Opening Remarks

Houman Goudarzi, Head of BI & Industry Engagement, IATA
The Air France-KLM case study

Leon Gommans, Science Officer, Air France-KLM
A CONSORTIUM GOVERNED DIGITAL DATA MARKETPLACE

Applied research into a trusted, fair and economic way to share (big) data assets in AI context to unlock value for our industry

IATA ADS AI Lab
June 27th 2019 Athens, Greece

Leon Gommans, PhD
Air France KLM Group IT Technology Office, R&D department
Researcher at University of Amsterdam, Systems & Networking Engineering Lab.
1950 “Can machines think?”
Alan Turing asked the question:
“Can a machine act as player in an imitation game?”

Now “Can AI replace the pilot?”
Creg Hyslop, CTO Boeing, asked the question:
“How do we maintain the existing levels of safety with an AI-based system in the cockpit?”
Charlotte Jee, “AI is set to change the aerospace industry - but won’t be flying planes anytime soon”, MIT Technology Review, Sep 13th 2018.

Industry standards bodies are joining to consider the many questions around the role of AI in aeronautical systems and applications considering its (data) needs:
• SAE International: G.34 Applied AI for Flight Critical Systems
• EUROCAE WG-114 Artificial Intelligence
• RCTA
• SAE ITC: ExchangeWell consortium initiative to create trusted implementations.

Parties need to collaborate: OAMs, OEMs, MRO’s, Operators, Regulatory bodies,..
All have parts of the puzzle. Need more involvement of OPERATORS – Role for IATA?
RESEARCHING DATA SHARING SOLUTIONS:
A DIGITAL DATA MARKETPLACE GOVERNED BY AN INDUSTRY CONSORTIUM

Digital Data Marketplace
- Data owners
- Algorithm Developers

Algorithm Developers
- Computer science
- Data science
- Math and statistics
- Competitive Domain knowledge

enabling access and use

Al (service) User
- Planning, Prediction, Prevention, Effectiveness, Efficiency, etc.
- (Near) Real Time Operational Data

Decision Support Systems
- Competitive Choice

Algorithm

6
RESEARCH PROBLEM

AI QUALITY DEPENDS ON DATA AVAILABILITY: HOW TO ENABLE ACCESS TO AS MUCH DATA AS POSSIBLE?

Current solution direction

Digital Data Marketplace solution

Sovereign Data Owners

Data Exchange Infrastructure

Data Science Platforms

Digital Data Marketplace A

Digital Data Marketplace B
RESEARCH PROBLEM

AI QUALITY DEPENDS ON DATA AVAILABILITY: HOW TO ENABLE ACCESS TO AS MUCH DATA AS POSSIBLE?

Current solution direction

Digital Data Marketplace solution

Sovereign Data Owners

Data Exchange Infrastructure

Data Science Platforms

Digital Data Marketplace A

Digital Data Marketplace B
WHAT IS A DIGITAL MARKETPLACE ABOUT?
ORGANIZING TRUST, FAIRNESS AND COMPETITION TO SERVE INNOVATION

• Serves a common benefit no single organization can achieve on its own.

• Is created and governed by an industry consortium as a means to reduce risk, ensuring competition and fairness.

• Supply members advertise their assets, contracts arrange asset access and usage by other members.

• To prevent data asset exposure, members can use a consortium governed data exchange infrastructure to execute data science scenario’s

• Allows consortia to implement (digitally) enforceable contracts, whilst supporting dispute resolution by immutable logging.
JOURNEY OF THE DATA SCIENTIST / ENGINEER

ROLE OF THE DIGITAL DATA MARKETPLACE

ACQUIRE MORE AND DIVERSE DATA

JOURNEY START

IDEA

1. DEFINE
2. COLLECT
3. EXPLORE

EXPERIMENT

flexibility
Feasible Model

BUSINESS CASE
go-nogo

PRODUCT

11. PREDICT

10. SETUP MONITORING

9. FEEDBACK LOOP

8. CONTINUOUS INTEGRATION

7. AUTO TRAIN
6. DATA FLOW

5. VALIDATE

4. MODEL

3. EXPLORE

2. COLLECT

1. DEFINE

DETERMINE

WHAT IS THE END PURPOSE?
HOW WILL IT ADD VALUE?
USE CASE, DATA SCOPE AND
STAKEHOLDERS IDENTIFICATION

EXPLORE

COLLECT AND EXPLORATORY DATA,
RESEARCH DATA SCIENCE MODEL
PROTOTYPE, go/nogo TO PRODUCTION

MODEL

DELIVER THE SOLUTION IN PRODUCTION ENVIRONMENT
PRODUCT GO LIVE

VALIDATE

FEASIBLE MODEL

INDUSTRIALIZE

RELIABILITY

SELL PREDICTIVE PRODUCTS

MW

TEAMWORK

NOTE:
KNOWLEDGE SHARING IN OTHER PHASES (4,7,9,10) MAY ALSO BE A GOALS OF COLLABORATION IN A MARKETPLACE COMMUNITY.
### Digital Data Marketplace Governance

**Implementation via a Four Step Approach**

<table>
<thead>
<tr>
<th>Consortium</th>
<th>Provider</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Common Benefit</strong></td>
<td><strong>Implement Infrastructure</strong></td>
</tr>
<tr>
<td>Define and agree common benefit no single organization can achieve on its own.</td>
<td>Research operationalization of Digital Data Marketplace concepts</td>
</tr>
<tr>
<td><strong>Group Rules</strong></td>
<td><strong>Organize Trust</strong></td>
</tr>
<tr>
<td>Define consortium rules considering data use, access and benefit sharing</td>
<td>Organize power and trust as a <em>means to reduce risk</em> for participating members</td>
</tr>
</tbody>
</table>

*Source: Airfrance KLM*
DIGITAL DATA MARKETPLACE ARCHITECTURE

IMPLEMENTING ESSENTIAL ELEMENTS

Data Exchange Infrastructure

Digital Data Marketplace Consortium

Market rules

Member admission

National Law & Regulations

Agreement

Registry

Data Science

Centralized

distributed

Testbed

Algorithm

Dispute

Resolution

Accounting & Auditing

Software Definable Global Digital Data Market Infrastructure
KEY COMPONENT: FEDERATED ANALYTICS
PREVENTS RAW DATA EXPOSURE AS ONLY THE ALGORITHM SEES THE DATA

Centralized
- Raw data transferred from dispersed data zones to a central repository for analysis

Federated
- Raw data stays in place. Model trained through orchestration of local (at each data zone) and global computations

Centralized Repository

Virtual Computing Cluster

Data-zone Fabric

Data-zone Fabric
MARKETPLACE WORKFLOW
IMPLEMENTING THE INDUSTRIALIZATION PHASE

NEXT: “EXPERIMENT PHASE” OF THE DATA SCIENTIST JOURNEY
We can only see a short distance ahead, but we can see plenty there that needs to be done.

