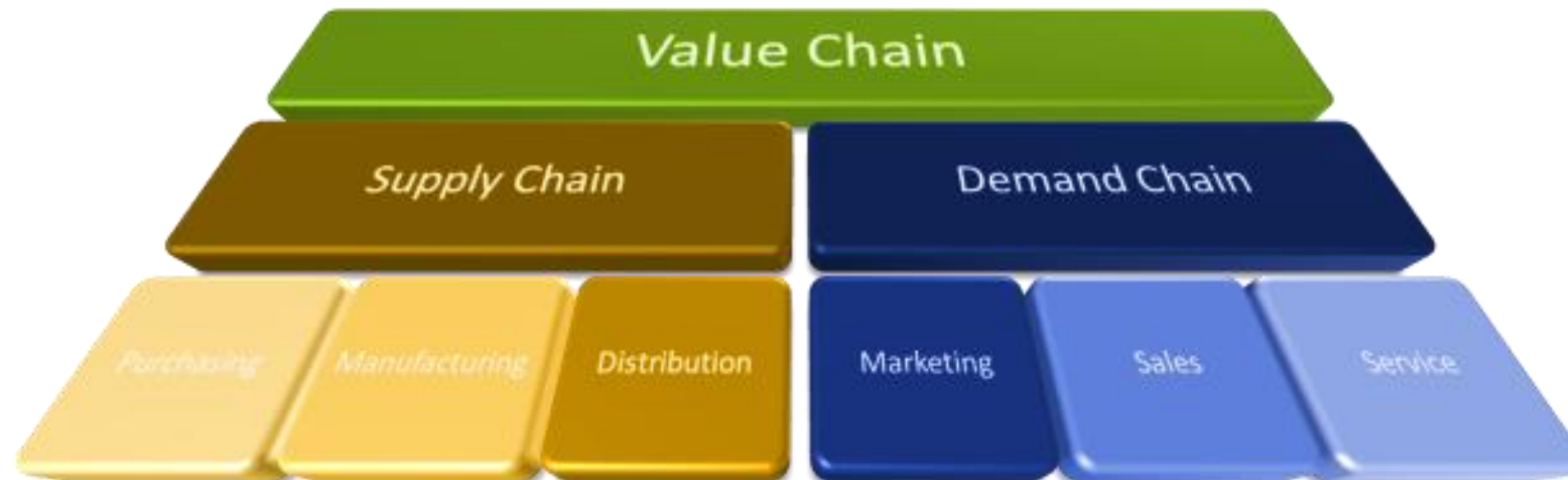
**3<sup>rd</sup> Business Analytics and Data Science Conference  
Bangkok, Thailand**

**October 30, 2018**



# RM: Complement of SCM

Revenue Management (RM)	Supply Chain Management (SCM)
RM concerned with <i>demand-management</i> decisions.	SCM concerned with <i>supply</i> decisions.
“Interface with the market”	Logistics of the firm
Objective: Maximize total profit	Objective: Minimize total cost



Credit: [http://en.wikipedia.org/wiki/Demand\\_chain](http://en.wikipedia.org/wiki/Demand_chain)

Synonymous names:

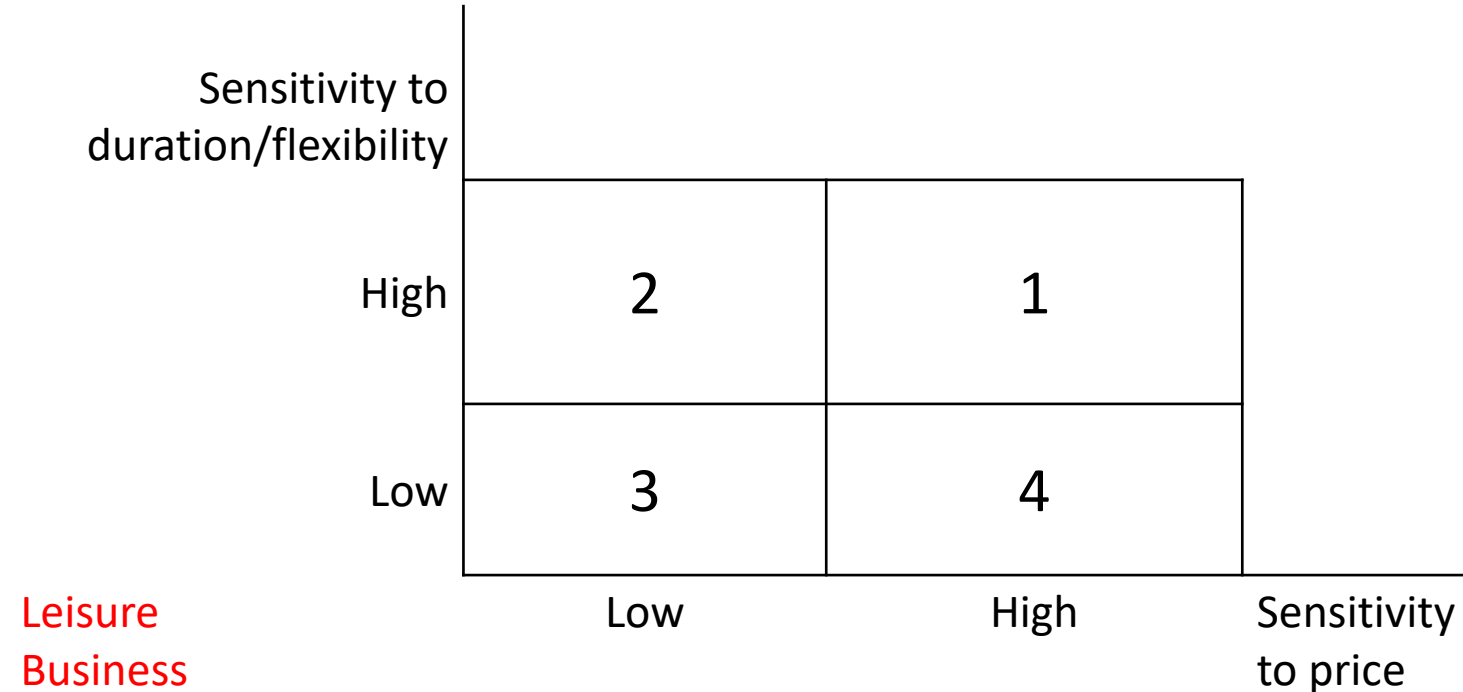
Yield management.

Pricing and revenue optimization.

