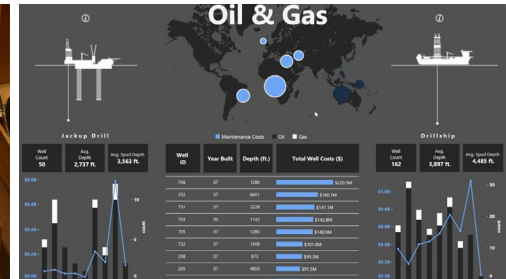


History of Analytics

Doug Gray

Roots of Analytics

- 1940s: World War II
- 1950s–60s: manufacturing
- 1970s: oil
- 1980s: airlines
- 1990s: cruise lines/hotels
- 2000s: financial/FANG
- 2010: big data/IOT/mass adoption
- Present



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Competition

Doug Gray

Airline Deregulation

Optimize to compete or die

Regulation vs. Deregulation

- Competition
 - *Porter's five forces model*
- Pricing
 - *"You're at the mercy of your stupidest competitor,"*
Bob Crandall, AA, CEO
- Capacity
 - Load factor, RASM
- Consumer choice
 - Cheapest fare, flight frequency, non-stops, loyalty program, safety record, customer service

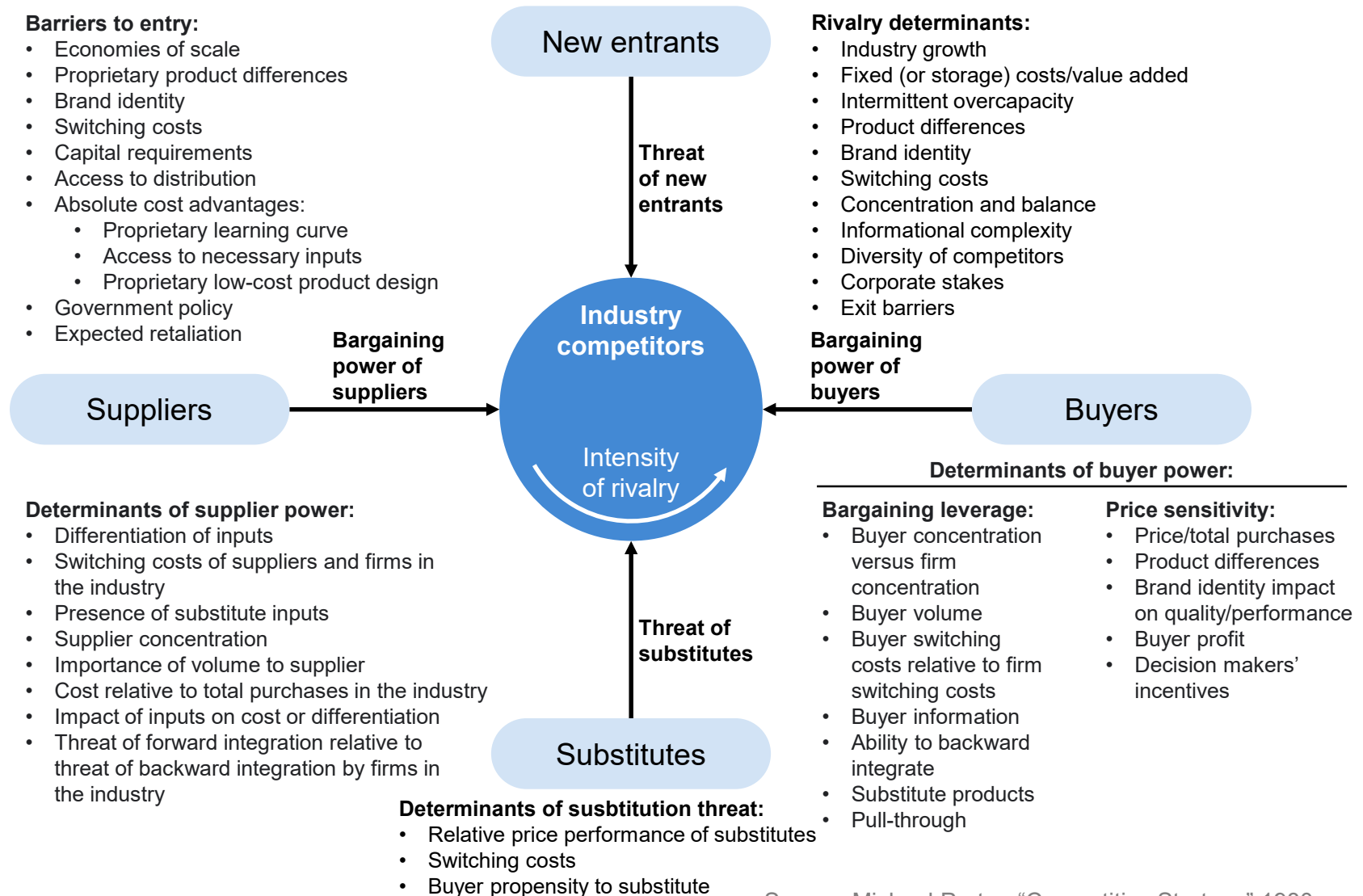


Regulation vs. Deregulation

- **Competition**
 - *Porter's five forces model*
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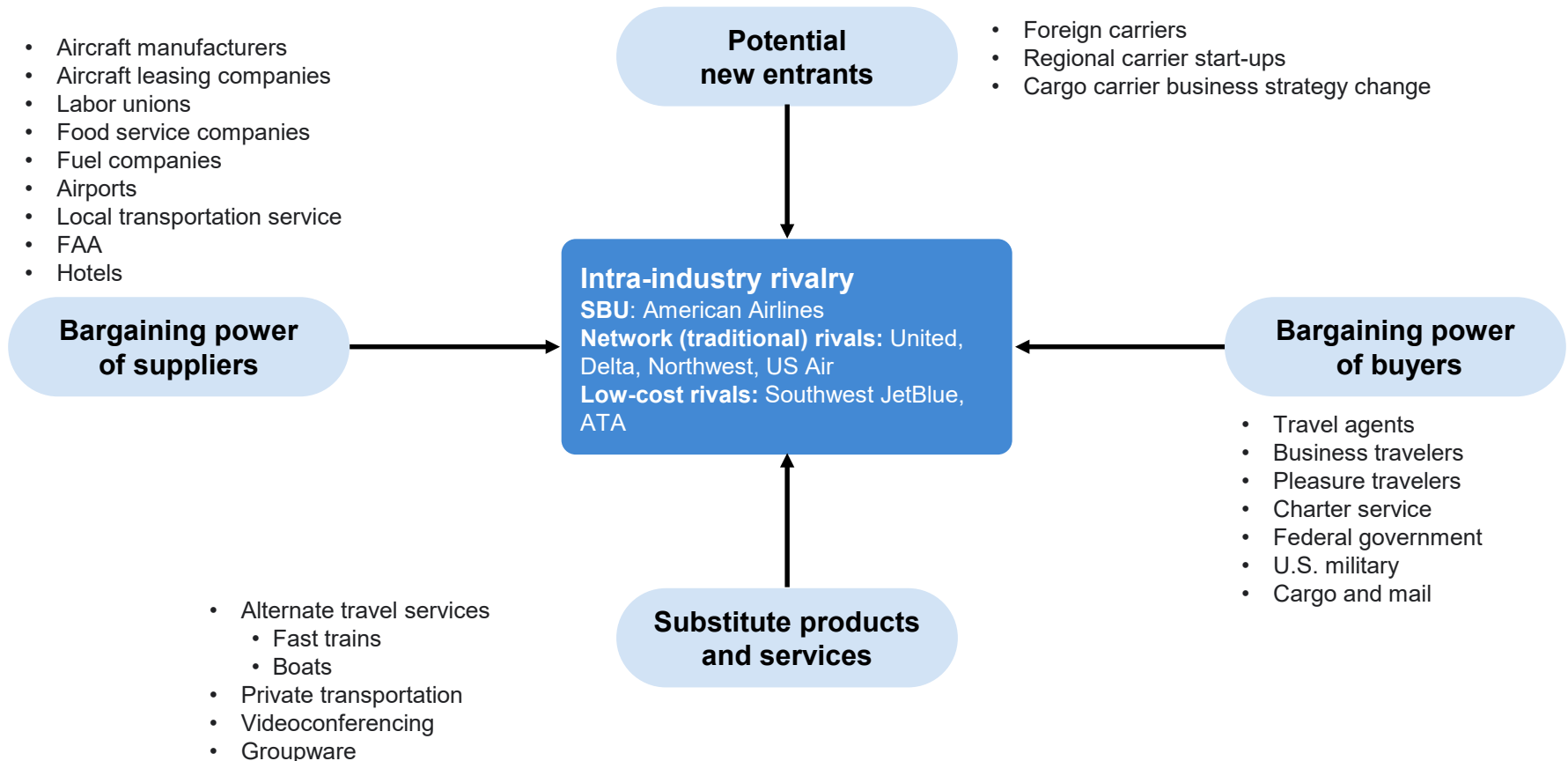
Porter's Five Forces Model



Porter's Five Forces Model: Airline Edition

Porter competitive model

Airline industry analysis: U.S. market



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Pricing

Doug Gray

Regulation vs. Deregulation

- Competition
 - *Porter's five forces model*
- Pricing
 - ***“You’re at the mercy of your stupidest competitor,”***
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Capacity

Doug Gray

Regulation vs. Deregulation

- Competition
 - *Porter's five forces model*
- Pricing
 - *"You're at the mercy of your stupidest competitor,"*
Bob Crandall, AA, CEO
- **Capacity**
 - **Load factor, RASM**
- Consumer choice
 - Cheapest fare, flight frequency, non-stops, loyalty program, safety record, customer service