Alan Turing

leon.gommans@klm.com
Improving the Operation, One Model at a Time

Michael Shores, Director of Data Science, United Airlines
Improving the Operation, One Model at a Time

Michael Shores
United Airlines
June 2019
Where we were in 2018

What we changed in 2019

What we’re doing

Where we’re headed
Last year I spoke about machine learning in the personalization context.
But something big was noticeably absent....

The Operation
After careful thought, we made a few changes
We used machine learning to drive quicker responses to our customers

- **Why**: Reading and understanding customer feedback is critical but time consuming
- **What We Did**:
  - Automatically identify the topic customers discuss
  - Predict how to compensate a customer
- **Result**: Responses per hour up nearly 2x
- **What’s Next**: We’re building a sentiment analysis tool to help with case prioritization and routing
Time series modeling helped our Polaris Clubs plan more efficiently

- **Why**: The Polaris Clubs are a unique experience for our customer which presents unique logistical challenges

- **What We Did**: Built a time series model to predict the number of customers coming to our Polaris Clubs over the next week

- **Result**: Improved ability to manage staffing and catering requirements

- **What’s Next**: We’re looking at better long term forecasting and expanding our model to other clubs
We leveraged text analytics to help understand maintenance trends

- **Why**: Mechanics carefully detail airplane issues but it’s hard for analysts to read so much text

- **What We Did**: Used text classification to identify the ATA chapter corresponding to the Log Page

- **Result**: Better trending and trouble shooting of aircraft issues

- **What’s Next**: Predicting which parts will be needed to remedy particular issues
What’s Next?

• More to come in Operations
• Accelerate model sharing and deployment
• Image? Video? Voice?
• Catch my team at ODSC India in August!
Google’s application of Machine learning for Flights Data

Allan Fraser, Manager, Software Engineering, Google
Google’s Application of Machine Learning to Flights Data

Allan Fraser
Manager, Software Engineering
allanfraser@google.com
Mission

Our mission is to be the trusted place where travelers go for the most useful information to make fast, effortless decisions.
Google Flights Pillars

- Flight Search
- Airline Partners
- Intelligent Assistance
Flight Price Insights - Know when to book your flights
Route Coverage Tool - Leverage insights from user queries

Flights Route Coverage Tool (Beta)

Opportunity Finder: Last 90 Days

<table>
<thead>
<tr>
<th>Filters</th>
<th>Account</th>
<th>Volume</th>
<th>Opportunity Score</th>
<th>(9)</th>
<th>Covered</th>
<th>Yes</th>
<th>FII</th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Language</td>
<td>Device</td>
<td>NDCG</td>
<td>Nonstop Service</td>
<td>Domestic</td>
<td>Origin</td>
<td>Country</td>
<td>Region</td>
<td>Destination</td>
</tr>
</tbody>
</table>

Competitive Routes
Performance over last 90 days for in-network routes (flight to 0 and 1 stop flights). 2 stop flights are included if they have a duration of 1.0 or less and a duration rank of 50%. Only routes with 5 or more operating carriers are displayed.

<table>
<thead>
<tr>
<th>Origin City</th>
<th>Destination City</th>
<th>NDCG</th>
<th>Routes</th>
<th>Queries (Q)</th>
<th>Impression Coverage</th>
<th>Click Coverage</th>
<th>Click Share</th>
<th>Click Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Perth</td>
<td>London</td>
<td>LON-PER</td>
<td>PER-LHR, PER-LON</td>
<td>60,000</td>
<td>0.2%</td>
<td>+0.0%</td>
<td>9.2%</td>
<td>0.2%</td>
</tr>
<tr>
<td>2. Boston</td>
<td>Chicago</td>
<td>BOS-ORD</td>
<td>BOS-CHI, BOS-ORD</td>
<td>60,000</td>
<td>0.9%</td>
<td>0.6%</td>
<td>7.3%</td>
<td>6.7%</td>
</tr>
<tr>
<td>3. Boston</td>
<td>Los Angeles</td>
<td>BOS-LAX</td>
<td>BOS-LAX</td>
<td>60,000</td>
<td>1.4%</td>
<td>1.2%</td>
<td>19.3%</td>
<td>18.1%</td>
</tr>
<tr>
<td>4. London</td>
<td>Sydney</td>
<td>LON-SYD</td>
<td>LON-SYD, LHR-SY</td>
<td>50,000</td>
<td>12.4%</td>
<td>0.8%</td>
<td>17.4%</td>
<td>16.6%</td>
</tr>
<tr>
<td>5. Chicago</td>
<td>Boston</td>
<td>BOS-ORD</td>
<td>BOS-BOS, ORD-BOS</td>
<td>50,000</td>
<td>0.7%</td>
<td>0.4%</td>
<td>7.0%</td>
<td>6.6%</td>
</tr>
<tr>
<td>6. Warsaw</td>
<td>London</td>
<td>LON-WAW</td>
<td>WAW-LPR, WAW-LHR</td>
<td>50,000</td>
<td>2.8%</td>
<td>0.5%</td>
<td>6.2%</td>
<td>5.7%</td>
</tr>
<tr>
<td>7. Dubai</td>
<td>Manila</td>
<td>DXB-MNL</td>
<td>DXB-MNL</td>
<td>50,000</td>
<td>3.9%</td>
<td>1.9%</td>
<td>8.6%</td>
<td>6.6%</td>
</tr>
<tr>
<td>8. Paris</td>
<td>Bangkok</td>
<td>BKK-PAR</td>
<td>CDG-BKK, PAR-BKK</td>
<td>50,000</td>
<td>0.1%</td>
<td>+0.0%</td>
<td>5.9%</td>
<td>5.9%</td>
</tr>
<tr>
<td>9. Paris</td>
<td>Los Angeles</td>
<td>LAX-PAR</td>
<td>LAX-LAX, PAR-LAX</td>
<td>50,000</td>
<td>15.5%</td>
<td>5.7%</td>
<td>31.1%</td>
<td>25.4%</td>
</tr>
<tr>
<td>10. Guadalajara</td>
<td>Tijuana</td>
<td>GDL-TLU</td>
<td>GDL-TLU</td>
<td>40,000</td>
<td>8.6%</td>
<td>1.0%</td>
<td>22.5%</td>
<td>21.5%</td>
</tr>
<tr>
<td>11. Brisbane</td>
<td>London</td>
<td>BNE-LDN</td>
<td>BNE-LHR, BNE-LDN</td>
<td>40,000</td>
<td>1.1%</td>
<td>0.3%</td>
<td>57.9%</td>
<td>57.5%</td>
</tr>
</tbody>
</table>
Carriers May Apply Machine Learning to Gain Business Insights