Demand-chain management <sub>3</sub>

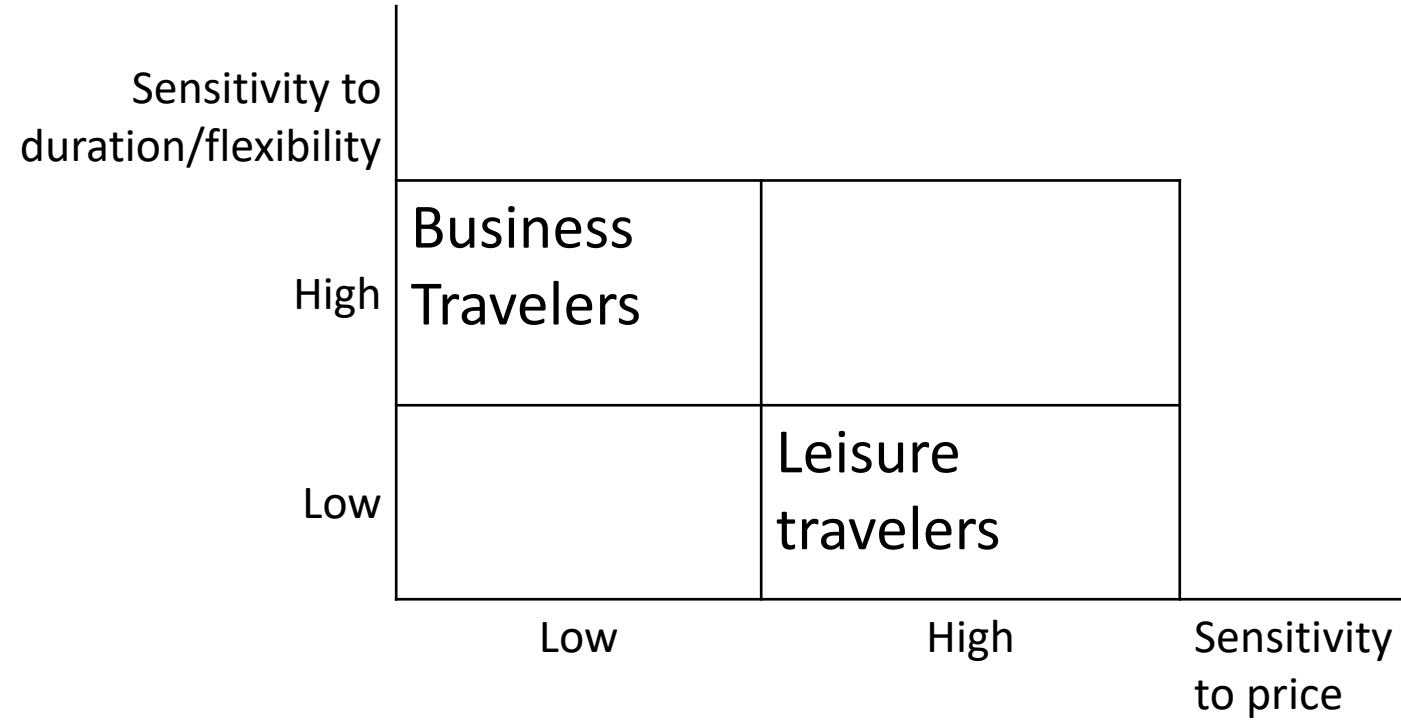


# Market Segmentation in Airline Industry



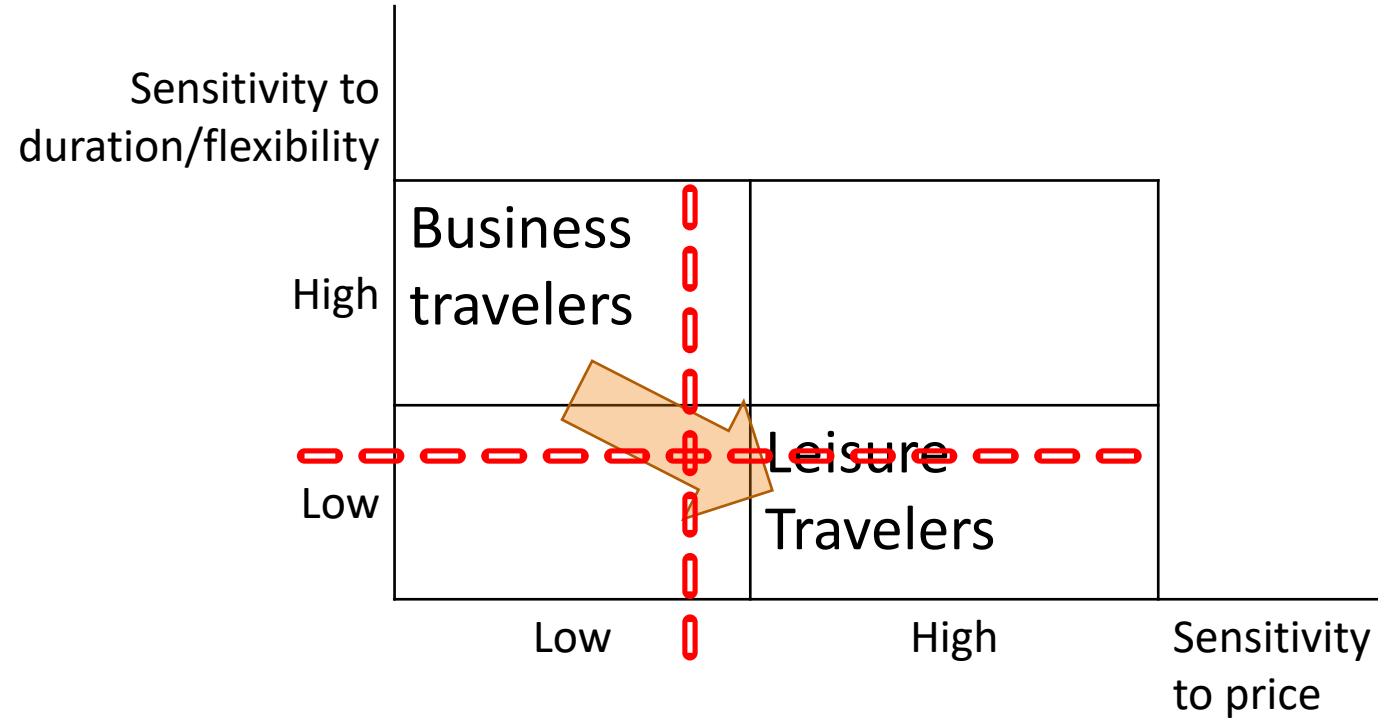
Source: Simchi-Levi, D., & Kaminsky, P., & Simchi-Levi, E. (2007). Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies. Boston: McGraw-Hill.

# Market Segmentation in Airline Industry



Source: Simchi-Levi, D., & Kaminsky, P., & Simchi-Levi, E. (2007). Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies. Boston: McGraw-Hill.

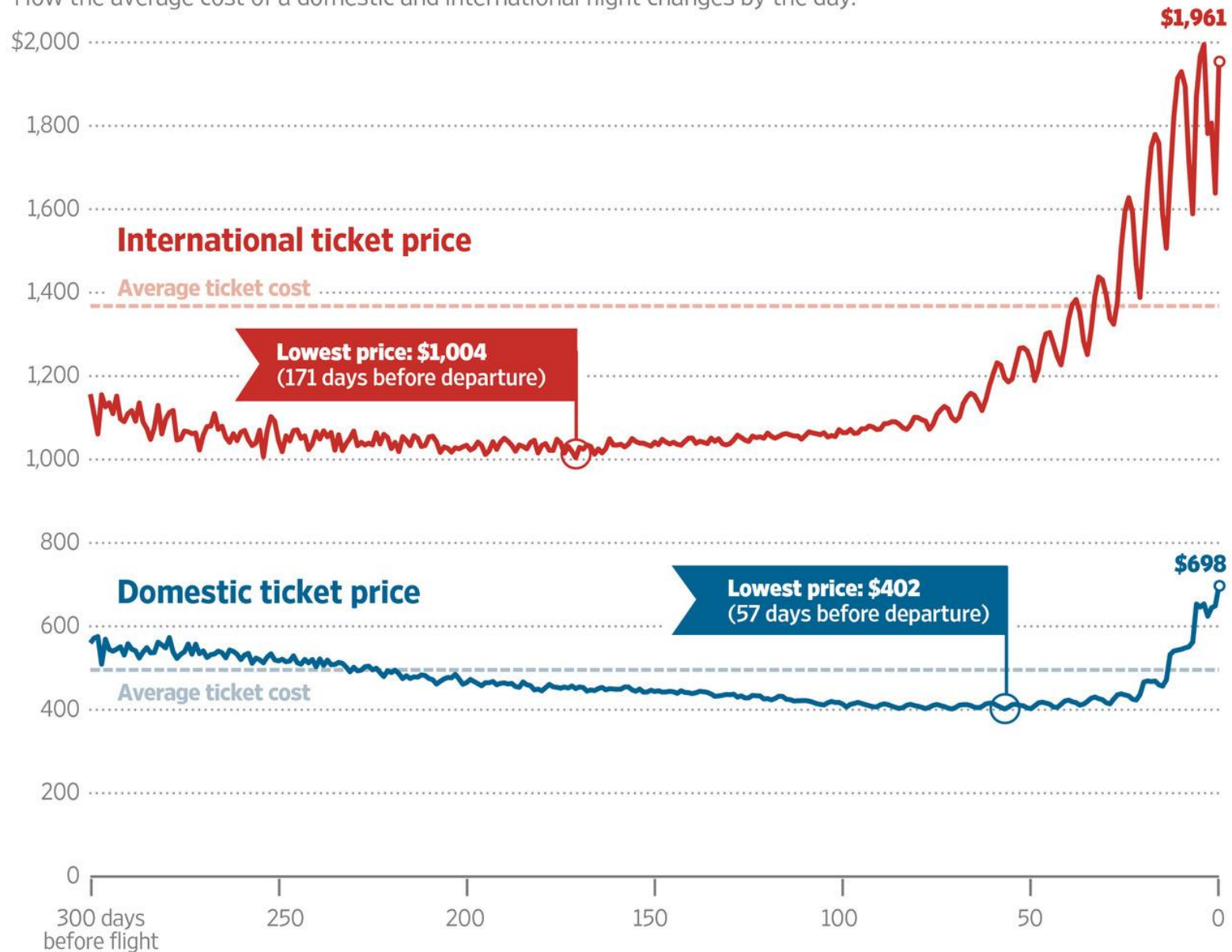
# Market Segmentation in Airline Industry