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Consumer Choice

Doug Gray

Regulation vs. Deregulation

- Competition
 - *Porter's five forces model*
- Pricing
 - *"You're at the mercy of your stupidest competitor,"*
Bob Crandall, AA, CEO
- Capacity
 - Load factor, RASM
- **Consumer choice**
 - **Cheapest fare, flight frequency, non-stops, loyalty program, safety record, customer service**



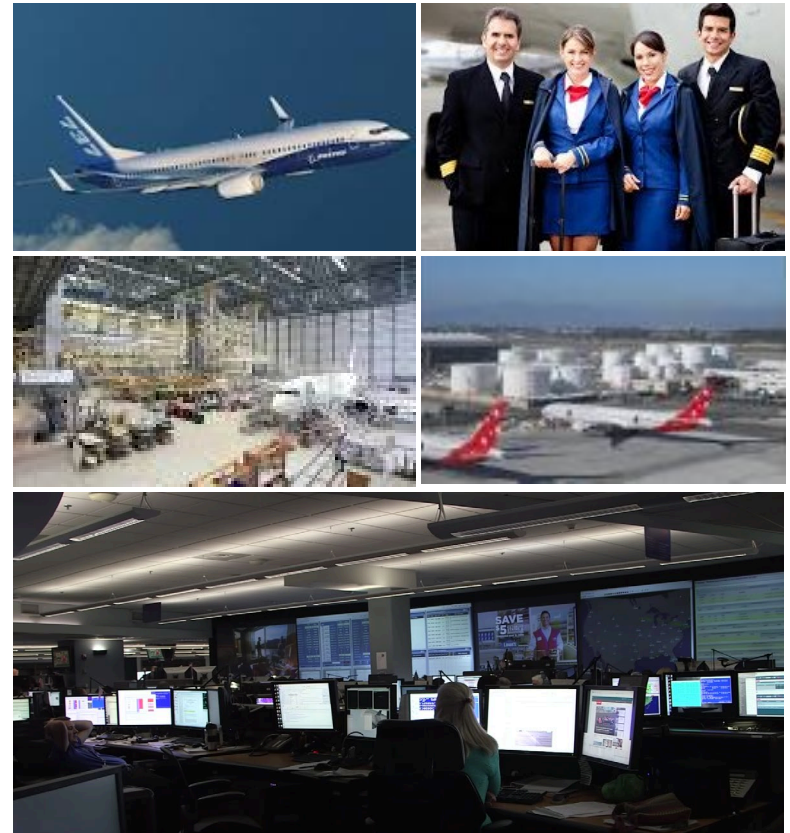
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Airline Industry Characteristics

Doug Gray

Airline Industry Characteristics

- Commodity, differentiation is difficult, loyalty is lacking
- Capital expenditure intensive
- Operating expense intensive
- Labor unions
- Factors out of your control
 - Strategic
 - Tactical
- Logistically complex
- Safety and work rules



Perishable commodity product	Nine schedules/ year	Schedules published months in advance	50% of seats purchased within 60 days prior to DOD	Dynamic, competitive pricing
ATC	TSA	Logistically complex; lots of moving parts	Highly skilled, high cost, nearly all unionized labor	B2C, B2B, and B2G
OPEC I Fuel prices	Everyday weather			CapEx and OpEx intensive
Third party utilities	Extreme weather events	Real-time 24/7/365		
NPS I OTP ROIC MBR RASM CASM	Operations subject to acts of God	DEP+5 ARR+15 SAL	100+ destinations US and abroad	4,000+ flights per day

“If the Wright brothers were alive today Wilbur would have to fire Orville to reduce costs.”

— Herb Kelleher, Southwest Airlines, CEO

“If you want to become a millionaire, start with a billion dollars and start an airline.”

— Sir Richard Branson, Virgin Group, Virgin Atlantic, Virgin Airways

“You @#\$%^ academic eggheads! You don't know \$@#. You can't deregulate this industry. You're going to wreck it. You don't know a @#\$%^ thing!”*

— Robert L. Crandall, CEO American Airlines, addressing a Senate lawyer prior to airline deregulation, 1977

“The deregulated U.S. airline industry is the closest thing to all out warfare in business today.”

— Bob Crandall, American Airlines, CEO

“My Pricing and Yield Management is the most strategic weapon I have in the war of airline deregulation.”

— Bob Crandall, American Airlines, CEO

People's Express CEO Don Burr, blamed AA's SuperSaver program and revenue management system for driving his airline out of business.

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DELTAA & Targets

Doug Gray

Analytics and Optimization at Southwest Airlines Videos and Webinar

<https://www.youtube.com/watch?v=WcJ7YK95ukY>

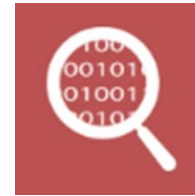
<https://youtu.be/fNrVJqMkE00>

[https://www.brighttalk.com/webcast/14379/306359/
making-analytics-fly-at-southwest-airlines](https://www.brighttalk.com/webcast/14379/306359/making-analytics-fly-at-southwest-airlines)

- (BTW: You do have to fill out a short registration form to access the IIA webinar.)

D-E-L-T-T-A-A (Evolved: 2017)

- **Data**
- **Enterprise**
- **Leadership**
- **Targets**
- ***Technologies***
- ***Analytical Techniques***
- **Analysts**



Data



**Enterprise
view**



**Leadership
support**



Targets



Analysts

Targets

RASM

Revenue per Available
Seat Mile

$= f(\text{Price, Demand, Capacity, Competition Economy,...})$

CASM

Cost per Available
Seat Mile

CapEx OpEx

OTP

On Time Performance

MBR

Mishandled Baggage
Ratio

NPS

Net Promoter Score

Hospitality

Reliability

Efficiency

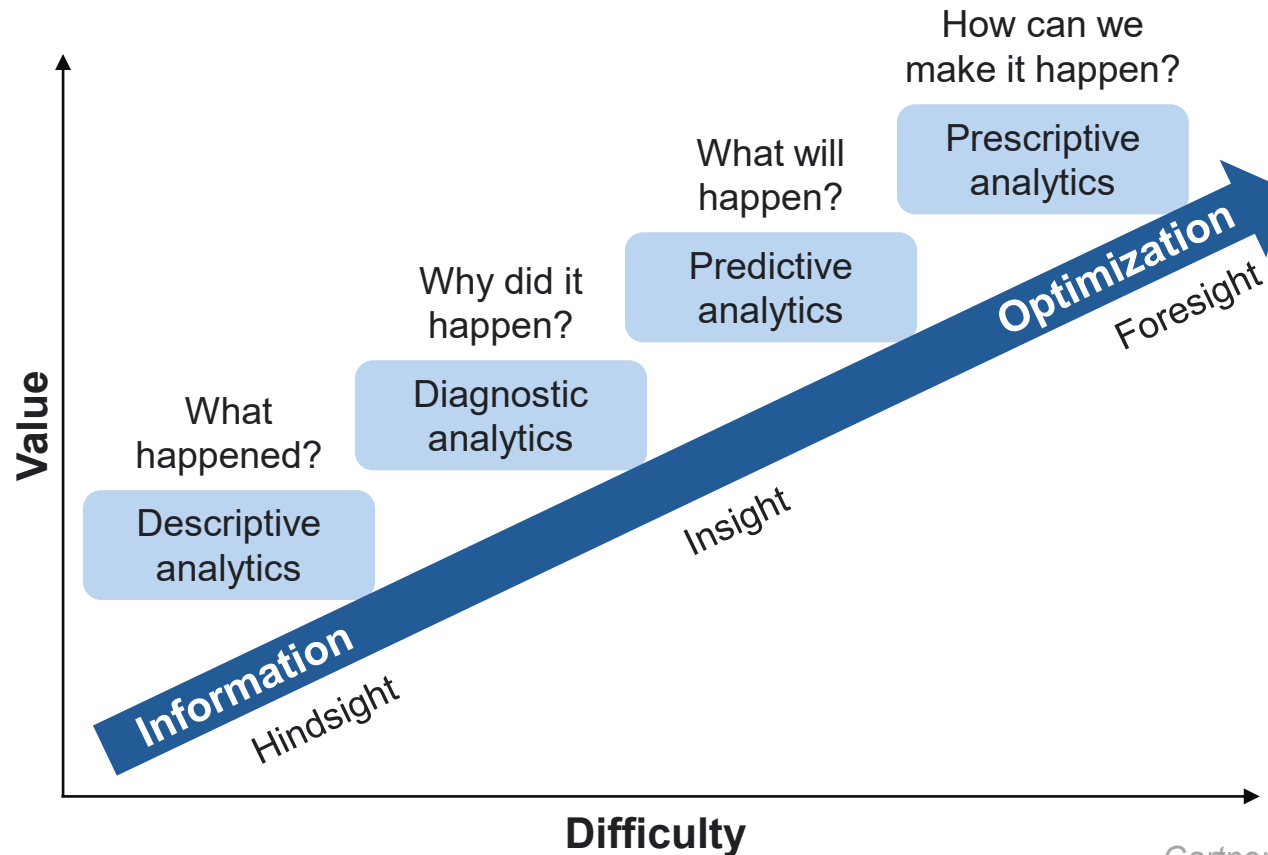
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Why Analytics?