- Availability and Pricing Data
- Segmentation Data
- Revenue Management Data
- Inventory Data
- Booking Data

(Confidential and Proprietary information of ITA Software by Google. Do not transmit or otherwise disseminate this document without prior written consent)
Google Cloud Machine Learning Workflow

1. Source and prepare your data
2. Code your model
3. Train, evaluate and tune your model
4. Deploy your trained model
5. Get predictions from your model
6. Monitor the ongoing predictions
7. Manage your models and versions
### Flights Data & Google Cloud Infrastructure

<table>
<thead>
<tr>
<th>Service</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Flight Data</strong></td>
<td>Fares, schedules, availability, pricing, flight status.</td>
</tr>
<tr>
<td><strong>Big Query</strong></td>
<td>Enables storage of petabytes of data and slicing &amp; dicing data across many dimensions.</td>
</tr>
<tr>
<td><strong>Cloud Data Flow</strong></td>
<td>Fully managed service for developing and managing and executing a wide range of data patterns.</td>
</tr>
<tr>
<td><strong>Cloud SQL</strong></td>
<td>Query petabytes of data to find answers to questions like, which markets have the lowest rate of selling, or order markets and flights legs by load factor.</td>
</tr>
<tr>
<td><strong>Cloud ML</strong></td>
<td>Lets developers and data scientists build and run superior machine learning models in production.</td>
</tr>
<tr>
<td><strong>Cloud AutoML</strong></td>
<td>Enables developers with limited machine learning expertise to train high-quality models specific to their business needs.</td>
</tr>
</tbody>
</table>
Conclusion

Machine learning is making a difference for Google Flights users and airline partners.
Leveraging AI to drive commercial success

Jaime Zaratiegui, Director Data Science, Accelya Group
Leveraging AI to Drive Commercial Success

Jaime Zaratiegui
Director Data Science @Accelya

IATA ADS 2019
27 June 2019
Commercial Success
Commercial Success
Know Your Customer
Know Your Customer?

4.3 bn passengers 2018 worldwide
Know Your Customer?

4.3 bn passengers 2018 worldwide
Know Your Customer+AI
Know Your Customer + AI
Predict with AI
Commercial Success
Commercial Success
Thank you for your time
IATA AVIATION DATA SYMPOSIUM

ATHENS, GREECE  25 – 27 JUNE 2019

AI Lab

Sponsored by: OpenJaw
High-performance Computing: Aviation Use Cases

Massimo Morin, Head, Worldwide Business Development, Travel, AWS
The Power of Data:
HPC & ML/Al Use Cases

Massimo Morin, Head, AWS Travel
27th June, 2019
Long time ago...
The airline industry is a complex business.
## AWS is Here to Help: The Amazon ML Stack

<table>
<thead>
<tr>
<th><strong>AI SERVICES</strong></th>
<th>Easily add intelligence to applications without machine learning skills</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>VISION</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>ML SERVICES</strong></th>
<th>Build, train and deploy machine learning models fast</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DATA LABELING</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>ML FRAMEWORKS &amp; INFRASTRUCTURE</strong></th>
<th>Flexibility and choice, high-performing infrastructure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SUPPORT FOR ML FRAMEWORKS</td>
</tr>
</tbody>
</table>
# AWS is Here to Help: The Amazon ML Stack

## AI SERVICES
- **VISION**
  - Rekognition (Image | Text)
  - Textract
- **SPEECH**
  - Polly
  - Transcribe
- **LANGUAGE**
  - Translate
  - Comprehend
- **CHATBOT**
  - Lex
- **FORECASTING**
  - Forecast
  - Personalize

## ML SERVICES
- **BUILD**
  - Ground Truth
  - ML/AI Marketplace
- **TRAIN**
  - Discrete training & tuning
  - Neo model compiler
  - Reinforcement Learning
- **DEPLOY**
  - One-Click Deployment

## ML FRAMEWORKS & INFRASTRUCTURE
- **FRAMEWORKS**
  - TensorFlow
  - MXNet
  - Keras
  - PyTorch
- **INTERFACES**
  - EC2 P3 & P3N
  - EC2 C5
  - FPGAs
- **INFRASTRUCTURE**
  - Greengrass
  - Elastic Inference

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The **scalability of cloud computing**, and ingestion of rich datasets from external sources, allows Qantas to continually assess and adjust planned paths en-route.

This delivers **increased safety** through more **accurate fuel prediction** and **efficiency via fuel savings**.

Results to date for Qantas include **0.6 percent lower fuel burn** per flight, leading to lower carbon emissions.

Ben Vogel, Editor, Jane’s Airport Review
Fuel Saving

Reduce Turbulences

Improve On Time Performance

Improve Safety

Reduce CO2 Emission

Network Planning Optimization

Rotation / Maintenance Optimization

Fleet Planning Optimization
Air New Zealand’s Carma

“... this allows us to move more than ever before with the same amount of aircraft (adding more than 40 tonnes of capacity a day).”

Jonathon Dale
Manager Commercial Insight, Air New Zealand

• Flag carrier of New Zealand
• 65 planes serving 51 destinations
• Cargo Advanced Revenue Management Assistant (CARMA): model predicting the likelihood of cargo freighting showing up on day of freight
• AWS enabled to leverage the managed services to carryout the data science models, from the ingestion, ETL, Modeling, Database to the output results.
• Carma: the real reward is seeing how we can expand volumes for supply chains of our Exporters across the world, providing more accessibility and reliability – Jonathon Dale

What are the implications of revenue increase by shipping more and being more efficient?

