Outline

- Concept
- Example
- Components
  - Real-Time Transaction Processing
  - Extracting, Transforming, and Loading Data
  - Forecasting
  - Optimization
  - Decision Support
- Non-Traditional Applications
- Further Reading and Special Interest Groups
Revenue Management and Dynamic Pricing

Revenue Management in Concept
What is Revenue Management?

- Began in the airline industry
  - Seats on an aircraft divided into different products based on different restrictions
    - $1000 Y class product: can be purchased at any time, no restrictions, fully refundable
    - $200 Q class product: Requires 3 week advanced purchase, Saturday night stay, penalties for changing ticket after purchase
  - Question: How much inventory to make available in each class at each point in the sales cycle?
What is Revenue Management?

Revenue Management:
- The science of maximizing profits through market demand forecasting and the mathematical optimization of pricing and inventory.

Related names:
- Yield Management (original)
- Revenue Optimization
- Demand Management
- Demand Chain Management
Rudiments

- Strategic / Tactical: Marketing
  - Market segmentation
  - Product definition
  - Pricing framework
  - Distribution strategy

- Operational: Revenue Management
  - Forecasting demand by willingness-to-pay
  - Dynamic changes to price and available inventory
Industry Popularity

- Was born of a business problem and speaks to a business problem
- Addresses the revenue side of the equation, not the cost side
  - 2 – 10% revenue improvements common
## Industry Accolades

<table>
<thead>
<tr>
<th>THE WALL STREET JOURNAL</th>
<th>Houston Chronicle</th>
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<tbody>
<tr>
<td>&quot;Now we can be a lot smarter. Revenue management is all of our profit, and more.”</td>
<td>&quot;PROS products have been a key factor in Southwest's profit performance.”</td>
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<tr>
<td>Bill Brunger, Vice President Continental Airlines</td>
<td>Keith Taylor, Vice President Southwest Airlines</td>
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“Revenue Pricing Optimization represent the next wave of software as companies seek to leverage their ERP and CRM solutions.”
- Scott Phillips, Merrill Lynch

“One of the most exciting inevitabilities ahead is ‘yield management.’”
- Bob Austrian, Banc of America Securities

“Revenue Optimization will become a competitive strategy in nearly all industries.”
- AMR Research
“An area of particular interest to operations research experts today, according to Trick, is revenue management.”

Information Week, July 12, 2002.

Dr. Trick is a Professor at CMU and President of INFORMS.
Academic Accolades

As we move into a new millennium, dynamic pricing has become the rule. “Yield management,” says Mr. Varian, “is where it’s at.”

“To Hal Varian the Price is Always Right,” strategy+business, Q1 2000.

Dr. Varian is Dean of the School of Information Management and Systems at UC Berkeley, and was recently named one of the 25 most influential people in eBusiness by Business Week (May 14, 2001)
Application Areas

Traditional

- Airline
- Hotel
- Extended Stay Hotel
- Car Rental
- Rail
- Tour Operators
- Cargo
- Cruise

Non-Traditional

- Energy
- Broadcast
- Healthcare
- Manufacturing
- Apparel
- Restaurants
- Golf
- More…
The distinction between revenue management and dynamic pricing is not altogether clear
- Are fare classes different products, or different prices for the same product?

Revenue management tends to focus on inventory availability rather than price
- Reality is that revenue management and dynamic pricing are inextricably linked
Traditional Revenue Management

- Non-traditional revenue management and dynamic pricing application areas have not evolved to the point of standard industry practices
- Traditional revenue management has, and we focus primarily on traditional applications in this presentation
Revenue Management and Dynamic Pricing

Managing Airline Inventory
A mid-size carrier might have 1000 daily departures with an average of 200 seats per flight leg.
Airline Inventory

- 200 seats per flight leg
  - $200 \times 1000 = 200,000$ seats per network day
- 365 network days maintained in inventory
  - $365 \times 200,000 = 73$ million seats in inventory at any given time
- The mechanics of managing final inventory represents a challenge simply due to volume
Revenue management provides analytical capabilities that drive revenue maximizing decisions on what inventory should be sold and at what price

- Forecasting to determine demand and its willingness-to-pay
- Establishing an optimal mix of fare products
Should a $1200 SEA-IAH-ATL M class itinerary be available? A $2000 Y class itinerary?
§ Should a $600 IAH-ATL-EWR B class itinerary be available? An $800 M class itinerary?
Fare Product Mix