Doug Gray

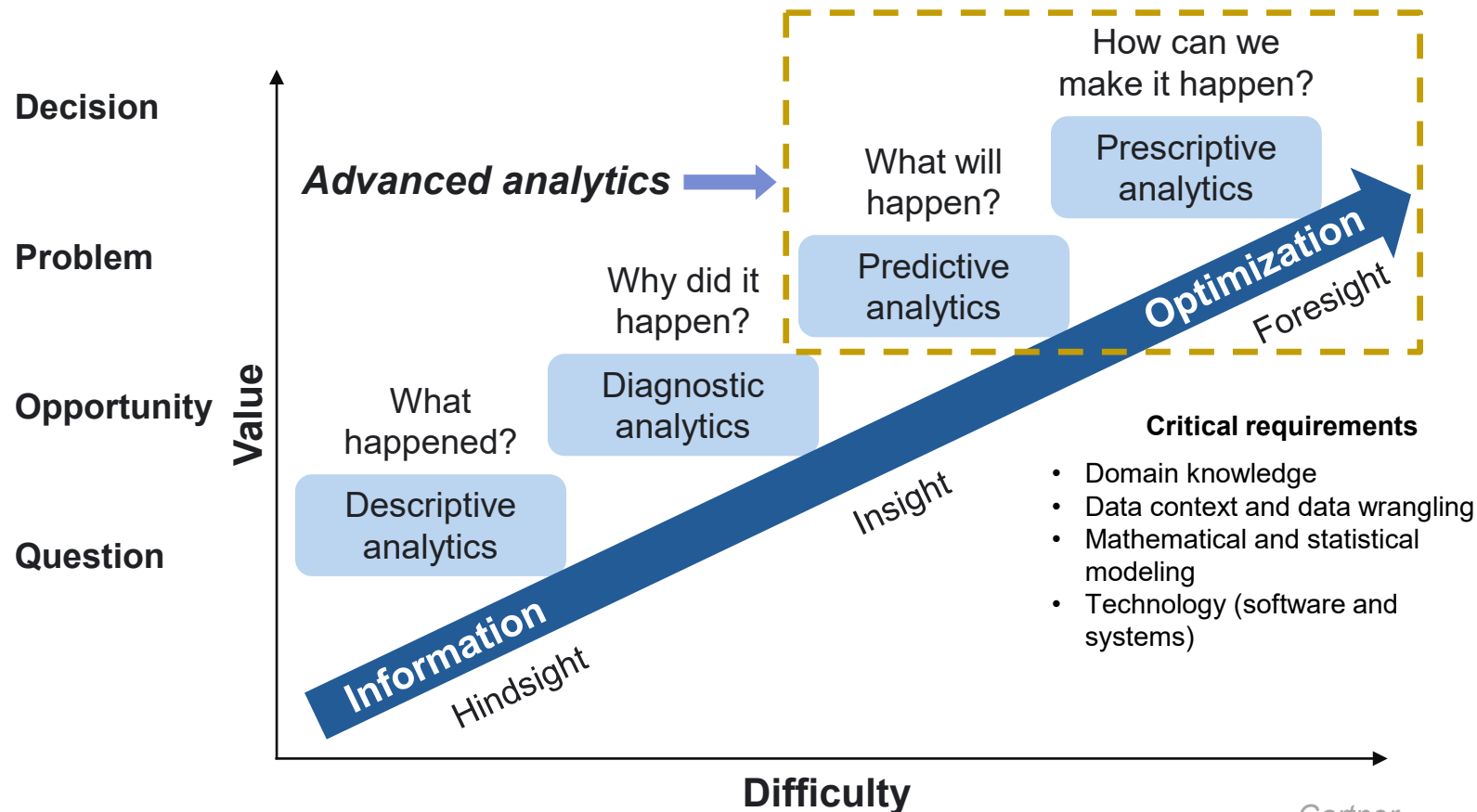
Why Analytics? Context

My team focuses on advanced analytics models and models *embedded* in (planning and near real-time) systems and processes.

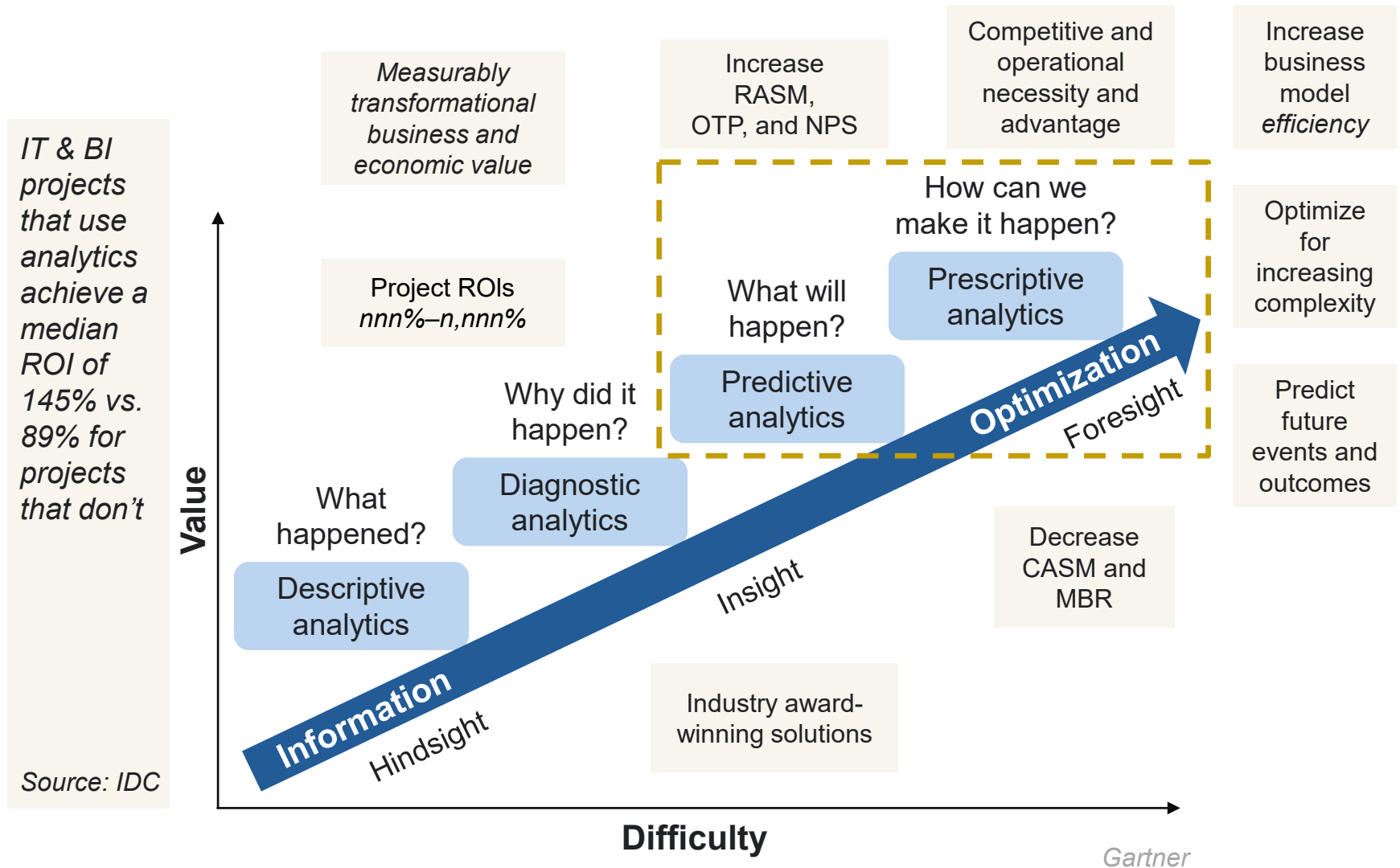


Why Analytics? Context

My team focuses on advanced analytics models and models *embedded* in (planning and near real-time) systems and processes.