- **Forecasting and Planning**
- **Marketing and Promotions to shift demand**
- **Delivery turn around**
Capitalize on Your ML/AI R&D

Machine Learning & Artificial Intelligence
Build intelligent applications with machine learning and data science software

Benefits of Machine Learning in AWS Marketplace

- Scalable
- Accessible and Fast
- Pay-as-you-go
Conclusion

1. Airline business is complex = lots of opportunities
2. AWS has the most comprehensive ML/AI ecosystem
3. Start small and experiment a lot
4. Capitalize on your investment
5. We are here to help
Leveraging Data & Machine Learning

Moderator: **Tanya Beckett**, Presenter, BBC News

**Kevin O'Sullivan**, Lead Engineer, SITA Lab

**Ian Painter**, CEO and Founder, Snowflake Software

**Ido Biger**, Chief Data Officer, EL AL Israel Airlines

**Virender Pal**, Chief Digital & Innovation Officer, flynas
Ingredients to enable efficient and effective use of AI

Minna Kärhä, Head of Data, Finnair
WE BOARD

40,000 PASSENGERS
40,000 BAGS
ON A NORMAL FRIDAY

WE TRANSFER

25% OF THESE PASSENGERS

WE LOAD

430,000 kg CARGO EVERY DAY INCLUDING

KING CRABS  SALMON  MEDICINE

OVER 100,000 FLIGHTS IN 2017

WE HAVE

660 CABIN CREW
240 PILOTS
150 HELAP AGENTS
100 MECHANICS
40 OPS AND MAINTENANCE CONTROL EXPERTS
WORKING DAILY FOR SAFETY AND CUSTOMER EXPERIENCE

AND AFTER ALL THIS...

83% OF FLIGHTS ARRIVE IN SCHEDULE
7 BAGS IN 1000 ARE LEFT BEHIND
The Ingredients

- Awareness
- Data
- Culture
- Value
Awareness

Understanding what AI is AND what it is not, to prevent unrealistic expectations and disappointment.

Understanding the potential – by knowing the real business challenges.

Understanding the required working methods – data science work cannot (usually) be done in a waterfall project and gaining real results will take time.
Airlines are actively looking for opportunities around AI.

AI solutions used by industry:

- Price optimization
- Market discovery
- Predictive maintenance
- Feedback analysis
- Customer comms automation
- Crew fatigue analysis
- Delay prediction
- Fuel optimization
- Catering optimization
- Social media analysis

*85% Virtual agents and chatbots, 66% Predictive analytics, 63% Targeted advertising/personalization, 54% Pattern recognition, 50% Brand perception improvement (e.g. social media/customer feedback analysis), 37% Automatic scheduling (e.g. of repairs/maintenance).*
Identified potential for Finnair

Chatbots
Workforce planning
Destination recommendation
Cargo
Customer recognition
Decision-making support
Disruption prediction
Network optimization
Customer service
Revenue forecast
Predictive maintenance
Ancillary sales
Identifying **what data is** – it is more than the Data Warehouse

Knowing **the inventory** – what do we really have

 Governing the data assets to ensure there is **enough quality data**

Ensuring **data is accessible** for anyone who needs to use it **(in a secure and compliant way)**
Various forms of data is created in daily operations for example:

- Flight planning & operations
- Workforce
  - Employee development and feedback
- Fleet
  - Capacity
  - Maintenance
- Network planning and operations
  - Partnerships
- Loyalty profiles
  - Customer’s transactions
- Baggage
  - Cargo
- Digital channels usage
  - Marketing activities
- Customer service
Data Science cannot be built in a separate "Data Science" -silo. The work needs to be embedded to the core business processes – and organization needs to be open for these new roles (data scientists, data engineers, visual story tellers, service designers…) to invest on them – and to learn from them.

Data Science is a continuous, cross-functional journey – company culture (and governance) needs to be ready for agile experimenting.

Reusability provides agility - Data Science community needs to also collaborate across projects.
AI development lifecycle

CRISP-DM model

- **Business/process owner, SME, Analyst, Service Designer**
- **Business/data analyst**
- **Data engineer**
- **Data scientist, AI developer**
- **SME, Analyst, Data scientist**
Value

Value of AI is only realized when the solutions are in active use and provide business value in forms of efficiency, better decisions, smoother journey for customers or employees...

Value also comes in a form of company brand and public image – AI needs to be compliant, ethical, transparent and continuously monitored.
To summarise: **AI provides opportunities for advanced use of company’s data asset for business value**

Only well managed data asset can provide quality results – the existing data inventory might surprise

Like any tool, also advanced analytics requires people with appropriate skills to use it – and organization that welcomes these new skills

Focus on the real business challenges – embrace agile and be brave to get started with small experiments
IATA AVIATION DATA SYMPOSIUM

ATHENS, GREECE 25 – 27 JUNE 2019

Al Lab

Sponsored by: OpenJaw
Predicting Passenger Choices considering Irrational Behavior

Rodrigo Acuna, Head of AI Research, Amadeus
Predicting Passenger Choices Considering Irrational Behavior

IATA ADS, June 26, 2019
Rodrigo Acuna-Agost
Head of AI Research, Amadeus
Credits:
Collaboration Academy + Industry

aMADEUS

Université Côte d'Azur
Université Nice Sophia Antipolis
skema BUSINESS SCHOOL
NC STATE UNIVERSITY
Which one? Cheapest? Fastest?

I am not sure, so how Airlines can be?
imagine an airline’s **CEO** when we tell her

“we can predict travelers’ choices”
Some applications

- Dynamic offering

- Sorting

- Recommender systems
our engine
Solved

Accuracy of predicting the preferred alternative (among 50 options)

More is better

0% 5% 10% 15% 20% 25% 30%

Random  MNL  ML: Random Forest  DL: Pointer Networks
why we cannot reach 100% accuracy?
Brain

An error has occurred. To continue:

Press Enter to return to Windows, or

Press CTRL+ALT+DEL to restart your computer. If you do this, you will lose any unsaved information in all open applications.

Error: 0E : 016F : BFF9B3D4

Press any key to continue _
there are more than 100 studied cognitive biases
Decoy Effect

Reference: Adding Asymmetrically Dominated Alternatives: Violations of Regularity and the Similarity Hypothesis
Joel Huber, John W. Payne and Christopher Puto
Preference Dimension 1 (eg., Discount)

Preference Dimension 2 (eg., Quality)

What is the impact of these decoys?

