IATA AVIATION DATA SYMPOSIUM

ATHENS, GREECE 25 – 27 JUNE 2019

AI Lab

IATA

Opening Remarks

Houman Goudarzi, Head of BI & Industry Engagement, IATA

The Air France-KLM case study

Leon Gommans, Science Officer, Air France-KLM

IATA AVIATION DATA SYMPOSIUM

AIRFRANCE 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.

Universiteit van Amsterdam | SURF | ESnet Energy Sciences Network
Research

Equinix | Dell Technologies | Nokia | Ciena
IT Industry

ExchangeWell A Program of SAE ITC
Industry consortium

CONTEXT: AERONAUTICAL SYSTEMS

AI GENERATES MANY QUESTIONS CREATING INITIATIVES TO ANSWER THEM

1950 “Can machines think?”

Alan Turing asked the question:

“Can a machine act as player in an imitation game?”

Alan Turing **“Computing Machinery and Intelligence”,** Mind 49: 433-460, 1950.

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:

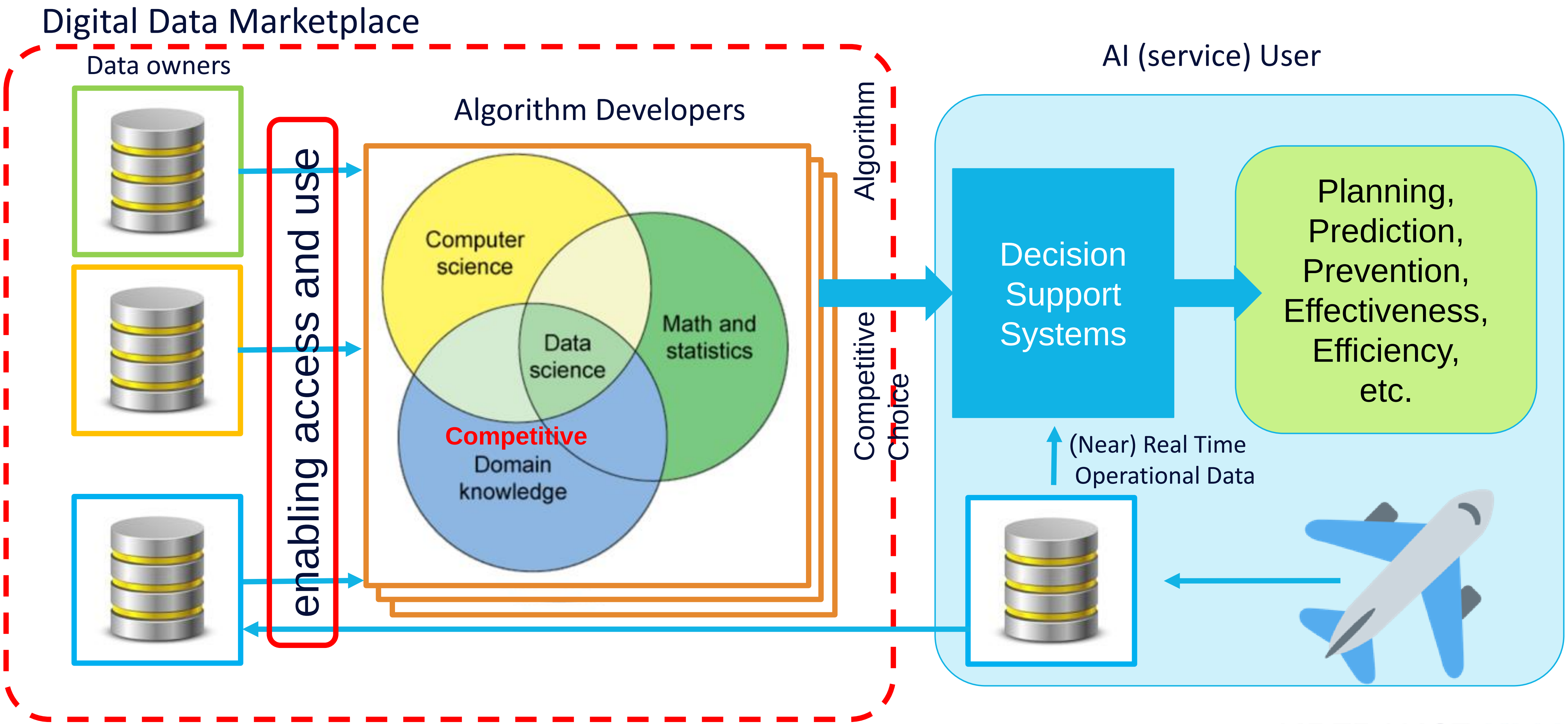
- SAE International: G.34 Applied AI for Flight Critical Systems
- EUROCAE WG-114 Artificial Intelligence
- RCTA
- SAE ITC: ExchangeWell consortium initiative to create trusted implementations.