- Optimization puts in place inventory controls that allow the highest paying collection of customers to be chosen.
- When it makes economic sense, fare classes will be closed so as to save room for higher paying customers that are yet to come.
Revenue Management and Dynamic Pricing

Components
The Real-Time Transaction Processor

Real Time Transaction Processor (RES System)

Requests for Inventory
The Revenue Management System

- Extract, Transform, and Load Transaction Data
- Forecasting
- Optimization

Revenue Management System

Real Time Transaction Processor (RES System)

Requests for Inventory
Analysts

Revenue Management System

Extract, Transform, and Load Transaction Data ➔ Forecasting ➔ Optimization ➔ Analyst Decision Support

Real Time Transaction Processor (RES System)

Requests for Inventory
The Revenue Management Process

- Extract, Transform, and Load Transaction Data
- Forecasting
- Optimization

Revenue Management System

Analyst Decision Support

Real Time Transaction Processor (RES System)

Requests for Inventory
Real-Time Transaction Processor

- The optimization parameters required by the real-time transaction processor and supplied by the revenue management system constitute the inventory control mechanism.
DFW-EWR: $1000 Y   $650 M   $450 B   $300 Q
Nested leg/class availability is the predominant inventory control mechanism in the airline industry.
A fare class must be open on both flight legs if the fare class is to be open on the two-leg itinerary.
Extract, Transform, and Load Transaction Data

- Complications
  - Volume
  - Performance requirements
  - New products
  - Modified products
  - Purchase modifications
Extract, Transform, and Load Transaction Data

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PSG 01 OA 2297 MYR IAH Q 010903 1140 010903 1255 010903 1540 010903 1655 HK OA 0 0
Demand Models and Forecasting

- How should demand be modeled and forecast?
  - Small numbers / level of detail
  - Unobserved demand and unconstraining
  - Elements of demand: purchases, cancellations, no shows, go shows
  - Demand model ... the process by which consumers make product decisions
  - Demand correlation and distributional assumptions
  - Seasonality
Demand Models and Forecasting

- Holidays and recurring events
- Special events
- Promotions and major price initiatives
- Competitive actions
Optimization

- Optimization issues
  - Convertible inventory
  - Movable inventory / capacity modifications
  - Overbooking / oversale of physical inventory
  - Upgrade / upward substitutable inventory
  - Product mix / competition for resources / network effects
# Decision Support


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<th>Phy Cap</th>
<th>Adj Cap</th>
<th>Upgrades</th>
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### Booking curve (Business)

![Booking curve (Business)](image)

### Booking curve (Economy)

![Booking curve (Economy)](image)
Revenue Management and Dynamic Pricing

Non-Traditional Applications
Two Non-Traditional Applications

- Broadcast
  - Business processes surrounding the purchase and fulfillment of advertising time require modification of traditional revenue management models

- Healthcare
  - Business processes surrounding patient admissions require re-conceptualization of the revenue management process
New Areas

- Contracts and long term commitments of inventory
- Customer level revenue management
- Integrating sales and inventory management
- Alliances and cooperative agreements
Revenue Management and Dynamic Pricing

Further Reading and Special Interest Groups
Further Reading

- For an entry point into traditional revenue management
Special Interest Groups

- INFORMS Revenue Management Section
  - www.rev-man.com/Pages/MAIN.htm
  - Annual meeting held in June at Columbia University

- AGIFORS Reservations and Yield Management Study Group
  - www.agifors.org
  - Follow link to Study Groups
  - Annual meeting held in the Spring
Revenue Management and Dynamic Pricing: Part II

E. Andrew Boyd
Chief Scientist and Senior VP, Science and Research
PROS Revenue Management
aboyd@prosrm.com
Outline

- Single Flight Leg
  - Leg/Class Control
  - Bid Price Control

- Network (O&D) Control
  - Control Mechanisms
  - Models
Revenue Management and Dynamic Pricing

Single Flight Leg
At a fixed point in time, what are the optimal nested inventory availability limits?