Your Product (a.k.a. Target)

Competitor

Decoy area (Asymmetrically Dominated Decoy)
Three Experiments

**Surveys:**
Fare Family Choice

*Impact in Choice Prediction accuracy?*

Survey Data
400k data points

**Online users:**
Itinerary Choice

*Impact in Conversion?*

Online users
30000 user sessions

**Live Lab:**
Flight Choice

*Understanding better: Fully controlled experiment in the lab*

Experimental Economics Lab
100 people
Three Experiments

**Surveys:**
*Fare Family Choice*

*Impact in Choice Prediction accuracy?*

Survey Data
400k data points

**Online users:**
*Itinerary Choice*

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Online users
30000 user sessions

**Live Lab:**
*Flight Choice*

Understanding better:
Fully controlled experiment in the lab

Experimental Economics laboratory
100 people
1) Fare Family Choice

*Impact in Choice Prediction Accuracy?*
Results: Classification Accuracy of Predictions

- **Random Forest**
  - Without Decoy: 56%
  - With Decoy: 64%

- **Random Forest + Decoy**
  - 64%

- **Neural Networks**
  - Without Decoy: 68%
  - With Decoy: 70%

- **Neural Networks + Decoy**
  - 70%
Three Experiments

Surveys: Fare Family Choice

Impact in Choice Prediction accuracy?

Survey Data
400k data points

Online users: Itinerary Choice

Impact in Conversion?

Online users
30000 user sessions

Live Lab: Flight Choice

Understanding better:
Fully controlled experiment in the lab

Experimental Economics laboratory
100 people
2) Impact in Conversion? (website)

two variations for this banner
Two variations

A

- **Cheapest**: 6h00 $200
- **Fastest**: 2h00 $350

B

- **Cheapest**: 6h00 $200
- **Fastest**: 2h00 $350
- **Featured**: 2h00 $400

versus
decoy
Results: does decoy improve conversion?

Click on “Highlight” Panel

Conversion Rate

No decoy | Decoy
---|---
No decoy | Decoy
5.00% | 5.50%
5.50% | 6.50%
6.00% | 7.00%
6.50% | 8.00%
7.00% | 7.50%
7.50% | 8.00%
8.00% | 8.00%
Three Experiments

Surveys:
Fare Family Choice

Impact in Choice Prediction accuracy?

Survey Data
400k data points

Online users:
Itinerary Choice

Impact in Conversion?

Online users
30000 user sessions

Live Lab:
Flight Choice

Understanding better:
Fully controlled experiment in the lab

Experimental Economics laboratory
100 people
3) Experimental Economics Lab

Setup:
• Experimental Economics laboratory (University of Cote d’Azur)
• 1 hour sessions

Data:
• 10 repeated choices x 100 people = 1000 observations mostly students

Incentives:
• 1/10 participant is paid (100-200€)
• Selected candidates “live” the flight experience they choose to get paid. Ex: come in 2 weeks to wait 1 hour in a room without cell phones, etc
3) Preliminary Results

Preliminary results are not conclusive (35% of data collected)

Collected Data

Conversion Rate(*)

(*) note that the experiment is calibrated to obtain relative high values of conversion rates.
Turnaround Management Optimization using AI

Stephane Cheikh, AI Program Director, SITA
\$39b = \text{flight delays cost to airlines}
\$7.4b = \text{related to turnaround}
\$420m = \text{saved directly by airlines, with technology & collaboration}\star
Lack of digitization, transparency and efficient collaboration

Turnaround Black Box
Where is the issue coming from?
Turnaround Timestamps
Using Computer Vision to extract “accurate” timestamps

Automate timestamps gathering
A single source of trustable data
Turnaround Timestamps
Using Computer Vision to extract "accurate" timestamps
Turnaround Timestamps

SITA is well positioned – access to diverse data to be meshed with timestamps
Turnaround Digital Twin
Ability to view live turnaround via an immersive platform
Turnaround Manager – Activity Flow
Delivers aircraft operation overview for Airlines operating a Hub or FS GH
Value-add integrator for turnaround data

Generating / capturing “raw” turnaround events data, cleansing / normalizing / aggregating data, enriching these data, **transforming these data into insights / information**

**Historical**: A single source of trustable data.
**Real time**: Transparency, collaboration efficiency, support quick decisions
**Future**: Predict patterns, avoid disruptions and delays before they happen.

---

**Turnaround Optimization**

How are we going to address this challenge?
Questions?

Stephane Cheikh
AI Program Director
SITA, Geneva
Alaska’s Transition to Real-Time Algorithmic Personalized Experiences

**Matt Hahnfeld**, Software Engineering Manager, Alaska Airlines

**Xavier Lucas**, Software Engineer III, Alaska Airlines
Alaska’s Transition to Real-Time Algorithmic Personalized Experiences

Matt Hahnfeld, Software Engineering Manager
Xavier Lucas, Software Engineer III
June 27, 2019
Highest in Customer Satisfaction Among Traditional Carriers in North America, Twelve Years in a Row.
Considering Alaska Airlines MVP Gold Tattoo

So I obviously have been known like all of us to be an Alaska junkie. I had the idea recently to get an Alaska MVP Gold seventy five K tattoo. Thinking maybe also adding underneath my first year at the status with a dash and then leave it blank for however many years I am fortunate enough to keep the level.

Am I insane? Cool idea, dumb idea? I won't be offended please let me know your opinions and if anyone wants to get one with me let me know lol!
Tech at Alaska is...
Earning miles the old way.