Why Analytics? Motivations

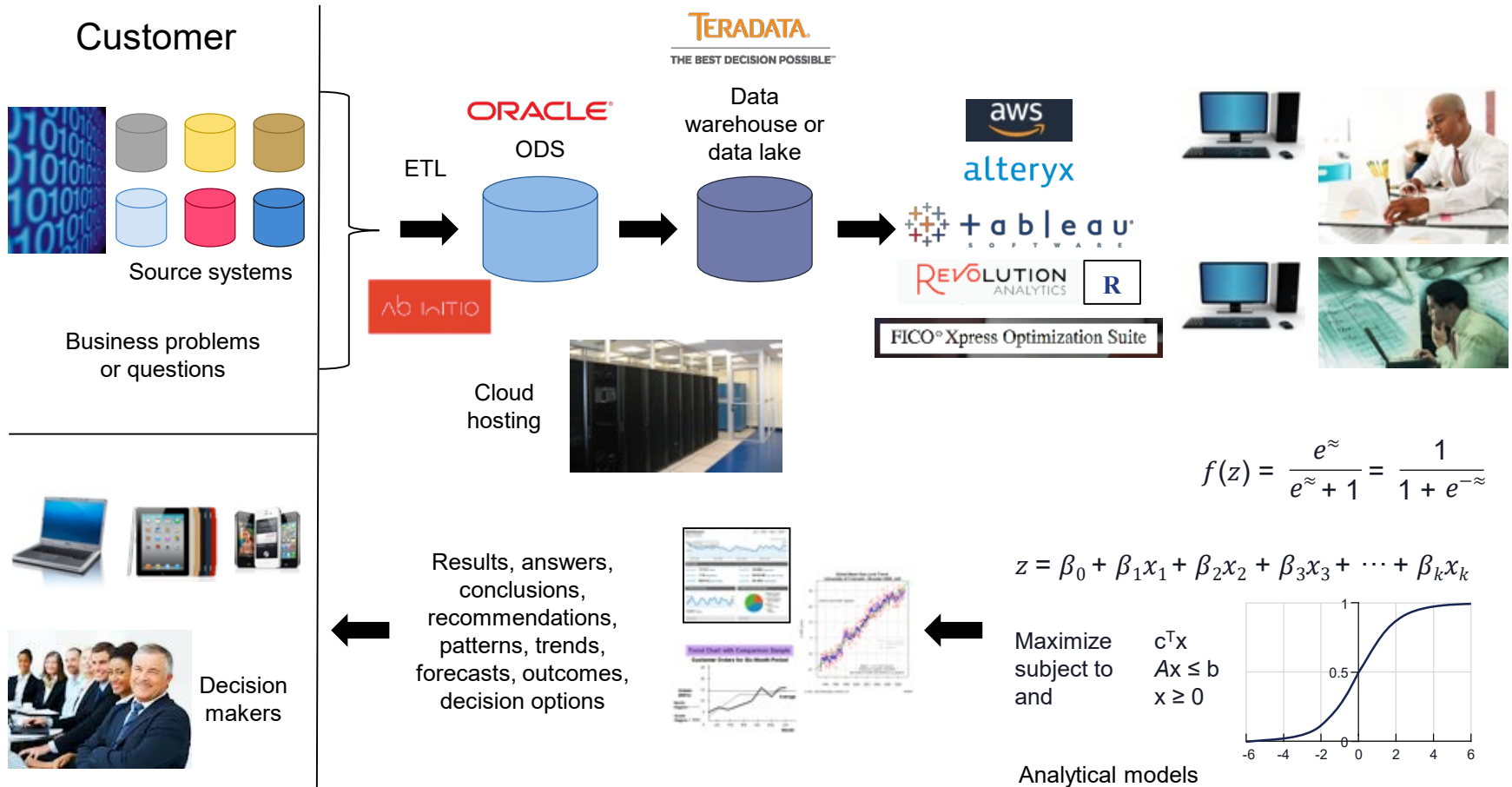


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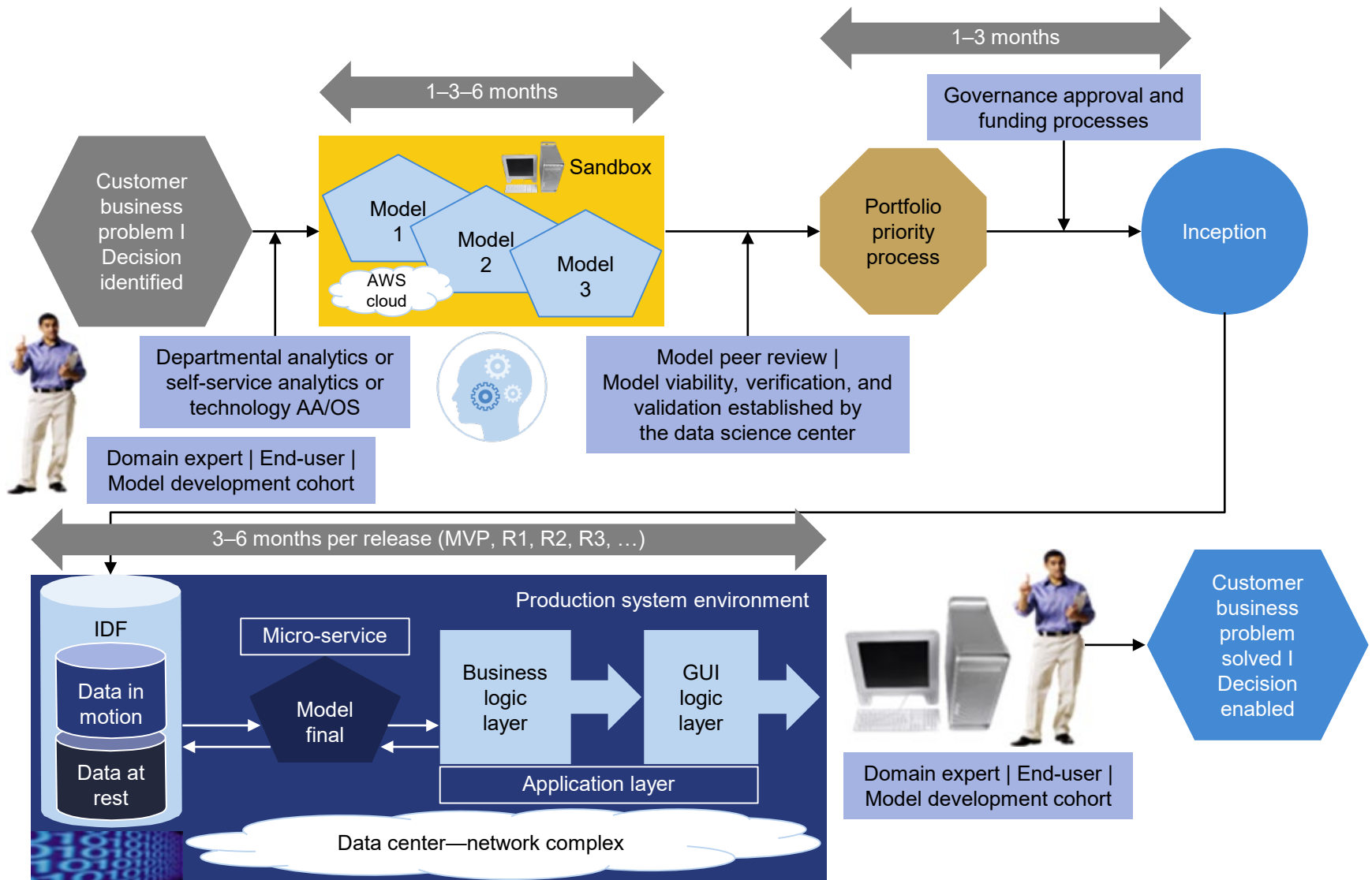
Delivery and Execution

Doug Gray

Analytics Architecture Flow

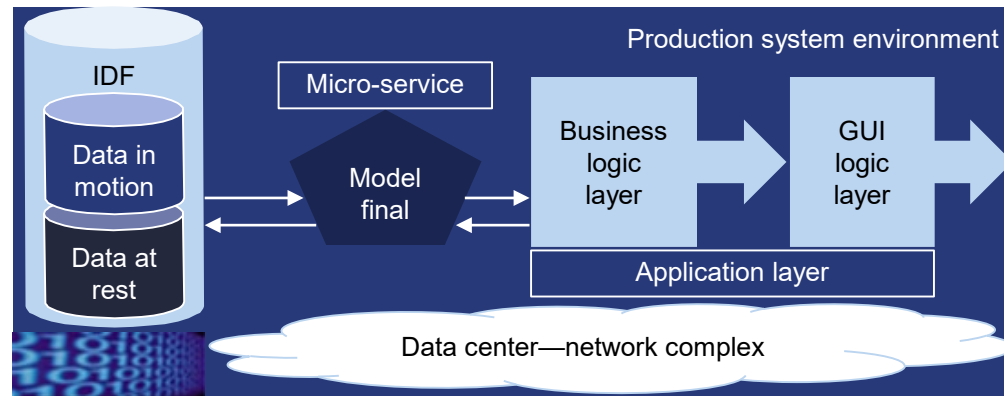


Analytics Project (Delivery Execution) Management

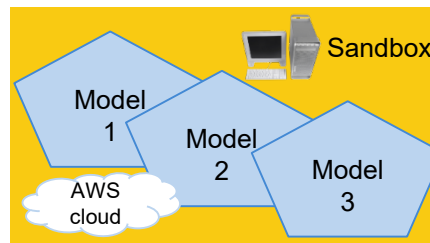


Analytics Project (Delivery Execution) Management

Relatively
difficult

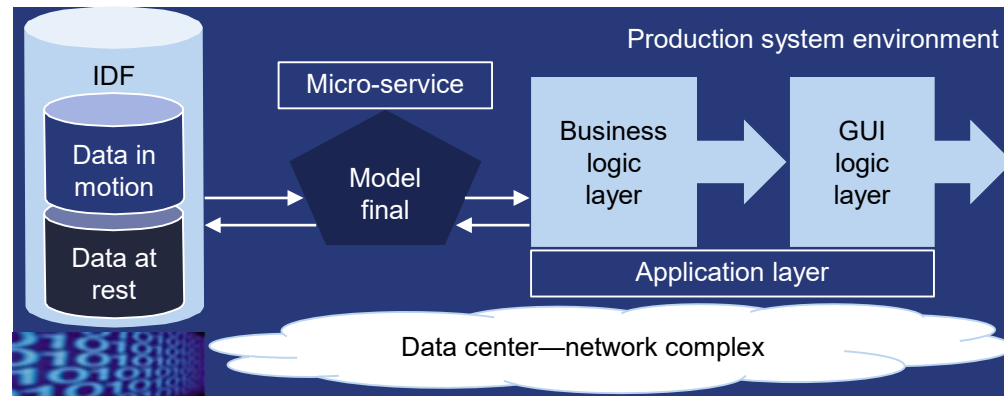


Relatively
simple



Analytics Project (Delivery Execution) Management

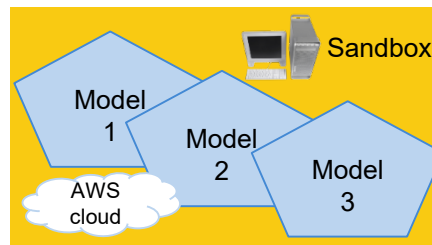
Relatively
difficult



*“Models make the enterprise smarter; models embedded in production systems that enable business process make the enterprise **more efficient**”*