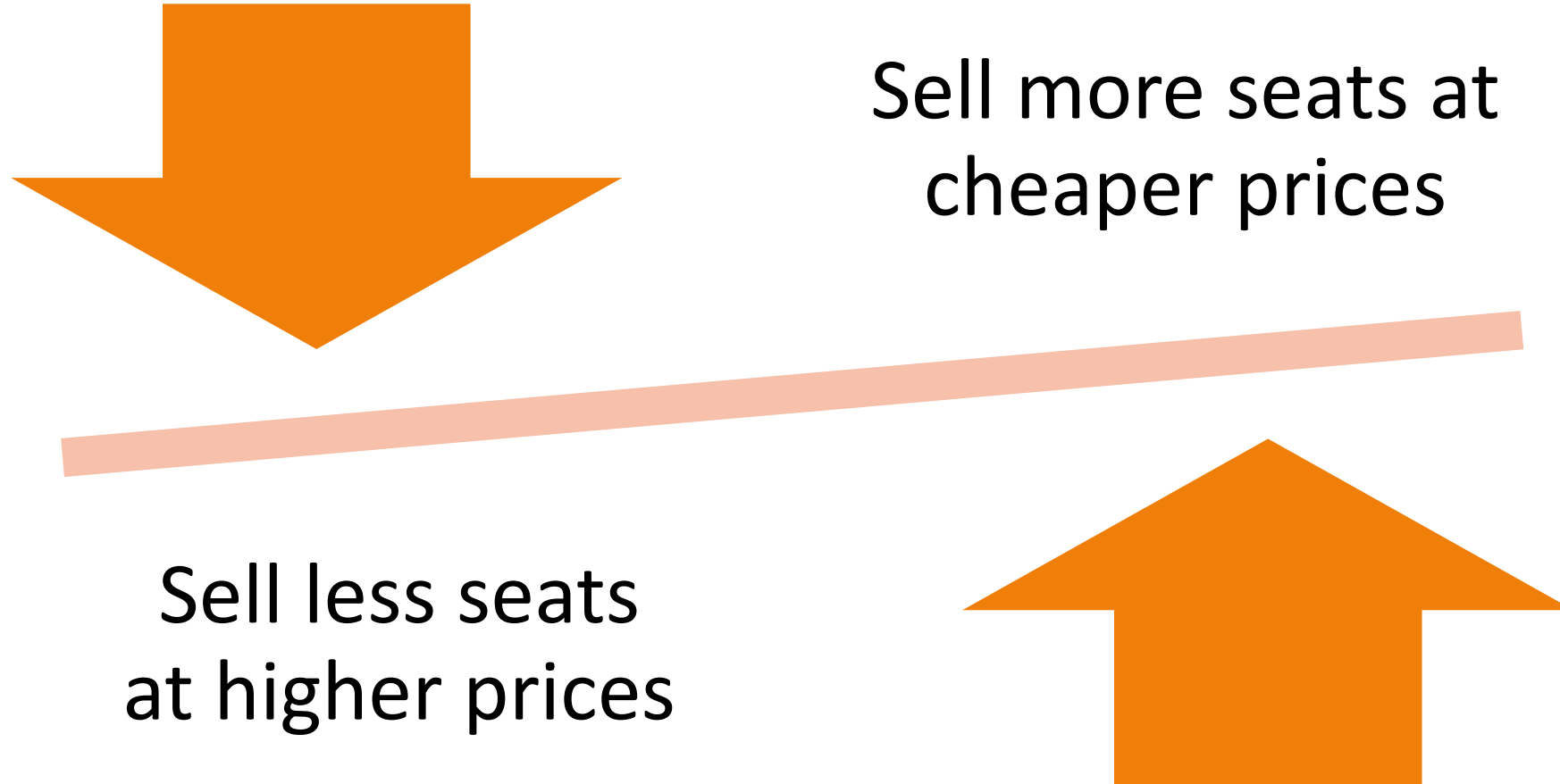
Source: Simchi-Levi, D., & Kaminsky, P., & Simchi-Levi, E. (2007). Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies. Boston: McGraw-Hill.

## How The Prices Change

How the average cost of a domestic and international flight changes by the day:

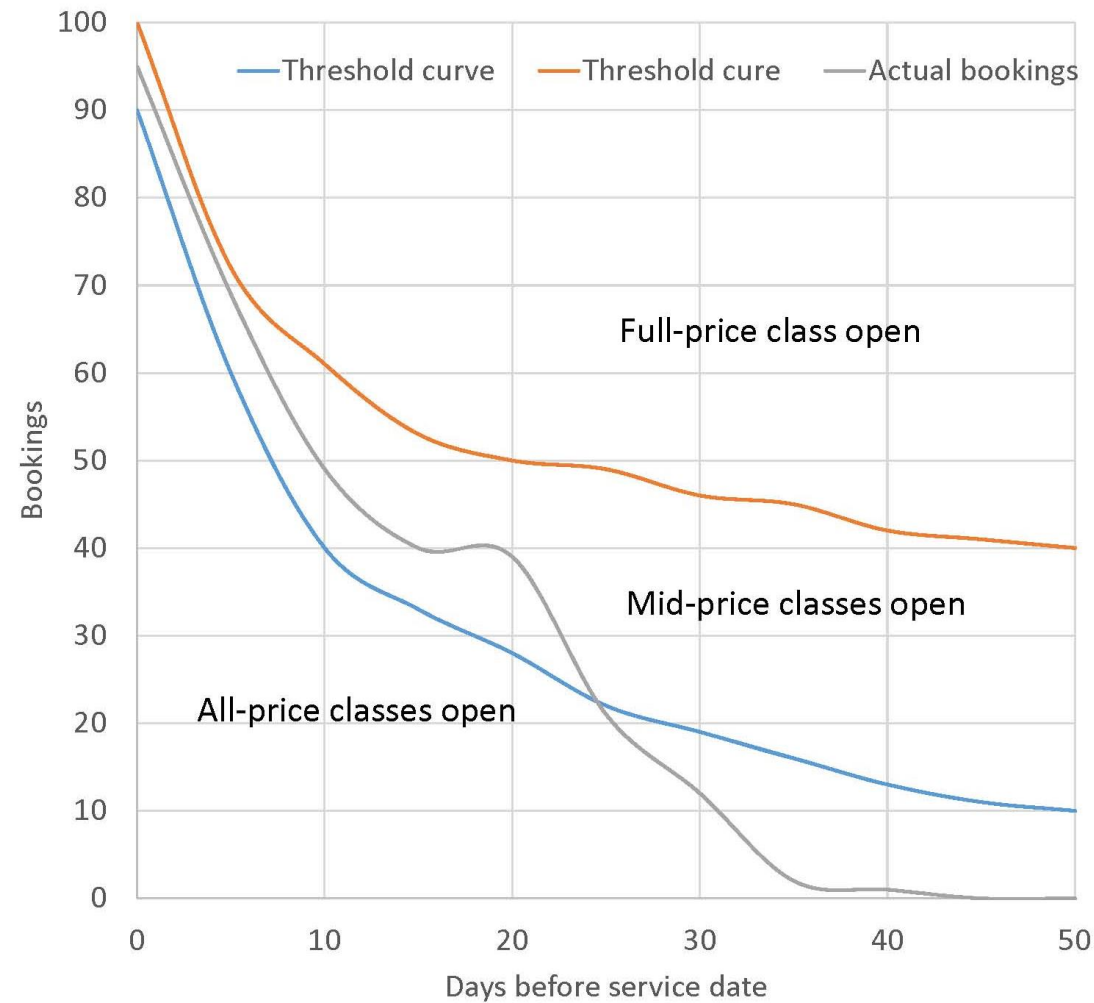


# What is capacity allocation problem?



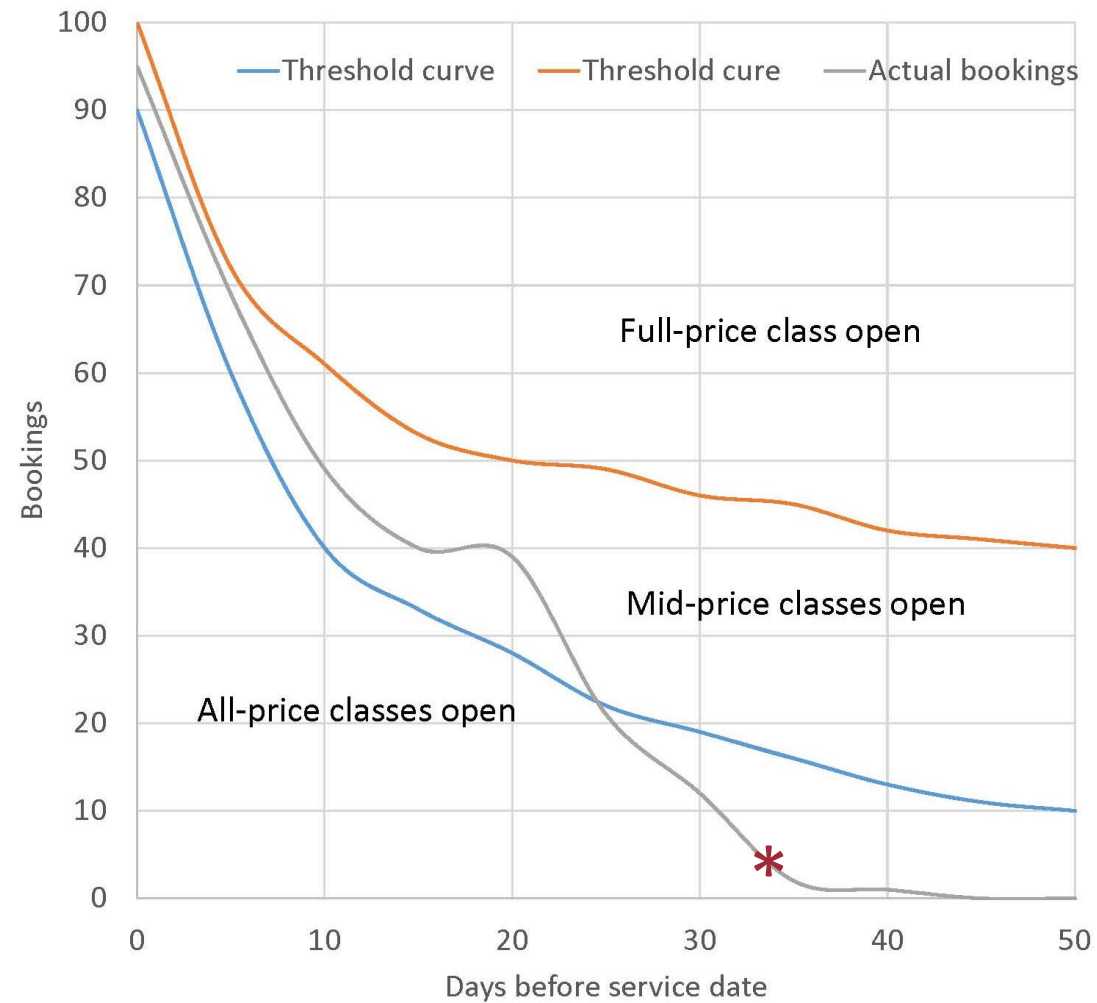


# Seat Inventory Control



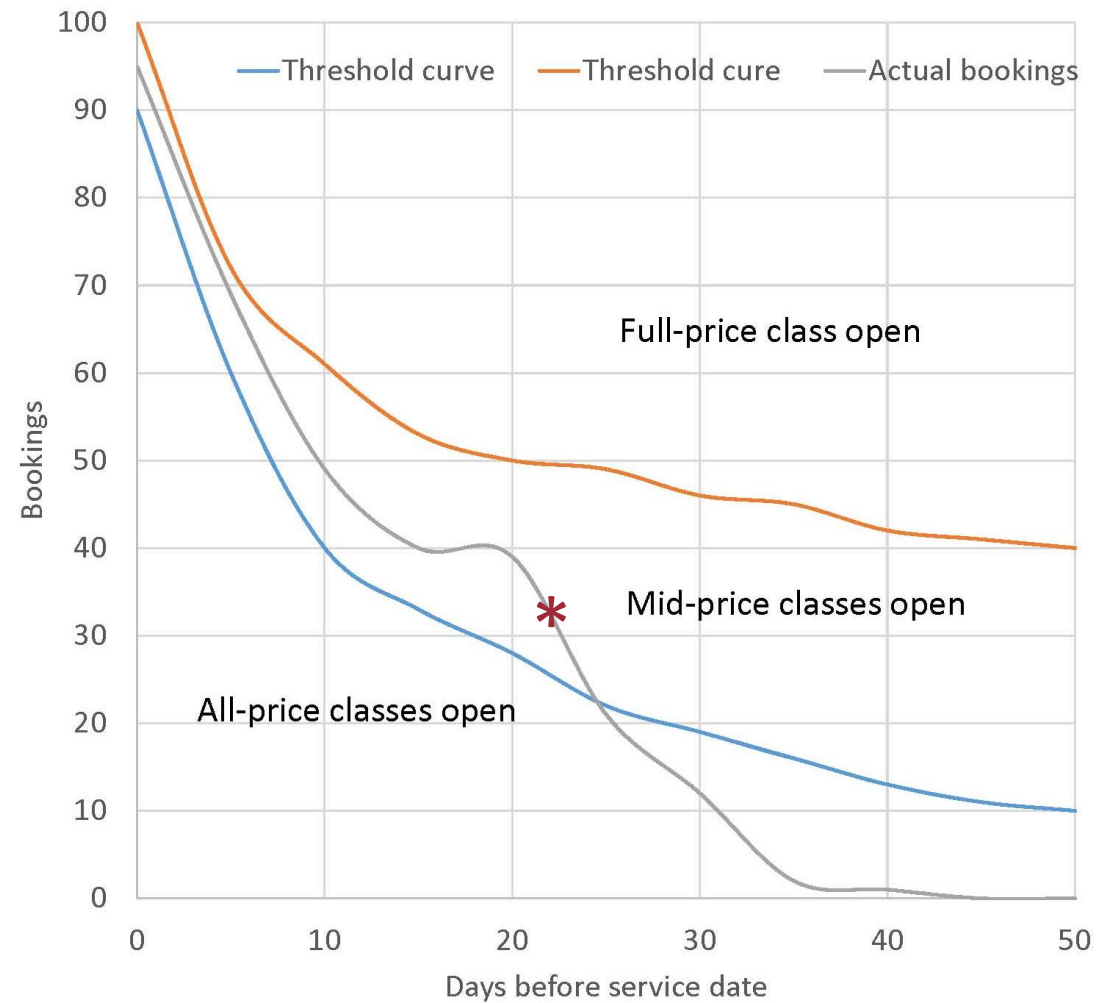
RM algorithm recommends opening and closing pre-existing classes (Modified from Weatherford (1998))

# Seat Inventory Control



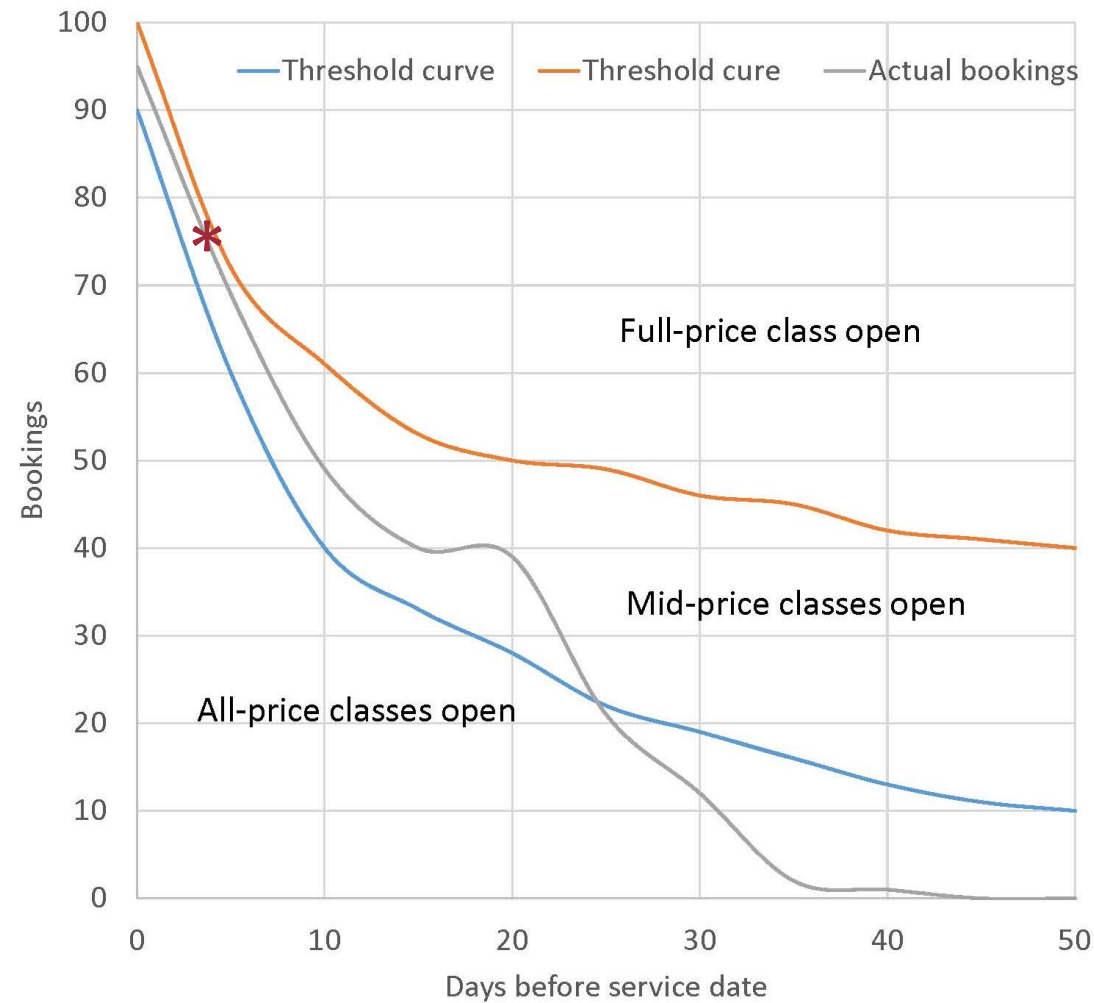
RM algorithm recommends opening and closing pre-existing classes (Modified from Weatherford (1998))