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?

AIRFRANCE KLM

RESEACHING DATA SHARING SOLUTIONS:

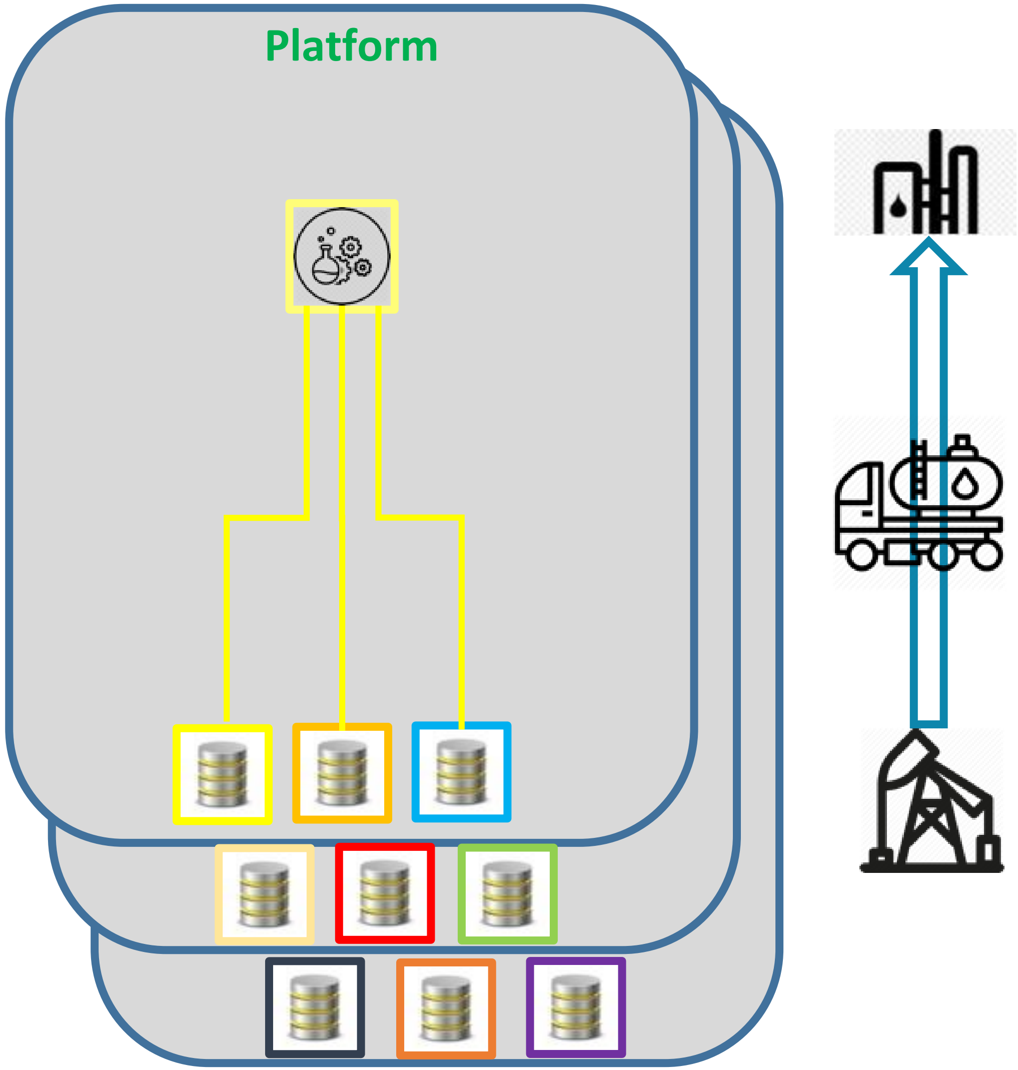