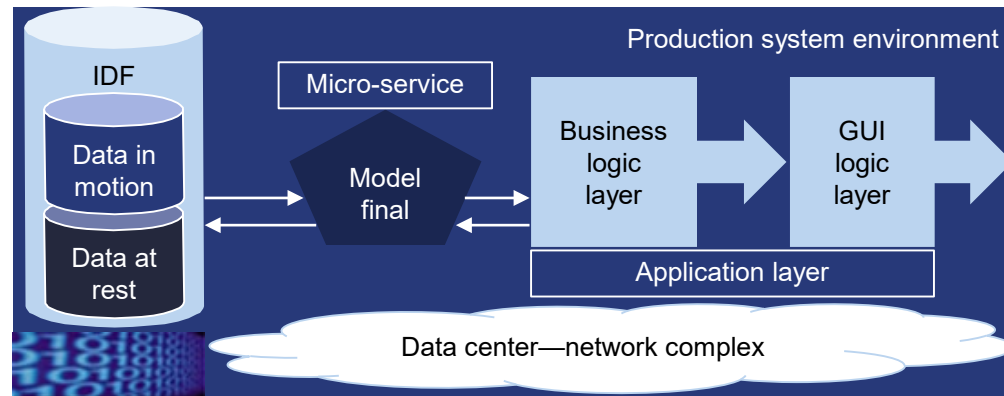
—Tom Davenport, author of **Competing on Analytics**

Relatively
simple



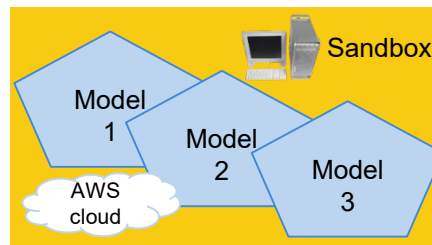
Analytics Project (Delivery Execution) Management

Relatively
difficult



Developing a model is $O(10^1-10^2)$ *less complex* than developing a *model-based enterprise-grade production system that supports a (real-time) business process*

Relatively
simple



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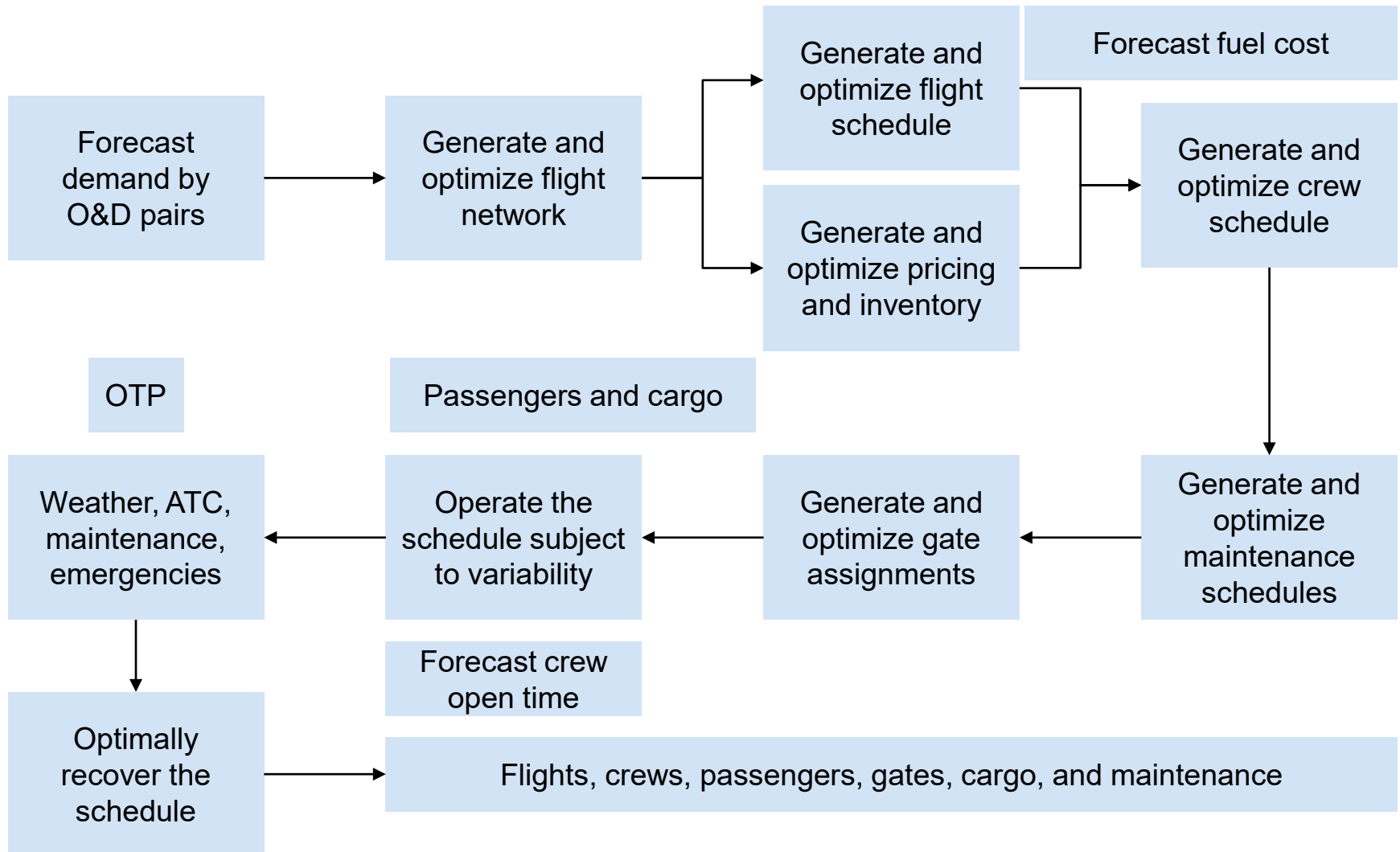
Airline Planning and Operations Process

Doug Gray

Flight and Crew Schedule Optimization

How airlines determine where, when, how often to fly to maximize revenue, while minimizing crew, fuel and other costs

Airline Planning and Operations Process



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Flight Schedule Development

Doug Gray

Flight Schedule Development

- Demand forecasting
 - Market size and quality of service index, discrete (multinomial logit) choice utility modeling
 - Spill and recapture
 - Revenue and cost allocation to estimate schedule profitability
- Fleet assignment model (FAM)
 - Leg- and O&D- and itinerary-based FAM
- Aircraft rotation model
- Aircraft maintenance opportunity routing model

Flight Schedule Development at SWA

- Enhanced (flight schedule) optimizer
 - “Clean sheet”; maximize profit subject to operational and timing constraints
 - Mathematical programming optimization model using FICO Xpress solver engine
- Flight schedule simulator
 - Evaluate flight schedule operability vs. KPIs like on time performance (OTP)
 - Discrete-event simulation model
- *Iterate* between these two models to optimize schedule performance and balance *profitability* and *operability* and *customer service*

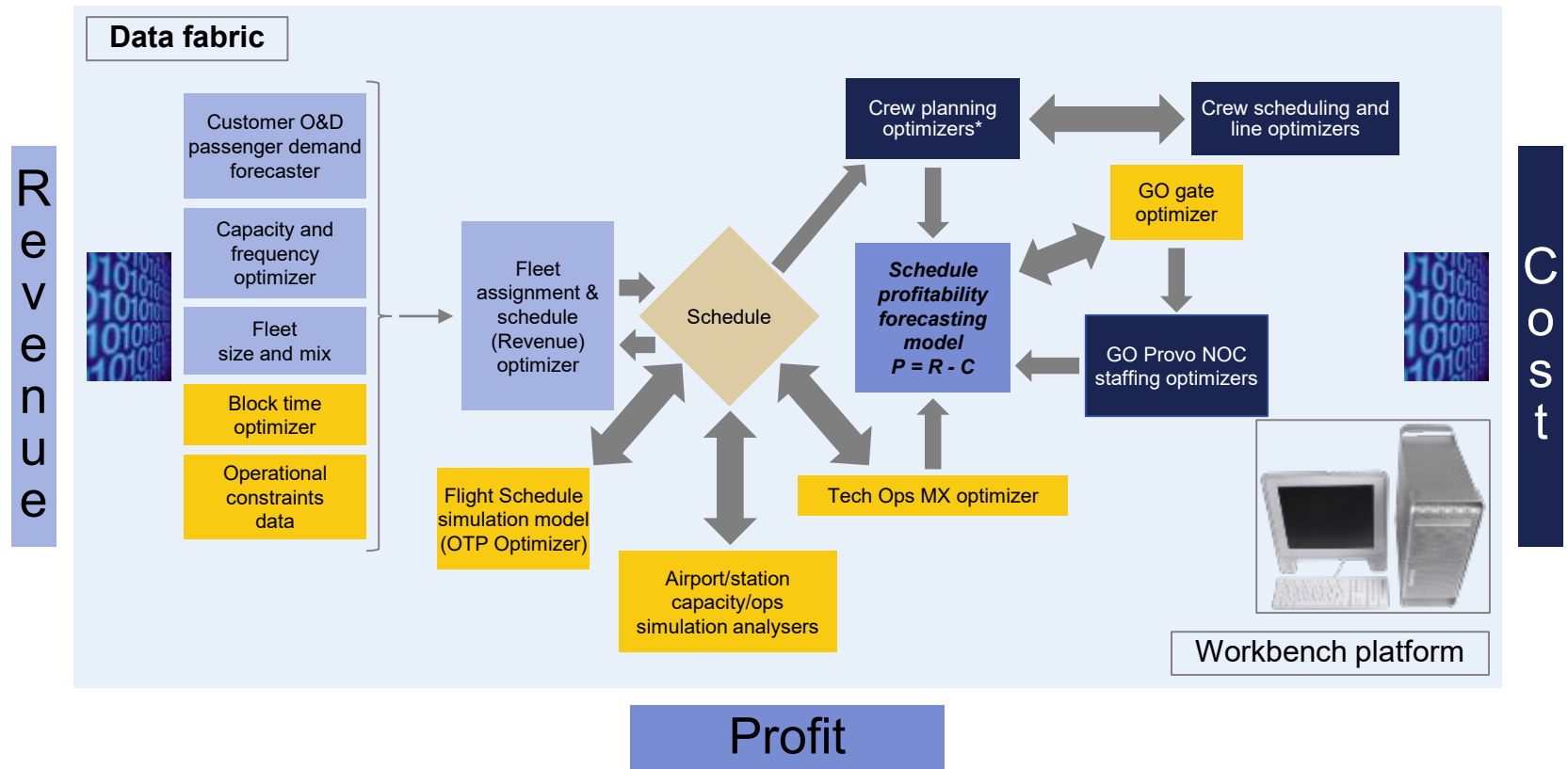
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Airline Profitability Planning Workbench