# Seat Inventory Control



RM algorithm recommends opening and closing pre-existing classes (Modified from Weatherford (1998))

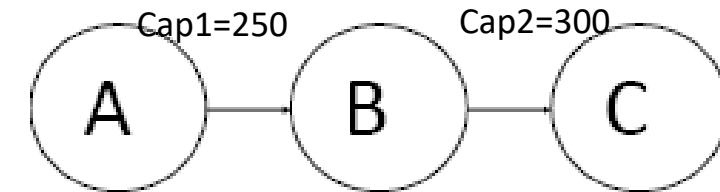
# Seat Inventory Control



RM algorithm recommends opening and closing pre-existing classes (Modified from Weatherford (1998))

# Network management

Airline. Container shipping



Hotel. Rental car

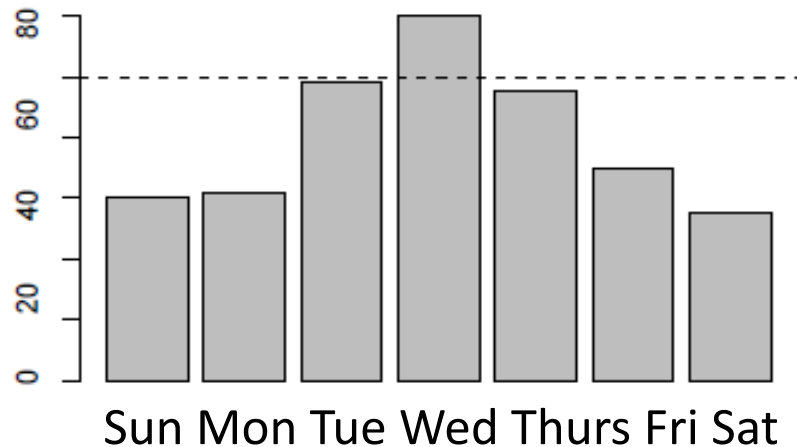
Description		$a_{i,j}$ ODF ( $j$ )	Resource ( $i$ )						
Arrival	Length of stay		Sun	Mon	Tue	Wed	Thu	Fri	Sat
Sun	1	1	1	0	0	0	0	0	0
Sun	2	2	1	1	0	0	0	0	0
Sun	3	3	1	1	1	0	0	0	0
Mon	1	4	0	1	0	0	0	0	0
Mon	2	5	0	1	1	0	0	0	0
Mon	3	6	0	1	1	1	0	0	0
Tue	1	7	0	0	1	0	0	0	0
Tue	2	8	0	0	1	1	0	0	0
Tue	3	9	0	0	1	1	1	0	0
Wed	1	10	0	0	0	1	0	0	0
Wed	2	11	0	0	0	1	1	0	0
Wed	3	12	0	0	0	1	1	1	0
Thu	1	13	0	0	0	0	1	0	0
Thu	2	14	0	0	0	0	1	1	0
Thu	3	15	0	0	0	0	1	1	1
Fri	1	16	0	0	0	0	0	1	0
Fri	2	17	0	0	0	0	0	1	1
Sat	1	18	0	0	0	0	0	0	1

Industry	Resource unit	Multi-resource product
Passenger airline	Seat on leg	Multi-leg itinerary
Hotel	Room night	Multi-night stay
Rental car	Rental day	Multi-day rental
Passenger train	Seat on a leg	Multi-leg trip
Container shipping	Cargo space on leg	Multi-leg routing

# Why network RM difficult?

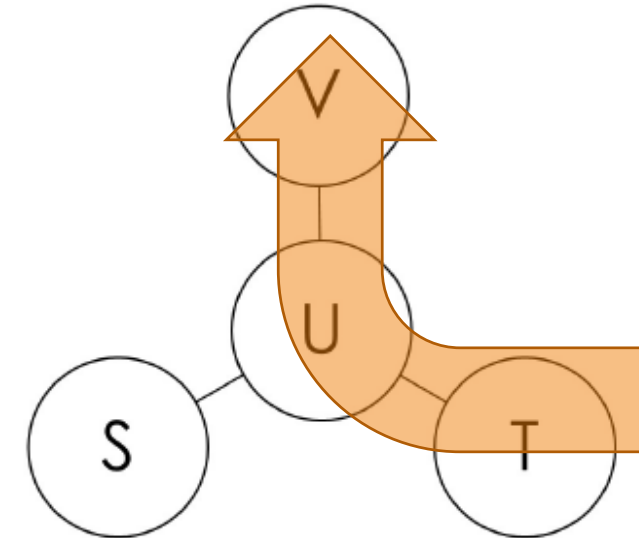
## Hotel RM

- Needs to consider both room rate and length of stay



## Airline RM

- Needs to consider both OD and fare (ODF)



Class	SU	TU	UV	SV	TV
1	41,000	16,000	12,000	48,000	19,000
2	15,000	14,000	9,700	17,000	16,000
3	9,200	13,000	6,700	8,300	8,400

# Bid pricing for hotels

	June						
	Mon	Tue	Wed	Thurs	Fri	Sat	Sun
	30	31	1	2	3	4	5
demand	89	90	113	106	103	66	79
bid price	3206	3502	5824	4274	3518	2065	2369
	6	7	8	9	10	11	12
demand	87	104	136	116	88	48	48
bid price	3361	4634	6542	5410	3637	1604	1232
	13	14	15	16	17	18	19
demand	64	88	109	100	90	74	64
bid price	2067	2750	4658	3803	3514	2100	2070
	20	21	22	23	24	25	26
demand	88	100	157	137	120	93	88
bid price	3388	4944	7596	6549	4643	3824	3233
	27	28	29	30	1	2	3
demand	85	91	110	99	80	58	72
bid price	3200	3555	5916	3843	2996	2050	2382

# Bid price calculation

Deterministic linear programming

For each resource  $i$

bid price = shadow price

Maximize  $\sum_{j=1}^n p_j x_j$

Subject to:

$\sum_{j=1}^n a_{ij} x_j \leq b_i$  for each  $i = 1, 2, \dots, m$

$0 \leq x_j \leq d_j$  for each  $j = 1, 2, \dots, n$



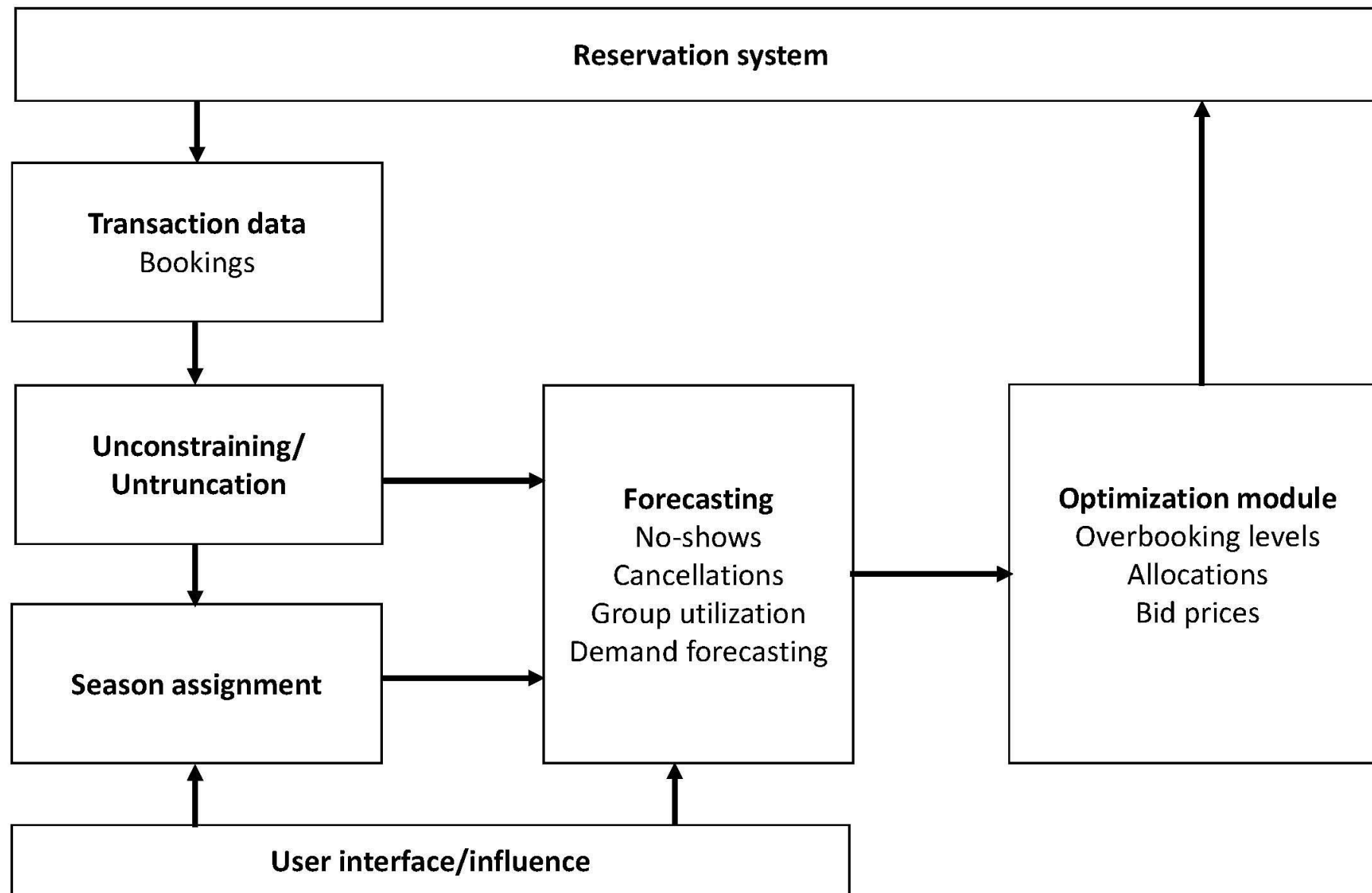
# Bid price calculation

- Deterministic linear programming
- Randomized linear programming
- Probabilistic nonlinear programming

$$\begin{aligned} \max \quad & \sum_{j=1}^n p_j x_j \\ \text{s.t.} \quad & \sum_{j=1}^n a_{ij} x_j \leq b_i \quad \text{for all } i = 1, 2, \dots, m \\ & 0 \leq x_j \leq d_j \quad \text{for all } j = 1, 2, \dots, n \end{aligned}$$

$$\begin{aligned} & (D_1^{(1)}, D_2^{(1)}, \dots, D_n^{(1)}) \\ & (D_1^{(2)}, D_2^{(2)}, \dots, D_n^{(2)}) \\ & \dots \\ & (D_1^{(\ell)}, D_2^{(\ell)}, \dots, D_n^{(\ell)}), \end{aligned} \quad \frac{1}{\ell} \sum_{k=1}^{\ell} \nu_i(\mathbf{b}, (D_1^{(k)}, D_2^{(k)}, \dots, D_n^{(k)})).$$

$$\begin{aligned} \max \quad & \sum_{j=1}^n p_j E[\min(X_j, y_j)] \\ \text{s.t.} \quad & \sum_{j=1}^n a_{ij} y_j \leq b_i \quad \text{for all } i = 1, 2, \dots, m \\ & y_j \geq 0 \quad \text{for all } j = 1, 2, \dots, n \end{aligned}$$



# B2B pricing analytics

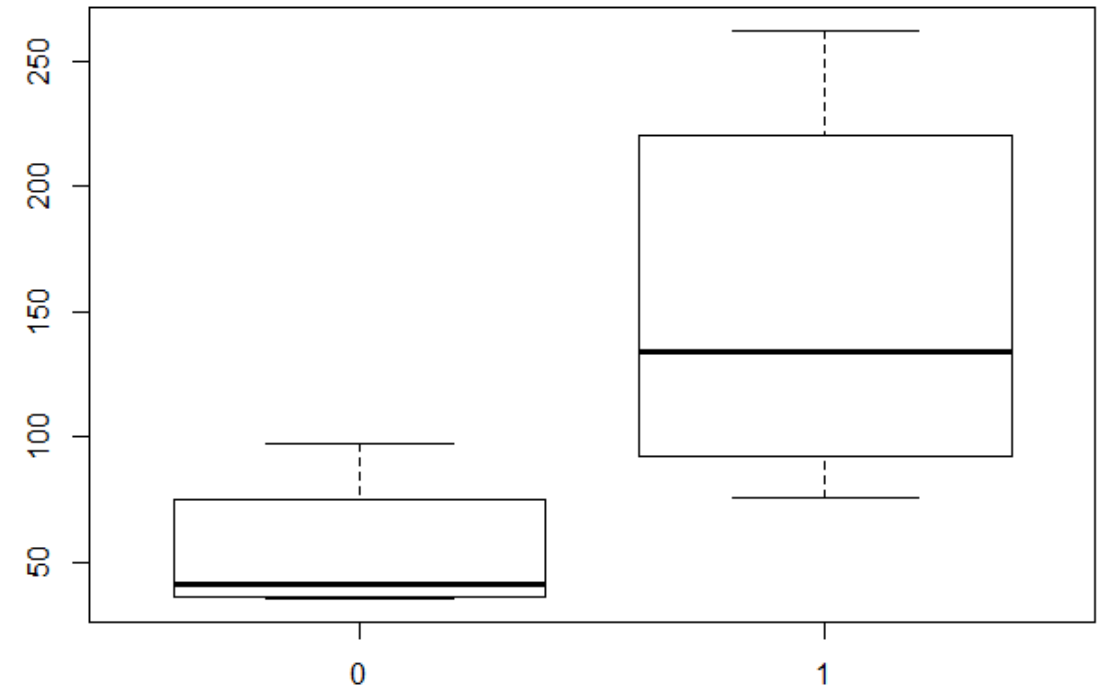
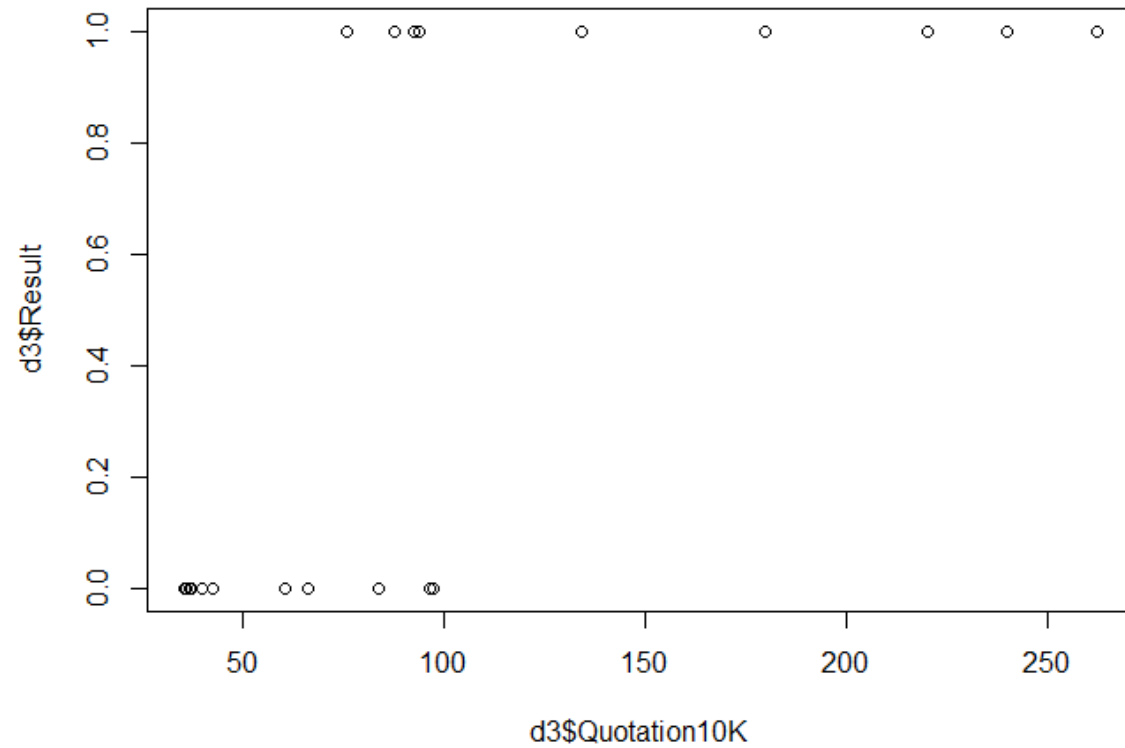
**B2B**