DFW-EWR: $1000 Y $650 M $450 B $300 Q
A Mathematical Model

- **Given:**
  - Fare for each fare class
  - Distribution of total demand-to-come by class
    - Demand assumed independent

- **Determine:**
  - Optimal nested booking limits

- **Note:**
  - Cancellations typically treated through separate optimization model to determine overbooking levels
A Mathematical Model

- When inventory is partitioned rather than nested, the solution is simple
  - Partition inventory so that the expected marginal revenue generated of the last seat assigned to each fare class is equal (for sufficiently profitable fare classes)
A Mathematical Model

- Nested inventory makes the problem significantly more difficult due to the fact that demand for one fare class impacts the availability for other fare classes
  - The problem is ill-posed without making explicit assumptions about arrival order
- Early models assumed low-before-high fare class arrivals
There exists a substantial body of literature on methods for generating optimal nested booking class limits

- Mathematics basically consists of working through the details of conditioning on the number of arrivals in the lower value fare classes

- An heuristic known as EMSRb that mimics the optimal methods has come to dominate in practice
An Alternative Model

- The low-before-high arrival assumption was addressed by assuming demand arrives by fare class according to independent stochastic processes (typically non-homogeneous Poisson).
  - Since many practitioners conceptualize demand as total demand-to-come, models based on stochastic processes frequently cause confusion.
A Leg DP Formulation

- With Poisson arrivals, a natural solution methodology is dynamic programming
  - Stage space: time prior to departure
  - State space within each stage: number of bookings
  - State transitions correspond to events such as arrivals and cancellations
Seats Remaining

n+3

n+2

n+1

n

Cancellation

No Event / Rejected Arrival

Accepted Arrival

Time to Departure

T  T-1  T-2  T-3  ...  1  0
A Leg DP Formulation

- \( V(t,n) \): Expected return in stage \( t \), state \( n \) when making optimal decisions
  - \( V(t,n) = \max_u \left[ p_0 \left( 0 + V(t-1,n) \right) \right. \quad \text{No event} \)
  - \( (1- p_0) \; \cdot_c \; (0 + V(t-1,n-1) ) + \quad \text{Cancel} \)
  - \( (1- p_0) \; \cdot_{i < u} \; (f_i + V(t-1,n) ) \quad \text{Arrival/Reject} \)
  - \( (1- p_0) \; \cdot_{i = u} \; (f_i + V(t-1,n+1) ) \quad \text{Arrival/Accept} \)

- \( u(t,n) \): Optimal price point for making accept/reject decisions when event in stage \( t \), state \( n \) is a booking request
A Leg DP Formulation

- DP has the interesting characteristic that it calculates $V(t,n)$ for all $(t,n)$ pairs
  - Provides valuable information for decision making
  - Presents computational challenges
- This naturally suggests an alternative control mechanism to nested fare class availability
  - Bid price control
\[ V(t, n) = \text{Expected Revenue} \]
Seats Remaining

\[ V(t, n) = \text{Expected Revenue} \]

\[ V(t, n+1) - V(t, n) = \text{Marginal Expected Revenue} \]
Bid Price Control:
With \( n+1 \) seats remaining, accept only arrivals with fares in excess of 345
Bid Price Control

- Like nested booking limits, there exists a substantial literature on dynamic programming methods for bid price control.

- While bid price control is simple and mathematically optimal (for its modeling assumptions), it has not yet been broadly accepted in the airline industry.
  - Substantial changes to the underlying business processes.
Bid Price Control

- Solutions from dynamic programming can also be converted to nested booking limits, but this technique has not been broadly adopted in practice.
- Bid price control can be implemented with roughly the same number of control parameters (bid prices) as nested fare class availability.
Revenue Management and Dynamic Pricing

Network (O&D) Control
Control Mechanisms
Network Control

- Network control recognizes that passengers flow on multiple flight legs
  - An issue of global versus local optimization
- Problem is complicated for many reasons
  - Forecasts of many small numbers
  - Data
  - Legacy business practices
Inventory Control Mechanism

- The inventory control mechanism can have a substantial impact on
  - Revenue
  - Marketing and distribution
    - Changes to RES system
    - Changes to contracts and distribution channels
Example: Limitations of Leg/Class Control

- **Supply:**
  - 1 seat on the SAT-DFW leg
  - 1 seat on the DFW-EWR leg

- **Demand:**
  - 1 $300 SAT-DFW Y passenger
  - 1 $1200 SAT-DFW-EWR Y passenger
Example:
Limitations of Leg/Class Control

- Optimal leg/class availability is to leave one seat available in Y class on each leg.
Example: Limitations of Leg/Class Control

With leg/class control, there is no way to close SAT-DFW Y while leaving SAT-DFW-EWR Y open.