Doug Gray

Airline Profitability Planning Workbench

On time performance (OTP)



Input data flow →

→ Data flow

Feedback loop ↔

Flight schedule goes out
Feedback from functions comes back

* LP relaxation for quick estimate of crew costs, or IP solution for actual pairings costs

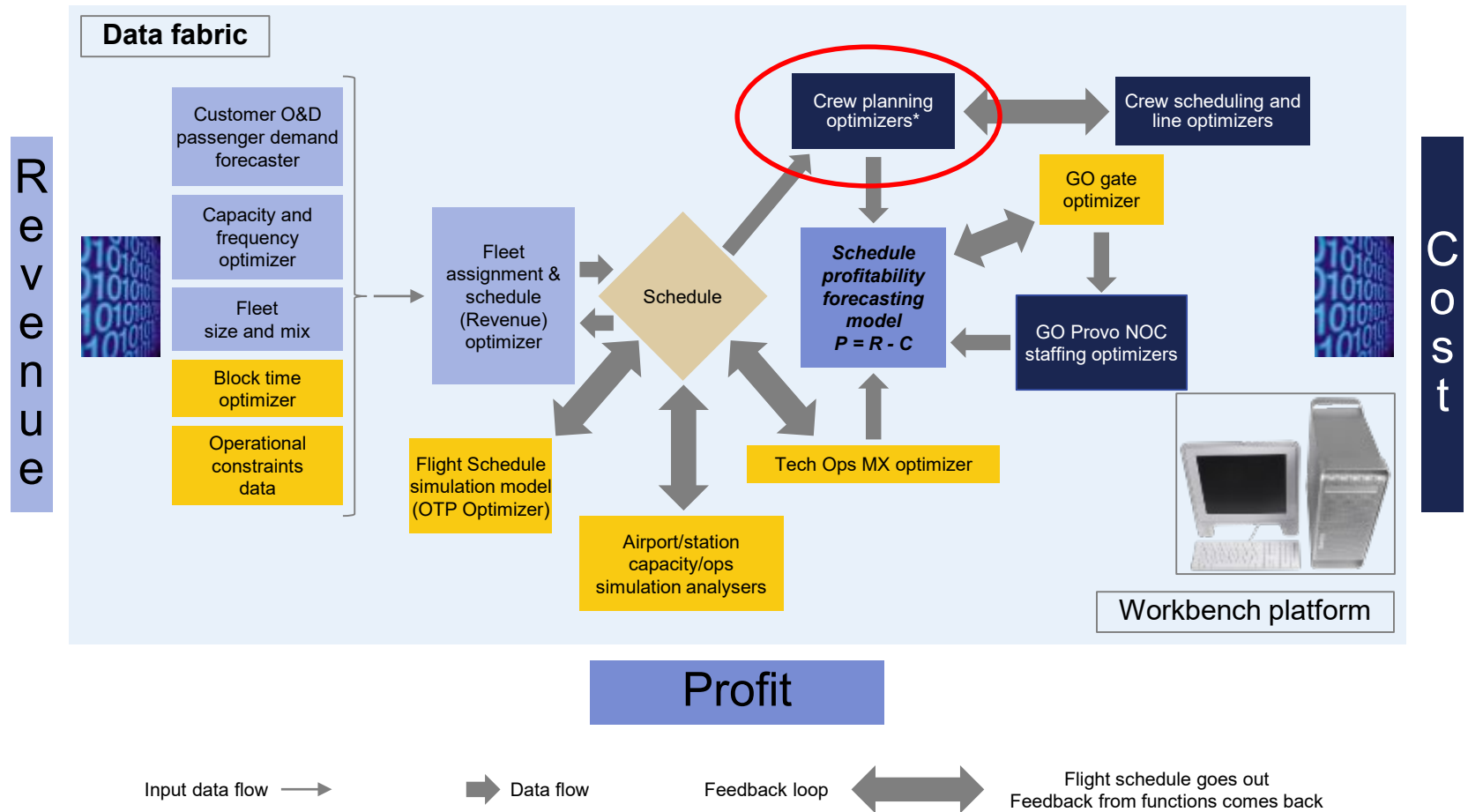
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Crew Schedule Development

Doug Gray

Airline Profitability Planning Workbench

On time performance (OTP)



* LP relaxation for quick estimate of crew costs, or IP solution for actual pairings costs

Frame and Solve: Analytics Solution Approach

Decision

Problem

- “How can we develop a crew schedule that complies with all contractual and regulatory work rules and covers the entire flight schedule at minimum cost?”

Rules represent **constraints** that must be satisfied; minimizing cost is an **objective** resulting from crew assignment decisions

Prescriptive

Deterministic

The flight schedule is a **plan** that is set/known; the crew schedule is a **plan** that must be set in advance of operation

Decision variables to assign flights to crew schedules are **integer** {1:Assign, 0: Not}
Duty times are **linear** $\{\geq 0\}$



- **Mathematical programming**
 - Linear and Integer Programming
 - Mixed Integer Programming (MIP)
 - Set Partitioning Problem Formulation

Crew Planning and Scheduling Optimization

- This problem has a remarkably simple set partitioning formulation:
 - Minimize $\sum \text{cost}_j * x_j$
 - subject to $\forall i, \sum x_j = 1$ (if trip x_j covers flight i)
 - Where x_j is binary (= 0 or 1)
- Nevertheless, the problem is remarkably complicated to solve, because:
 - There are thousands of flights i (28-40,000 per week)
 - There are trillions of x_j (legal trips that a crew could take, over multiple days, starting and ending at one of the crew bases)
 - The cost of x_j is not a linear summation of the costs of the flights i covered by x_j . It is instead a complicated nonlinear function specified in the contract with the pilot's and flight attendant's union—and it's different for both unions.

Crew Planning and Scheduling Optimization

- The result of the large solution space is like trying to choose several hundred needles out of several trillion haystacks. Or, selecting a hundred puzzle pieces out of a mountain of puzzle pieces, such that they all fit together and make a single, complete picture.
- This is probably the hardest problem airlines have to solve, and it's worth ***hundreds of millions of dollars a year*** to solve it correctly.
- Of course, you can't write down the full problem, with trillions of variables, let alone solve it. You have to use a subset of interesting variables, and those are typically created using various column generation techniques.
- If you want to know *exactly* how we solve it, you'll have to come work for an airline!

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Airline Seat Inventory (Product) & Revenue Management

Doug Gray

Airline Flight (Product) Inventory

Perishable commodity, subject to:

- Stochastic demand levels that vary according to seasonality, price elasticity
- Multiple fare classes (“buckets”, full fare coach, super saver fares)
- Consumer choice and preference by O&D market
- Dynamic price competition (“fare wars”)
- Fixed capacity at time of departure

Revenue Management

- Barry Smith, PhD et al win the INFORMS Edelman Prize for Best OR Application
- <https://techtv.mit.edu/videos/7797-american-airlines-decision-technologies-1991-winner>

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Introduction

Operations Planning Gate Optimization

Doug Gray

Operations Planning Gate Optimization

How airlines avoid making passengers and crew walk a mile to get to their connecting flights

Gate Assignment Optimization

- Assigning flights to gates is a typical scheduling problem.
 - It's easy if you have one gate and just a handful of flights.
 - Las Vegas will have ***over 200 arrivals per day in over 20 gates.***
- We want to achieve multiple goals in gate assignment:
 - All flights assigned to available gates
 - Proper spacing between gate operations
 - Make sure flights leaving late or arriving early do not delay the operation by blocking other gates
 - Even workload across gates for ground crews
 - Try to avoid having to tow aircraft around for positioning
 - Avoid simultaneous operations in alleys and on adjacent gates
 - Position flights with connecting passengers or crew on nearby gates

Gate Assignment Optimization

- A standard binary assignment problem:

Minimize $\sum_{ijk} \text{unassigned}_i \text{penalty}_i + \text{tow cost}_i * \text{tow operation}_{ijk} + \text{workload cost}_j * \max \text{workload}_g$

Subject to $\forall i, \sum_j x_{ij} + \text{unassigned}_i = 1$
 $x_{ij} + x_{kj} \leq 1$
(if flights i and k cannot both be assigned to gate j)
 $x_{ij} + x_{i'k} - \text{tow operation}_{ijk} \leq 1$
(if assigning flight i to gate j and flight i' to gate k requires towing)

Where $\forall j, \sum_i x_{ij} \leq \max \text{workload}_g$
 x_{ij} is 1 if flight i is assigned to gate j , 0 otherwise
 unassigned_i and $\text{tow operation}_{ijk}$ are binaries
 $\max \text{workload}_g$ is a nonnegative integer

Gate Assignment Optimization

- We solve the gate assignment problems using the FICO Xpress MIP solver, tuned to the problem set, along with a couple of custom heuristics that we've created.
- Solution times:
 - 1–3 gates, 1–30 flights: less than 10 seconds
 - More than 20 gates, more than 200 flights: five minutes

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Airline Network Irregular Operations Control