**B2C**

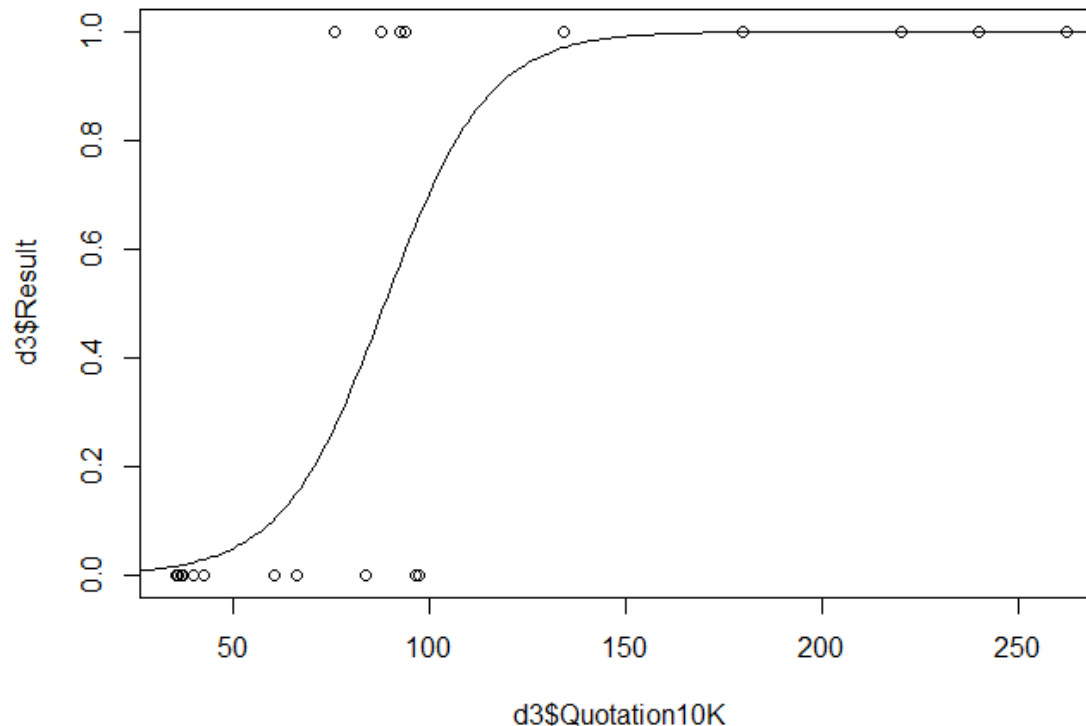
# Historical record: Palletizer bidding result

0 = Win

1 = Lose



# Logistic regression (binary classification)



Let  $p = P(Y = 1)$  prob of losing.

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right) = \theta_0 + \theta_1 x$$

$$p = \frac{1}{1 + \exp(-(\theta_0 + \theta_1 x))}$$

where  $x$  is the quotation (in 10K).

```
> exp(mylogit3$coefficient[2])
Quotation10K
1.079593
```

```
> mylogit3 <- glm(Result~Quotation10K, data=d3, family = "binomial")
```

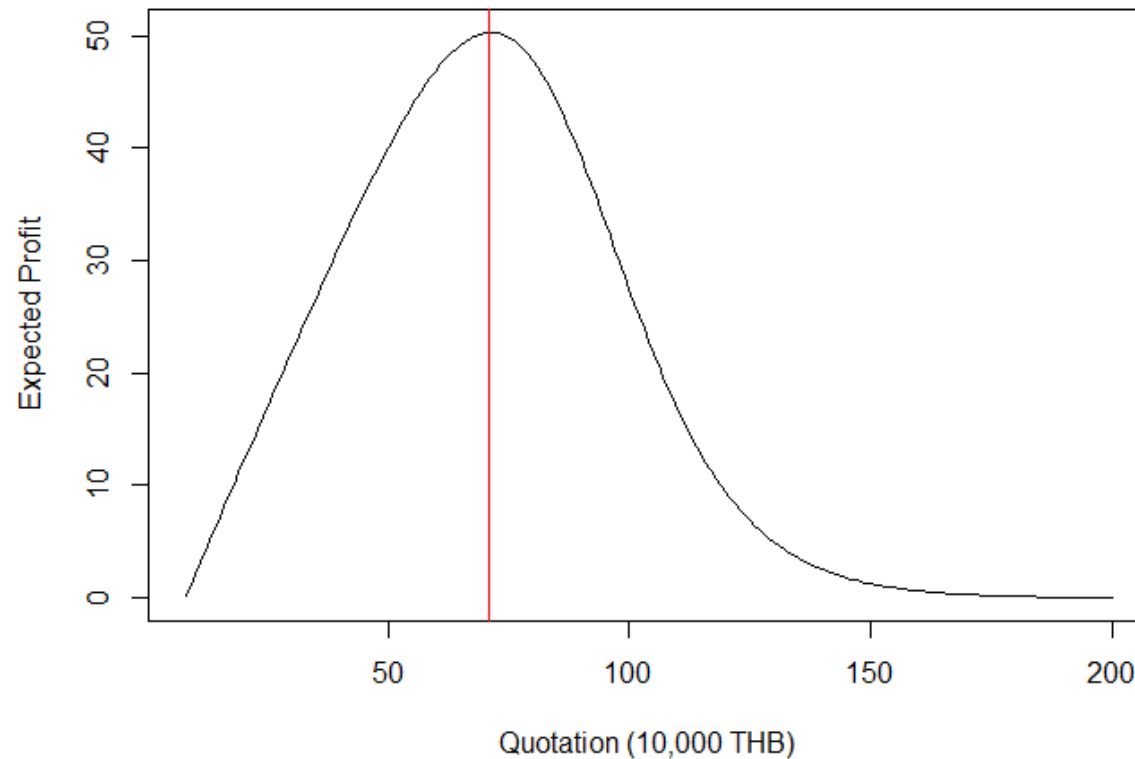
Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-6.79908	3.51682	-1.933	0.0532 .
Quotation10K	0.07658	0.04090	1.873	0.0611 .