A DIGITAL DATA MARKETPLACE GOVERNED BY AN INDUSTRY CONSORTIUM



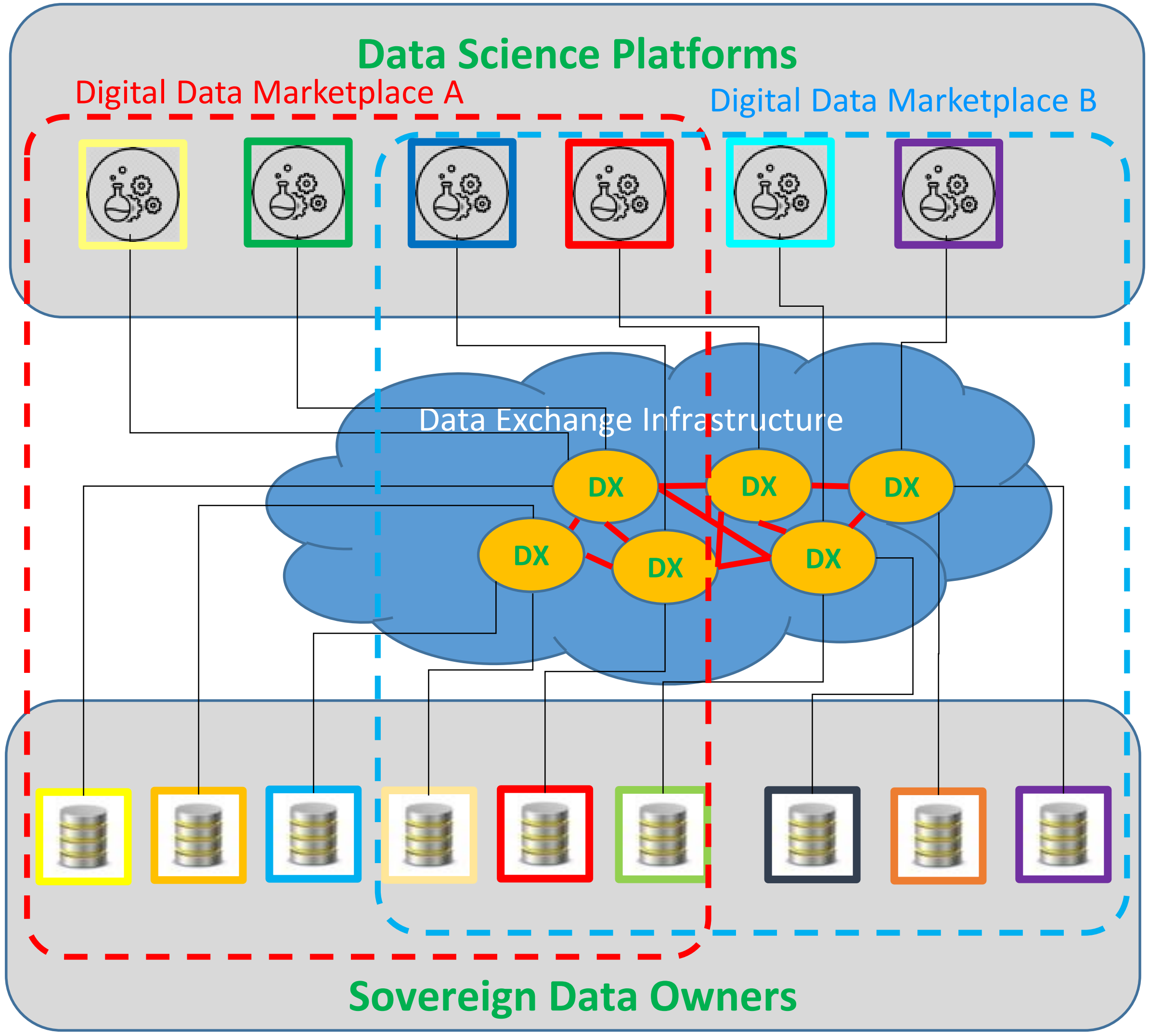
AIRFRANCE KLM