Doug Gray

Airline Network Irregular Operations

- ***How airlines recover (planes, crew, maintenance, cargo, and passengers) when the weather, ATC, airport traffic, tc. makes the plan hit the fan***
- ***Deloitte Insights white paper***

Airline Operations States

- Regular operations
 - Flight schedule operating exactly as planned (This never happens!)
- Normal operations
 - Isolated aircraft out of service events, flight delays, flight cancellations
- Irregular operations
 - One or more isolated airport capacity reductions (percentage reductions)
 - One or more isolated airport shutdown (no flight operations)
- Severely irregular operations
 - One or more entire regions impacted, e.g., east coast, Midwest, South

Airline Operations Targets

- On-time performance (OTP)—arrivals and departures
 - Flight, passenger, crew delays
- Cancellation rates
- Passenger itinerary completion

Airline Operations Tools

- Flight delays
- Aircraft swaps
- Flight cancellations

DELTTAA—FACE—PACHINKO

Predictive

Forecast OTP as a function of several variables, including yesterday's OTP, airport, day of week, month of year, weather, load factor, extreme weather events, airport visibility

Prescriptive

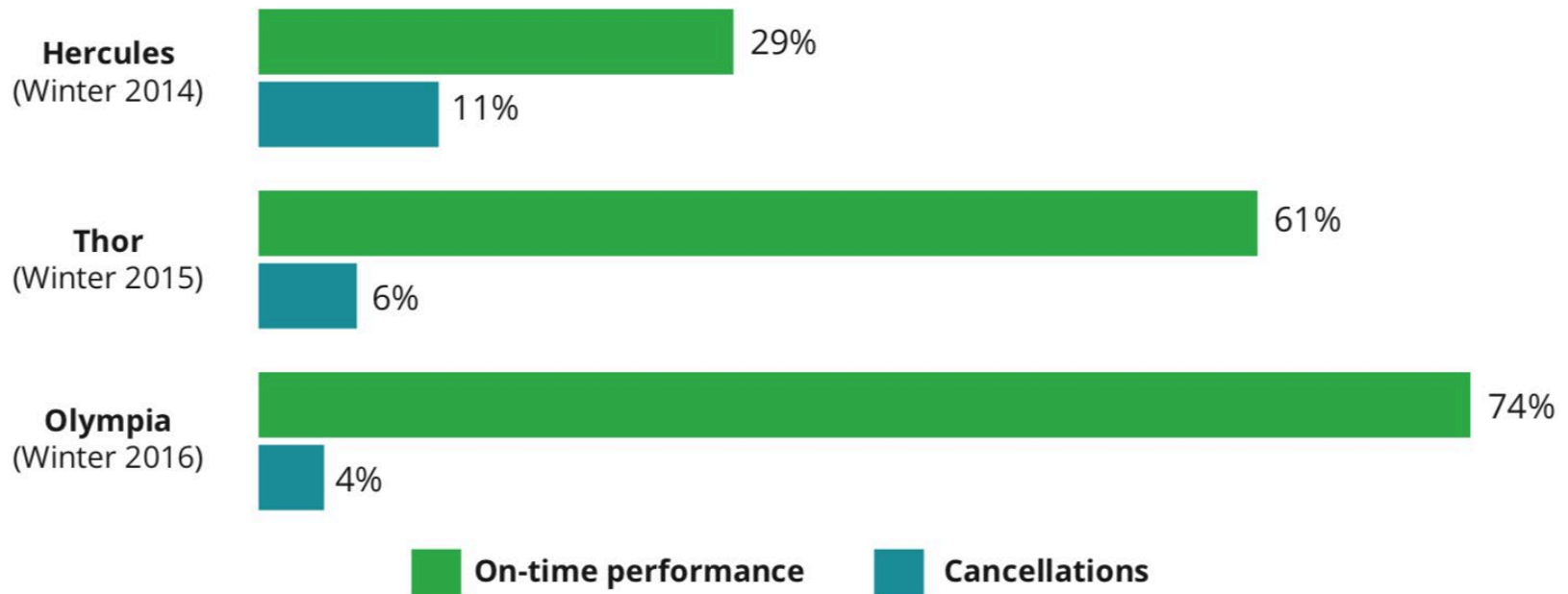
Minimize the total “cost or penalties” of all irregular operations impacts, including flight/passenger/crew delays, swaps, cancellations, airport curfews, maintenance events, subject to a myriad of operational constraints

Business Value Impact

- OTP for all Southwest flights increased by 2.11%
- Cancelled 900 fewer flights than prior to Baker
- Total number of customers delayed reduced by two or more hours by 95%
- Cancelled flight passengers notified with advanced warning (DEN)
 - Up to 10 hours in advance vs. less than two hours
- Dramatic increase in itinerary completion percentage

Business Value Impact: Before/After Baker Launch in November 2015

Figure 2. Southwest winter storm performance, 2014-16



Source: Southwest Airlines.

Deloitte Insights | deloitte.com/insights

Business Value Impact

- Better decision-making, resulting in better irregular operations solutions
 - Streamlining, automating, optimizing decisions involving *billions* of possible combinations of variables, parameters, and conflicting objectives and constraints
- More timely decision-making
 - Minutes as opposed to hours, when seconds and minutes count
 - Situations deteriorate significantly over a period of hours
- Dramatically improved quality of work life and stress levels for NOC personnel

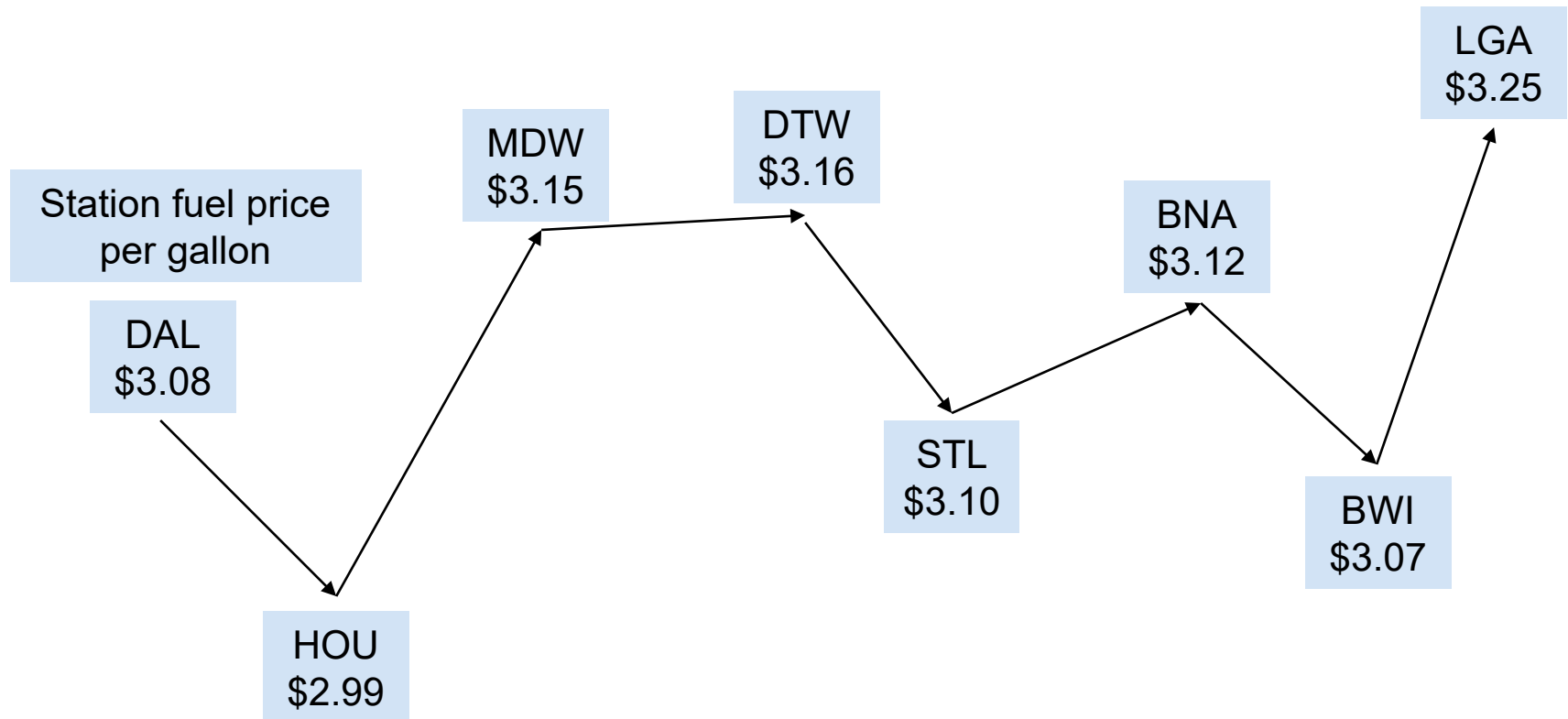
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Fuel Tankering