- Supply:
  - 1 seat on the SAT-DFW leg
  - 1 seat on the DFW-EWR leg

- Demand:
  - 1 $300 SAT-DFW Y passenger
  - 1 $1200 SAT-DFW-EWR Y passenger
Limitations of Leg/Class Control

- The limitations of leg/class availability as a control mechanism largely eliminate revenue improvements from anything more sophisticated than leg/class optimization.
- For this reason, carriers that adopt O&D control also adopt a new inventory control mechanism:
  - Requires tremendous effort and expense to work around the legacy inventory environment.
Alternative Control Mechanisms

- While there are many potential inventory control mechanisms other than leg/class control, two have come to predominate O&D revenue management applications:
  - Virtual nesting
  - Bid price
- Note that the concept of itinerary/fare class (ODIF) inventory level control is impractical.
Virtual Nesting

- A primal control mechanism similar in flavor to leg/class control
  - A small set of virtual inventory buckets are determined for each leg
  - Nested inventory levels are established for each bucket
  - Each leg in an ODIF is mapped to a leg inventory bucket and an ODIF is available for sale if inventory is available in each leg bucket
Virtual Nesting

SAT-DFW-EWR Y maps to virtual bucket 3 on leg SAT-DFW and virtual bucket 1 on leg DFW-EWR

Total availability of 10 for SAT-DFW-EWR Y
Virtual Nesting

- SAT-DFW Y maps to virtual bucket 4 on leg SAT-DFW
- SAT-DFW Y is closed
Bid Price Control

- A dual control mechanism
  - A bid price is established for each flight leg
  - An ODIF is open for sale if the fare exceeds the sum of the bid prices on the legs that are used
Bid Price Control

SAT-DFW-EWR Y is open for sale because
$1200 \geq 400 + 600$

Bid Price = $400
Bid Price = $600
SAT-DFW Y is closed for sale because $300 < $400
Intermediate control between optimization points is achieved by having a different bid price for each seat sold in inventory.
After a seat is sold the bid price increases, reflecting the reduced inventory availability.
Virtual Nesting

- **Advantages**
  - Very good revenue performance
  - Computationally tractable
  - Relatively small number of control parameters
  - Comprehensible to users
  - Accepted industry practice

- **Disadvantages**
  - Not directly applicable to multi-dimensional resource domains
  - Proper operation requires constant remapping of ODIFs to virtual buckets
Bid Price Control

- **Advantages**
  - Excellent revenue performance
  - Computationally tractable
  - Comprehensible to users
  - Broader use than revenue management applications
    - Places a monetary value on unit inventory

- **Disadvantages**
  - Growing user acceptance, but has not reached the same level as primal methods
Revenue Management and Dynamic Pricing

Network (O&D) Control Models
A Model

- The demand allocation model (also known as the demand-to-come model) has been proposed for use in revenue management applications, but is typically not employed.

- For all of its limitations, the demand allocation model brings to light many of the important issues in revenue management.
Demand Allocation Model

\[
\begin{align*}
\text{Max} & \quad \sum_{i \in I} r_i x_i \\
\text{s.t.} & \quad \sum_{i \in I(e)} x_i \leq c_e \quad e \in E \quad (\lambda_e) \\
& \quad x_i \leq d_i \quad i \in I \quad (\omega_i) \\
& \quad x_i \geq 0 \quad i \in I
\end{align*}
\]

$I = \text{set of ODIFs}$  \hspace{1cm} $d_i = \text{demand for ODIF } i$

$E = \text{set of flight legs}$  \hspace{1cm} $r_i = \text{ODIF } i \text{ revenue}$

$c_e = \text{capacity of flight } e$  \hspace{1cm} $I(e) = \text{ODIFs using flight } e$

$x_i = \text{demand allocated to ODIF } i$
The variables $x_i$ can be rolled up to generate leg/class availability.
Virtual Nesting

\[
\begin{align*}
\text{Max} & \quad \sum_{i \in I} r_i x_i \\
\text{s.t.} & \quad \sum_{i \in l(e)} x_i \leq c_e \quad e \in E \quad (\lambda_e) \\
& \quad x_i \leq d_i \quad i \in l \quad (\omega_i) \\
& \quad x_i \geq 0 \quad i \in l
\end{align*}
\]

Once ODIFs have been assigned to leg buckets, the variables \(x_i\) can be rolled up to generate leg/class availability.
Bid Price Control