Today

Big Complex
Legacy Computer

4 Days Later
From the archives.
Two years ago in Miami.
On-demand personalization.

1. Data Lake
   Slow but comprehensive analytics of trends, patterns.

2. Cloud Caches/DBs
   Quick, consolidated information for personalization.

3. APIs
   Easy access from any application.
This is where we started to have fun.

Events/Correlation
Act immediately. Be there for our guests at the right time, right place.
Instant Gratification Requires Thinking Differently

2019 Merkle HelloWorld Loyalty Report Reveals 54% of Consumers Want Swifter Reward Redemption

February 25, 2019
Southfield, MI

HelloWorld, a Merkle company, and a leading digital marketing solutions provider for the world’s largest

Instant Gratification Requires Thinking Differently

Citi’s new ‘Pay With Points’ feature lets ThankYou cardholders redeem points in real-time

Published Tue, Jun 25 2019 • 12:18 PM EDT • Updated Tue, Jun 25 2019 • 1:04 PM EDT

Alexandra White
@AWHITE_CREDIT
Instant Gratification Requires Thinking Differently

Markets

**Citigroup Kills Some Card Perks as It Unveils New Reward Options**

By Jennifer Surane

June 25, 2019, 5:04 PM GMT+3

*Updated on June 25, 2019, 7:00 PM GMT+3*

- Citi will end price-protection, trip-insurance benefits
- Bank to introduce real-time rewards redemption for some cards

“**A recent Citigroup survey of 1,000 cardholders found that customers were 86% more likely to redeem rewards points if they could be used in real time.**”

Real-Time Requires Thinking Differently
Earning miles the new way.
Real time. Real guest wins.

- Trips
- Acquisition
- Inflight
- First Class Upgrades
- Revenue Mgmt
“Just a note of thanks as I’ve noticed credit for my flights getting added to my account and visible on the app much sooner than it had in years/months past. I appreciate the improved turnaround as it reinforces (even if just subliminally) customer loyalty. Nicely done!”

- Actual Customer
The future is bright.
Thank you.

Matt Hahnfeld, Software Engineering Manager
Xavier Lucas, Software Engineer III
Loyalty and Non-Flight Partners
How to use AI and modern architecture to create an automated agent

Brian Lewis, Chief Technology Officer, OpenJaw
How to use AI and modern architecture to create an automated agent

Brian Lewis
Chief Technology Officer

brian.lewis@openjawtech.com
OpenJaw Technologies

- 6 Offices across the globe
- 350 Staff
- 30+ Customers

Dublin – Group HQ
Dalian – China HQ
Hong Kong – Asia Pacific HQ
Krakow – Delivery Centre
Madrid – Delivery Centre
Galway – Delivery Centre
Global Customer Base
OpenJaw: three platforms

Data Driven Customer Centricity

Dynamic Offer Creation

Intelligent Chat Interfaces

t-Data
OpenJaw

t-Retail
OpenJaw

t-Social
OpenJaw
OpenJaw: three platforms

Data Driven Customer Centricity

Dynamic Offer Creation

Intelligent Chat Interfaces

t-Data
OpenJaw

t-Retail
OpenJaw

t-Social
OpenJaw
‘Intelligent Conversational Interfaces’?
The Roadmap for Conversational Intelligence

#1 Interaction

#2 Intelligence

#3 Integration
3 Stages of Maturity

1. Interaction
   - Model: Standard FAQ
   - ‘What time do I need to be at the airport?’
   - Source: FAQ, hard coded, decision tree or rules based

2. Intelligence
   - Model: Inference & Intent
   - ‘I want to sit in an exit row’
   - Source: NLP, AI, Machine Learning

3. Integration
   - Model: Augment + Combine
   - I’m flying to London, can I change my flight to tomorrow
   - Source: NLP, AI, Machine Learning, PSS, Booking, DCS, CRM data
<table>
<thead>
<tr>
<th>Feature</th>
<th>Value to Organisation</th>
<th>Value to Passenger</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Advisory (FAQ)</td>
<td>Decrease volume to call centre</td>
<td>Quicker response time</td>
</tr>
<tr>
<td>Agent w. Escalation</td>
<td>Brand experience</td>
<td>Quicker response times to common questions</td>
</tr>
<tr>
<td>Flying with Us</td>
<td>Decrease call centre volumes</td>
<td>Quicker response times to common questions</td>
</tr>
<tr>
<td>MMB</td>
<td>Decrease call centre volumes</td>
<td>Quicker response times to common questions</td>
</tr>
<tr>
<td>Help FAQs</td>
<td>Decrease call centre volumes</td>
<td>Quicker response times to common questions</td>
</tr>
<tr>
<td>Contact Us</td>
<td>Route calls to appropriate agents, cut down wastage</td>
<td>Find correct agent more quickly.</td>
</tr>
<tr>
<td>Feature</td>
<td>Value to Organisation</td>
<td>Value to Passenger</td>
</tr>
<tr>
<td>---------</td>
<td>-----------------------</td>
<td>--------------------</td>
</tr>
<tr>
<td>Deep linking system to generate URLs to link to MMB, Check-in and Flight Sales</td>
<td>Increase conversion by directing to correct web page.</td>
<td>Precise answers</td>
</tr>
<tr>
<td>MMB Conversational Flow</td>
<td>MMB handled via a conversation interface</td>
<td>Friction reduction; fast results</td>
</tr>
<tr>
<td>Online Check-in Conversational Flow</td>
<td>Check-in via conversation interface</td>
<td>Faster and easier to find complete check-in experience</td>
</tr>
<tr>
<td>Flight Selling Conversational Flow</td>
<td>Enable flight selling with specific offer page</td>
<td>Engage customer with natural language in a private message flow</td>
</tr>
</tbody>
</table>
## #3 Integration

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value to Organisation</th>
<th>Value to Passenger</th>
</tr>
</thead>
<tbody>
<tr>
<td>Check-in w/ Ancillary Sales</td>
<td>Decrease volume to call centre, provide conversational opportunity for upsell</td>
<td>Ability to check-in online via Facebook Messenger or WhatsApp</td>
</tr>
<tr>
<td>Flights Status, FIFO, and Regulatory Details</td>
<td>Reduce call centre volumes</td>
<td>Quicker response to queries.</td>
</tr>
<tr>
<td>MMB Baggage and Seat Upsell</td>
<td>Decrease call centre volumes and increase baggage and seat sales</td>
<td>Reduce friction in seat sales bag sales</td>
</tr>
</tbody>
</table>
How do we use AI?
23. Rewrite the following `switch` statement as a nested `if` statement using a series of `else...if` statements:

```csharp
string birdName;
switch (birdName)
{
    case "Pelican":
        Console.WriteLine("Lives near water.");
        break;
    case "Cardinal":
        Console.WriteLine("Beautiful in the snow.");
        break;
    case "Owl":
        Console.WriteLine("Night creature.");
        break;
    case "Eagle":
        Console.WriteLine("Keen vision");
        break;
    case "Flamingo":
        Console.WriteLine("Pretty and pink.");
        break;
    default:
        Console.WriteLine("Can fly.");
        break;
}
```
Measure and monitor accuracy