Doug Gray

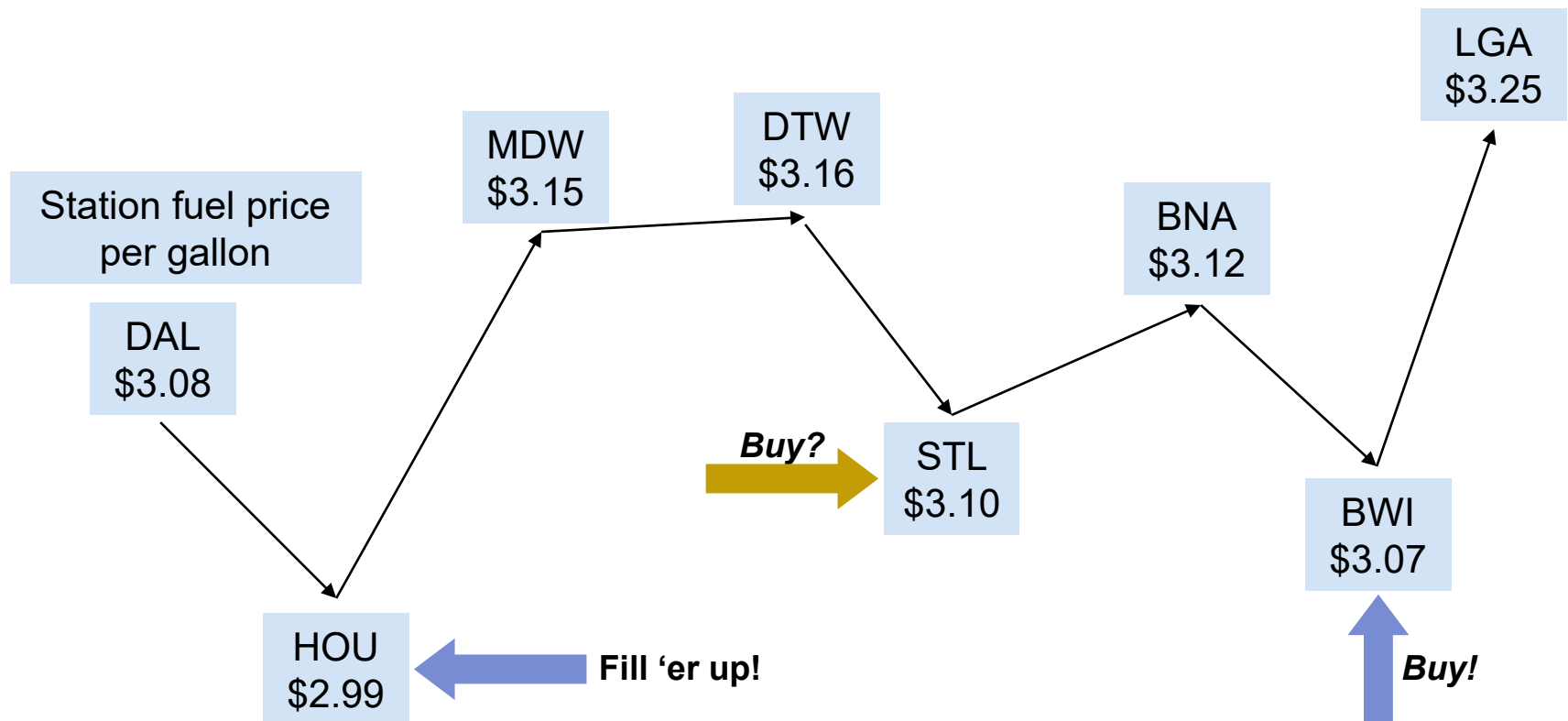
Fuel Tankering Optimization

- Airlines purchase **billions of dollars** in fuel every year, presenting a **huge** opportunity for cost optimization!
- Consider a single aircraft's routing:



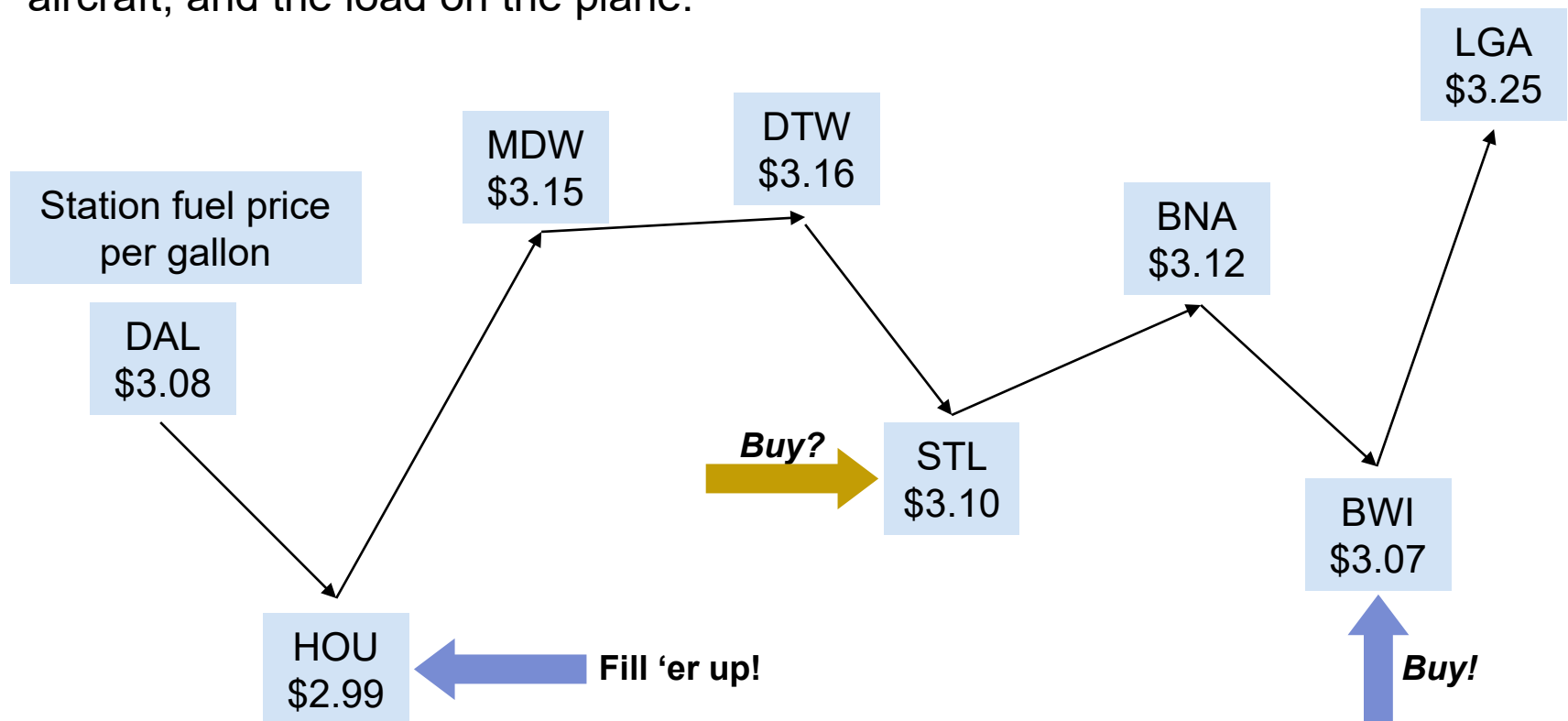
Fuel Tankering Optimization

The simple approach is to buy enough fuel at each stop in order to fly the next flight. *However*, there are opportunities to buy *less expensive* fuel and *carry* it down line.



Fuel Tankering Optimization

The *complexity* comes from the *cost of carrying* extra fuel. Additional (fuel) weight on the aircraft *increases* fuel burn, so a percentage of the extra fuel you're carrying burns off, *reducing the efficiency* of carrying the extra fuel. The *percentage* varies based on the length of the flight, the equipment on the aircraft, and the load on the plane.



Fuel Tankering Optimization

- A standard inventory LP with purchasing and carrying costs:

Minimize $\sum \text{cost}_i * x_i$

Subject to $y_i + x_i = \text{fuel burn } i + \text{reserve } i + z_i$ **Required fuel equation**

$y_i + x_i \leq \text{max fuel } i$ **Max fuel equation**

$y_i + 1 = \text{reserve } i + \text{retained } i * z_i$ **Arrival fuel equation**

Where $y_i \geq 0$ (the incoming fuel for flight i)

$x_i \geq 0$ (the purchased fuel for flight i)

$z_i \geq 0$ (the carried fuel for flight i)

Cost is the known price of fuel at the departure station; fuel burn, reserve, and max fuel are constants (fuel weights); retained is a constant (percentage of carried fuel that remains)

Fuel Tankering Optimization

- This generates a fairly simple Linear Programming (LP) Problem
 - Three variables and three equations per flight
- A typical aircraft scheduled for ten flights per day would give us a 30 by 30 LP, which solves in one second
 - Each aircraft is solved independently
- Calculating the *constants* is a bit more work, but we re-solve these equations *hundreds of times per day* as we get updated fuel weights (favorable winds caused us to land with more than expected, air traffic caused us to land with less than expected), passenger and cargo weights, or rerouted aircraft
- Given the fuel price differences across stations, and the amount we purchase, this simple LP is worth over **\$20 million** annually!

Summary

- Airlines are logistically and operationally complex, cost intensive enterprises, operating in an economically challenging and hyper-competitive business environment.
 - Analytics is necessary for survival and paramount to success.
- Analytics offers a powerful set of tools and capabilities to solve airline planning and operational challenges, and create new and better operating paradigms, and more economically efficient ways of doing business.
 - Analytics leads the way for continuous improvement in operational efficiency increased profitability, and improved customer service.
- Airlines represent an ideal environment and a veritable **wonderland** for Data Science & Analytics graduates, with an abundance of career development and advancement opportunities that can lead to professional success and personal satisfaction.

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Introduction

Case Analysis I

Doug Gray

Case Analysis I

Aircraft heavy maintenance check yield optimization and capacity planning

Important Points: Critical Success Factors Case Context (American Airlines)

- American Airlines: three data systems
 1. SABRE (reservation system) – 1958
 2. FOS (flight operating system) – 1970
 3. Teradata (enterprise data warehouse) – 1982
- Select a problem to solve using analytics that:
 - Is currently being solved using an Excel spreadsheet
 - Has high executive visibility and high relevance to corporate strategy execution
 - Has one or more quantifiable targets or KPIs
 - Has a significant financial, economic, and/or operational impact

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