Max \( \sum_{i \in I} r_i x_i \)

s.t. \( \sum_{i \in I(e)} x_i \leq c_e \quad e \in E \quad (\lambda_e) \)

\( x_i \leq d_i \quad i \in I \quad (\omega_i) \)

\( x_i \geq 0 \quad i \in I \)

The dual variables \( \lambda_e \) associated with the capacity constraints can be used as bid prices
Network Algorithms: Leg/Class Control

- Network algorithms for generating nested leg/class availability are not typically used
  - Limitations of the control mechanism and fare structure eliminate much of the value
Network Algorithms: Virtual Nesting Control

- Optimization consists of determining the ODIF to leg/bucket mapping, and then calculating nested leg/bucket inventory levels
  - Best mappings prorate ODIF fares to legs, and then group similar prorated fares into the same bucket
    - The best proration methods depend on demand forecasts and realized bookings, and change dynamically throughout the booking cycle
  - With ODIFs mapped to buckets, nested bucket inventory levels are calculated using the nested leg/bucket algorithm of choice
Bid prices are normally generated directly or indirectly from the dual solution of a network optimization model.
Resource Allocation Model

- Observations
  - A 200 leg network may have 10,000 active ODIFs, leading to a network optimization problem with 10,000 columns and 10,200 rows
  - With 20,000 passengers, the average number of passengers per ODIF is 2
  - Typically, 20% of the ODIFs will carry 80% of the traffic, with a large number of ODIFs carrying on the order of .01 or fewer passengers per network day
Max \[ \sum_{i \in I} r_i x_i \]
s.t. \[ \sum_{i \in l(e)} x_i \leq c_e \quad e \in E \quad (\lambda_e) \]
\[ x_i \leq d_i \quad i \in l \quad (\omega_i) \]
\[ x_i \geq 0 \quad i \in l \]

Many small numbers
Level of Detail Problem

- The level of detail problem remains a practical consideration when setting up any revenue management system
  - What level of detail do the existing data sources support?
  - What level of detail provides the best revenue performance?
    - At what point does forecast noise overcome improvements from more sophisticated optimization models?
Level of Detail Problem

- As a rule, even with the many small numbers involved, network optimization algorithms perform consistently better than non-network algorithms.
- Dual solutions are typically much more robust and of better quality than solutions constructed from primal ODIF allocations.
Revenue Management and Dynamic Pricing

Network (O&D) Control Optimization Challenges
A Network DP Formulation

Network DP formulation

- Stage space: time prior to departure
- State space within each stage: multidimensional, with number of bookings on each of M flights
- State transitions correspond to events such as ODIF arrivals and cancellations
A Network DP Formulation

- $V(t, n_1, ..., n_M)$: Expected return in stage $t$, state $(n_1, ..., n_M)$ when making optimal decisions
- $u(t, n_1, ..., n_M, k)$: Optimal price point for making accept/reject decisions when event in stage $t$, state $(n_1, ..., n_M)$ is a booking request for ODIF $k$
A Network DP Formulation

- Observations
  - A 200 leg network with an average of 150 seats per flight leg would have $150^{200}$ states per stage.
  - With 10,000 active ODIFs, assuming only single passenger arrivals and cancellations, each state would have ~20,000 possible state transitions.
    - Gives rise to ~20,000 “bid prices” per state.
Consider a booking request at time $t$ for ODIF $k$ in a specific state $(n_1, \ldots, n_M)$. Suppose the request, if accepted, would cause a move to state $(m_1, \ldots, m_M)$. The booking should be accepted if the fare of ODIF $k$ exceeds

$$u(t, n_1, \ldots, n_M, k) = V(t, n_1, \ldots, n_M) - V(t, m_1, \ldots, m_M)$$

Note that only two values of
An Alternative View of DP

- Note that the only difference of two values of $V(\cdot)$ are required for making the decision.
- This leaves open the possibility of using any variety methods for estimating $V(\cdot)$.
  - Opportunity for “large, infrequent” inventory requests.
Active research on approximation techniques for very large scale dynamic programs

- Will this work lead to demonstrably better results for traditional revenue management...
  - ... in the existing distribution environments?
  - ... in new but practical distribution environments?
  - ... under a variety of demand assumptions?
Revenue Management and Dynamic Pricing

E. Andrew Boyd
Chief Scientist and Senior VP, Science and Research
PROS Revenue Management
aboyd@prosrm.com