**Intent Accuracy**

Accuracy % vs. Number of Training Questions

**Accuracy After Each Improvement Cycle**

- Fix Data
- Confusion
- Add Qs
- Onsite
- Split BDS
- Add
- Add Qs2

Accuracy: [1, 70, 70, 60, 50, 40, 30, 20, 10, 0]
Improve the data, fix misclassifications

Number of Questions

<table>
<thead>
<tr>
<th>Cluster ID</th>
<th>Size</th>
<th>z_score</th>
<th>mad_scores</th>
<th>to_check</th>
</tr>
</thead>
<tbody>
<tr>
<td>客票变更_改期 TRI 自动改期_问题类</td>
<td>228</td>
<td>2.208183</td>
<td>0.037072</td>
<td>True</td>
</tr>
<tr>
<td>客票变更_退票_咨询类</td>
<td>386</td>
<td>4.264052</td>
<td>0.067110</td>
<td>True</td>
</tr>
<tr>
<td>报销凭证_打印方查询</td>
<td>287</td>
<td>2.975881</td>
<td>0.048289</td>
<td>True</td>
</tr>
</tbody>
</table>
Architecting the eco-system
Middleware

Spring Boot based.
‘Core’ of the system
Integration and orchestration layers
Configuration
Queuing, Databases, Caches
Console UI

Built using React & Redux
ECharts visualisation framework
Material UI
Console UI
Chat Server

Built in Node JS
Simple to embed
Supports attachments
Connects via Rabbit MQ
Deployment

Deployed in Kubernetes in AWS.
Currently migrating to EKS using Helm & Tiller.
Deployed from GitLab repo proxy
Dashboard UI to see status of deployment/pods.
Errors/problems sent as messages to slack.
Prometheus metrics server & Grafana for visualization.
Conclusions

Maturity level - Decide where to start
Implement Training Metrics
Fully Instrument the solution
Gateway approach to handle new channels
Architect for the complete eco-system
Plan to deploy and run at scale
Thanks for listening!

brian.lewis@openjawtech.com
BrianLewis68

@BrianLewisCTO
www.linkedin.com/in/brian-lewis

OpenJaw
Project DeepSky: A playful approach towards Reinforcement Learning in Aviation

Dr. Dr. Mussie Beian, Senior Data Scientist, zeroG
Project DeepSky: A playful approach towards Reinforcement Learning

IATA Aviation Data Symposium 2019
Greece, Athens

Dr. Dr. Mussie Thomas Beian – Senior Data Scientist
Combining the best out of two worlds: zeroG & Lufthansa Systems

zeroG: a new breed of digital tech start up. We help airlines turn their data into value through advanced analytics and digitization. Our team comprises of young, dynamic & highly international technology professionals who bring along airline know-how & analytics expertise like two sides of a coin. In a nutshell, we support airlines through their digitization journey by unlocking the intrinsic power of data.
AI within Aviation
How game-like situations will transform the aviation world
What is Artificial Intelligence?
What is Artificial Intelligence?

A set of analytical technologies that augment human cognition.
The next step in AI

Increased computer power and data availability enables AI to go beyond insight and foresight, towards systems that act, learn, and adapt on the user’s behalf.
We take you on an AI Journey: Towards systems that act, learn and adapt on the user’s behalf.
Current status of AI in aviation

Many isolated AI use cases have been realized within the aviation world, but Reinforcement Learning is a revolutionary green field!
**How does Reinforcement Learning work?**

### Key Elements

<table>
<thead>
<tr>
<th>AI Agent</th>
<th>Autonomous system that will teach itself through trial and error.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environment</td>
<td>World in which the agent acts, learns and aims to influence.</td>
</tr>
<tr>
<td>Observation Input</td>
<td>Representation of environment that serves as the basis for the agent’s decisions.</td>
</tr>
<tr>
<td>KPI Driven Reward System</td>
<td>Essential KPI’s/goals that teaches Agent how well he is performing through reward and punishment.</td>
</tr>
</tbody>
</table>

### Situational Sketch

- **AI Agent**
- **Environment**
- **Observation Input**: Observation - \( O_t \)
- **Reward**: Reward - \( R_t \)
- **Action**: Action - \( A_t \)

**IMPACT:** agent independently develops strategy to optimize actions towards highest possible result
**Example 1: Alphabet’s (Google’s) AlpaGo**

<table>
<thead>
<tr>
<th>Key Elements</th>
<th>Situational Sketch</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AI Agent</strong> Alpha Go</td>
<td></td>
</tr>
<tr>
<td><strong>Environment</strong> Chinese game Go – the most complex game in the world!</td>
<td></td>
</tr>
<tr>
<td><strong>Observation Input</strong> Game environment, position of stones on the board, previous moves</td>
<td></td>
</tr>
<tr>
<td><strong>KPI Driven Reward System</strong> Beat opponent!</td>
<td></td>
</tr>
</tbody>
</table>

AlphaGo now beats the best human Go-Player in record time
### Example 2: zeroG’s DeepSky

<table>
<thead>
<tr>
<th>Key Elements</th>
<th>Situational Sketch</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AI Agent</strong></td>
<td></td>
</tr>
<tr>
<td>DeepSky</td>
<td></td>
</tr>
<tr>
<td><strong>Environment</strong></td>
<td></td>
</tr>
<tr>
<td>Air Bucks – an airline</td>
<td></td>
</tr>
<tr>
<td>management computer</td>
<td></td>
</tr>
<tr>
<td>game.</td>
<td></td>
</tr>
<tr>
<td><strong>Observation Input</strong></td>
<td></td>
</tr>
<tr>
<td>Bank balance, fleet</td>
<td></td>
</tr>
<tr>
<td>size, landing rights,</td>
<td></td>
</tr>
<tr>
<td>date, available airport</td>
<td></td>
</tr>
<tr>
<td>, company worth, etc.</td>
<td></td>
</tr>
<tr>
<td>**KPI Driven Reward</td>
<td></td>
</tr>
<tr>
<td>System**</td>
<td></td>
</tr>
<tr>
<td>Build an airline that</td>
<td></td>
</tr>
<tr>
<td>will generate biggest</td>
<td></td>
</tr>
<tr>
<td>company worth within</td>
<td></td>
</tr>
<tr>
<td>four (game) years.</td>
<td></td>
</tr>
</tbody>
</table>

DeepSky now beats every human airline manager in Air Bucks
After basic research and developing an own AI, zeroG is about to implement the first use cases.
Thanks for your attention!
zerog.aero
Contact

Senior Data Scientist
Dr. Dr. Mussie Beian

Phone: +49 151 589 218 12
Mussie.Beian@zerog.aero
Linkedin: Dr. Dr. Mussie Beian
AI driving Revenue Streams

Maria Toso, Manager, Pricing and Revenue Management Intelligence (PRMI) group, Copa Airlines
AGENDA

COPA AIRLINES
History and growth of Copa Airlines

COPA AIRLINES + AI
How is Copa Airlines using AI?