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# Optimal bid price



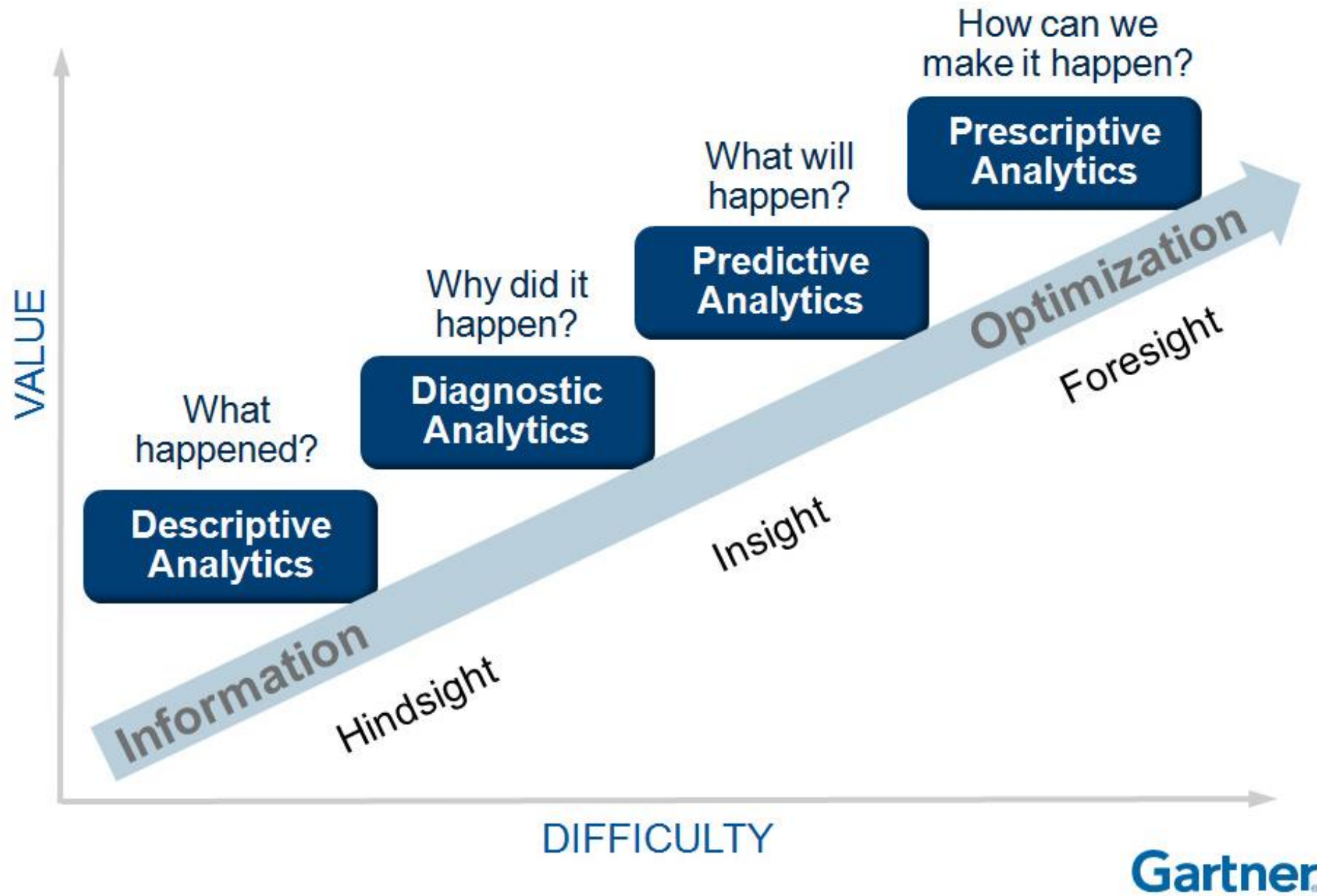
## Input

- Cost = 78,291 THB (installation & maintenance)
- Logistic regression

## Output

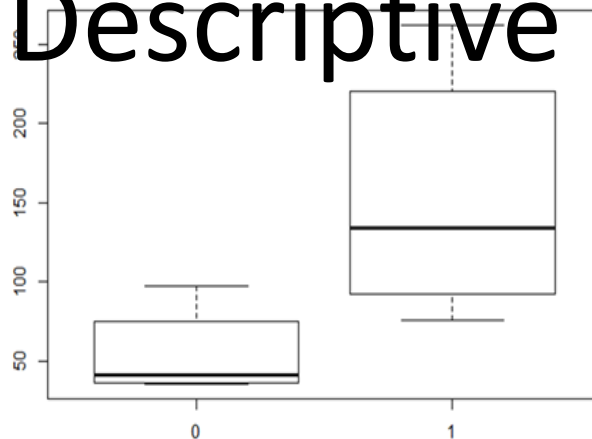
- Optimal bid price = 710,000 THB.
- Probability of winning =  $1 - 0.2040 = 0.7960$ .
- Optimal expected profit = 502,855 THB.

```
profit <- function(x){  
  cost <- 7.8291 #78,291 THB  
  probL <- predict(mylogit3, data.frame(Quotation10K=x), type="response")  
  myprofit <- (1-probL)*(x-cost)  
  return(myprofit)  
}
```

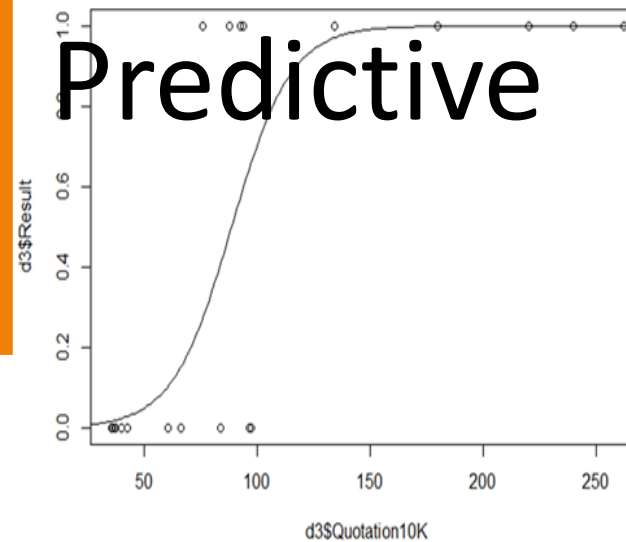


# Pricing Analytics

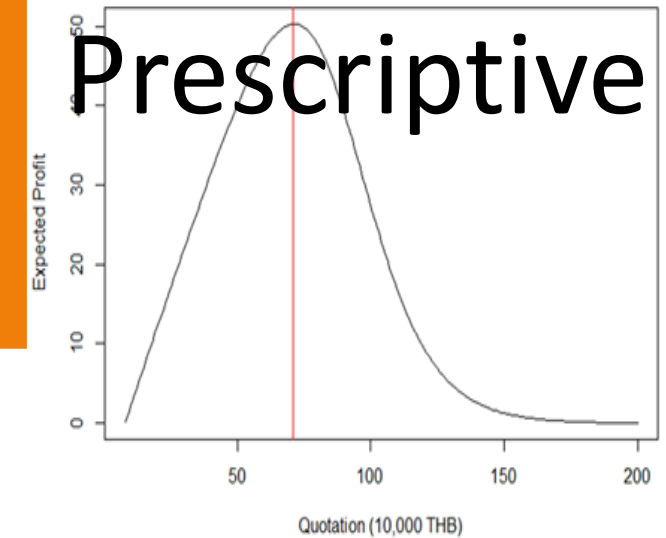
## Descriptive



## Predictive



## Prescriptive





# References

- Amaruchkul, K. (2018). *Revenue Optimization Models*. Bangkok: National Institute of Development Administration Press.
- Ingold, A., McMahon-Beattie, U., & Yeoman, I. (2000). *Yield Management: Strategies for the Service Industries*. London: Cengage Learning.
- International Air Transport Association. (2012). *Airline Revenue Management*. Montreal, International Aviation Training Program.
- Phillips, R. (2005). *Pricing and Revenue Optimization*. Stanford, CA: Stanford University Press.
- Talluri, K., & van Ryzin, G. J. (2004). *The Theory and Practice of Revenue Management*. Boston, MA: Kluwer Academic Publishers.
- Yeoman, I., & McMahon-Beattie, U. (2011). *Revenue Management: A Practical Pricing Perspective*. New York: Palgrave Macmillan.
- Yeoman, I., & McMahon-Beattie, U. (2004). *Revenue Management and Pricing: Case Studies and Applications*. London: Thomson Learning.

คู่มือเรียน - สอบ ▼

สาขาที่มีจำหน่าย : *Revenue Optimization Models*

หนังสือ

...

คู่มือเรียน - สอบ

อุดมศึกษา

สาขาที่มีจำหน่าย

อนุบาล

ประถม

มัธยม

อาชีวศึกษา

อุดมศึกษา

คู่มือสอบเข้า

คู่มือสอบเข้า - บรรจุ

คู่มือสอบเทียบ

เลื่อนชั้น

หนังสืออ่านนอกเวลา



**Revenue Optimization Models**

Addressing an emerging course in Revenue Management, this textbook covers the basic quantitative models in revenue management (RM) and price optimization.

ผู้เขียน **Kannapha Amaruchkul**

หนังสือ

~~550.00 บาท~~

**522.50 บาท**



ซื้อที่คณะสถิติประยุกต์ ลดเหลือ **440** บาท (จำนวนจำกัด)

# Revenue Optimization Models

Kannapha Amuruchkul



National Institute of Development Administration (NIDA)  
Bangkok, Thailand



Revenue Optimization Models

Kannapha Amuruchkul

# Revenue Optimization Models

Kannapha Amuruchkul

Graduate School of  
Applied Statistics



National  
Institute of  
Development  
Administration