AI DRIVING REVENUE STREAMS
What have been the tangible results of these AI applications?
LOS ANGELES
LAS VEGAS
BOSTON
NEW YORK
MIAMI
HAVANA
SANTIAGO
MIAMI
SAN FRANCISCO
CHICAGO
LIMA
SANTIAGO
ARGENTINA
SANTIAGO
CHICAGO
MEXICO DF
HAVANA
BRASIL
80 DESTINATIONS
32 COUNTRIES
105 AIRCRAFT
+15 MM PAX CARRIED
$2.7 BILLION REVENUE
ARTIFICIAL INTELLIGENCE

What is Artificial Intelligence?

“Any type of computer software that engages in humanlike activities, including learning, planning and problem solving”

1950-1970s
Neural Network
Early work in neural networks

1980s-2010s
Machine Learning
Machine Learning becomes popular

Present Day
Deep Learning
Deep Learning breakthroughs drive AI boom
Machine learning is one of the most common types of artificial intelligence in development for business purposes today.
Let's understand how classification algorithms work.

Classifying an apple:
- Red
- Circular
- Sweet smell

Mystery fruit:
- Yellow
- Smooth
- No smell

With the characteristics of an apple determined, we can classify if any fruit is an apple or not.
CLASSIFICATION BUSINESS CASES

Classification of sold-out too soon flights

Co-Brand credit card acquisition in loyalty
PREDICTING SOLD-OUT TOO SOON FLIGHTS
PREDICTING SOLD-OUT TOO SOON FLIGHTS

Extrapolate the classification and instead of an apple imagine a flight. What would you need to predict if a flight will sell out or not?

<table>
<thead>
<tr>
<th>Flight No</th>
<th>Origin</th>
<th>Destination</th>
<th>Departure</th>
<th>Remaining Seats</th>
<th>Sold-out flight?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1200</td>
<td>PTY</td>
<td>SFO</td>
<td>08/01/2019</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

- Define a sold-out to soon flight
- Manipulate training set so it can easily aid in prediction of future sold-out flights

14 days before departure the flight was full
PREDICTING SOLD-OUT TOO SOON FLIGHTS

Determine the characteristics of a sold-out too soon flight. These characteristics can include anything related to a flight or even complex relationships between variables.

- Current Booking
- Bid Price
- Bookings Velocity
- Remaining Seats
- Many more……

Once the variables are selected, test several classifications algorithms:

- Random Forest
- Neural Networks
- Gradient Boosting

With current characteristics of a future flight, it is expected that the flight will sell-out too soon.
PREDICTING SOLD-OUT TOO SOON FLIGHTS

A look into the implementation and results

2017
ALGORITHM IMPLEMENTED

+$1MM*
MONTHLY REVENUE OPPORTUNITY

~70% ACCURACY

DAILY ALERTS ARE SENT TO PRICING AND RM

PERSONALIZATION & SENSITIVE INFORMATION

RELEVANT TARGETING ALONG THE JOURNEY

ENCOURAGE & DRIVE ANALYST ENGAGEMENT

DAILY ALERT

Operations Research Team

<table>
<thead>
<tr>
<th>Endangered Flights</th>
<th>Today vs Yesterday</th>
</tr>
</thead>
<tbody>
<tr>
<td>34</td>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>New Endangered Flights</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
</tr>
</tbody>
</table>
CO-BRAND CREDIT CARD ACQUISITION
Copa Airlines launched its own loyalty program: **ConnectMiles** designed to strengthen Copa’s relationship with its frequent flyers.

- **PREFER MEMBER PROGRAM**: Award our loyal and frequent customers with the most exclusive benefits: preferential access, waivers, upgrades, and much more.
- **EARN MILES**: Embark on a mile-earning journey every time you fly on Copa Airlines and our partners.
- **PARTNERSHIPS**: Earn miles from non-airline activities such as hotels stays, car rentals and credit card purchases.
- **USE MILES**: Use miles on flights operated by Copa Airlines and on selected flights operated by Star Alliance member airlines.
CO-BRAND CREDIT CARD ACQUISITION

Supervised look-alike-classification model that:

- Identifies potential credit card holders in the countries where Copa Airlines offers a co-brand
- Creates acquisition tool to accelerate growth for new partners
- Identifies potential co-brand expansions where Copa Airlines does not have presence

The first step is to understand the customer

- Miles Balance
- Status
- Gender
- Survey Response
- Age
- Travel Frequency
- Miles accrued
- Membership age
The second step consists of developing a model that identifies potential customers.
CO-BRAND CREDIT CARD ACQUISITION

A look into the implementation and results

2018
ALGORITHM IMPLEMENTED

~500K
ANNUAL INCREMENTAL REVENUE

EMAILS ARE SENT TO CUSTOMERS

EXPANSION OPPORTUNITY IN NEW MARKETS

INCREASE PRESENCE IN COUNTRIES WITH NO PRESENCE

ENCOURAGE & DRIVE CUSTOMER ENGAGEMENT

IMPROVE PARTNERSHIPS

ALIGNING BUSINESS STRATEGIES AND GOALS
AI DRIVING REVENUE STREAMS

Artificial intelligence gives us the ability of not only generating revenue streams but also:

- Increase productivity and operational efficiencies
  Save time and money by automating routine processes and tasks

- Make faster business decisions
  Avoid mistakes and 'human error'

- Achieve cost savings
  Increase revenue by identifying and maximizing opportunities
THANK YOU!

Copa Airlines

Maria Agustina Toso
mtoso@copaair.com
Key Takeaways and Closing Remarks

Houman Goudarzi, Head of BI & Industry Engagement, IATA