RESEARCH PROBLEM

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



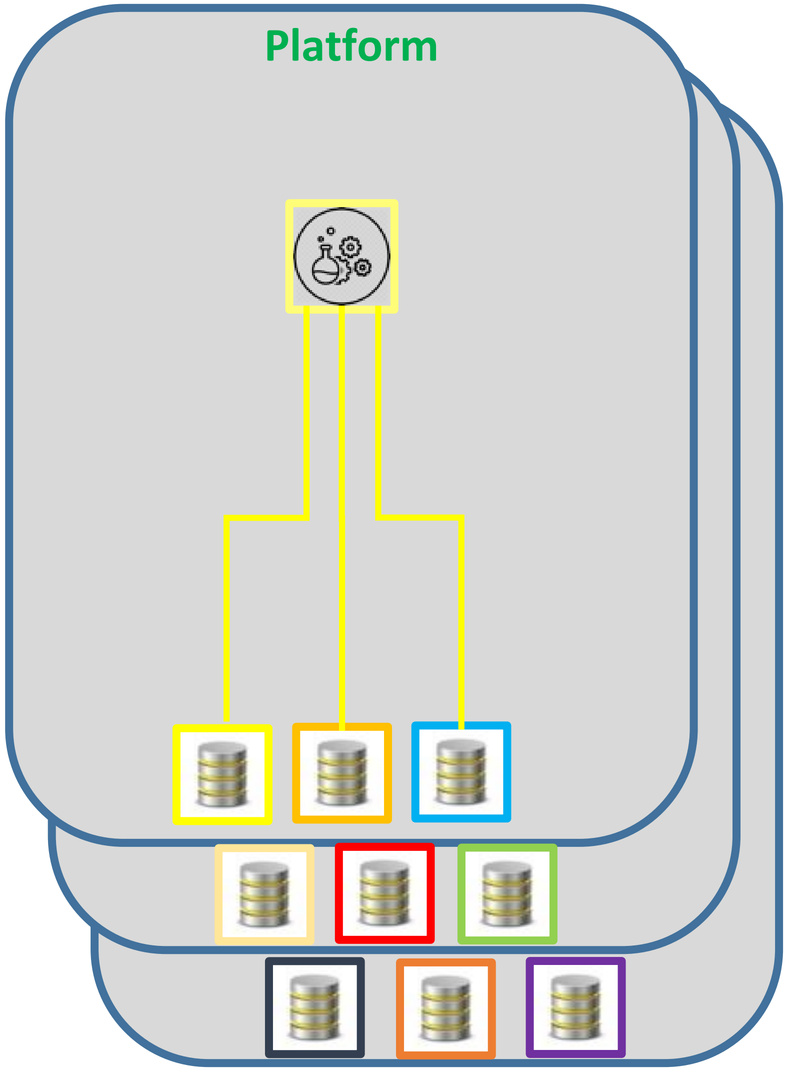
Current solution direction



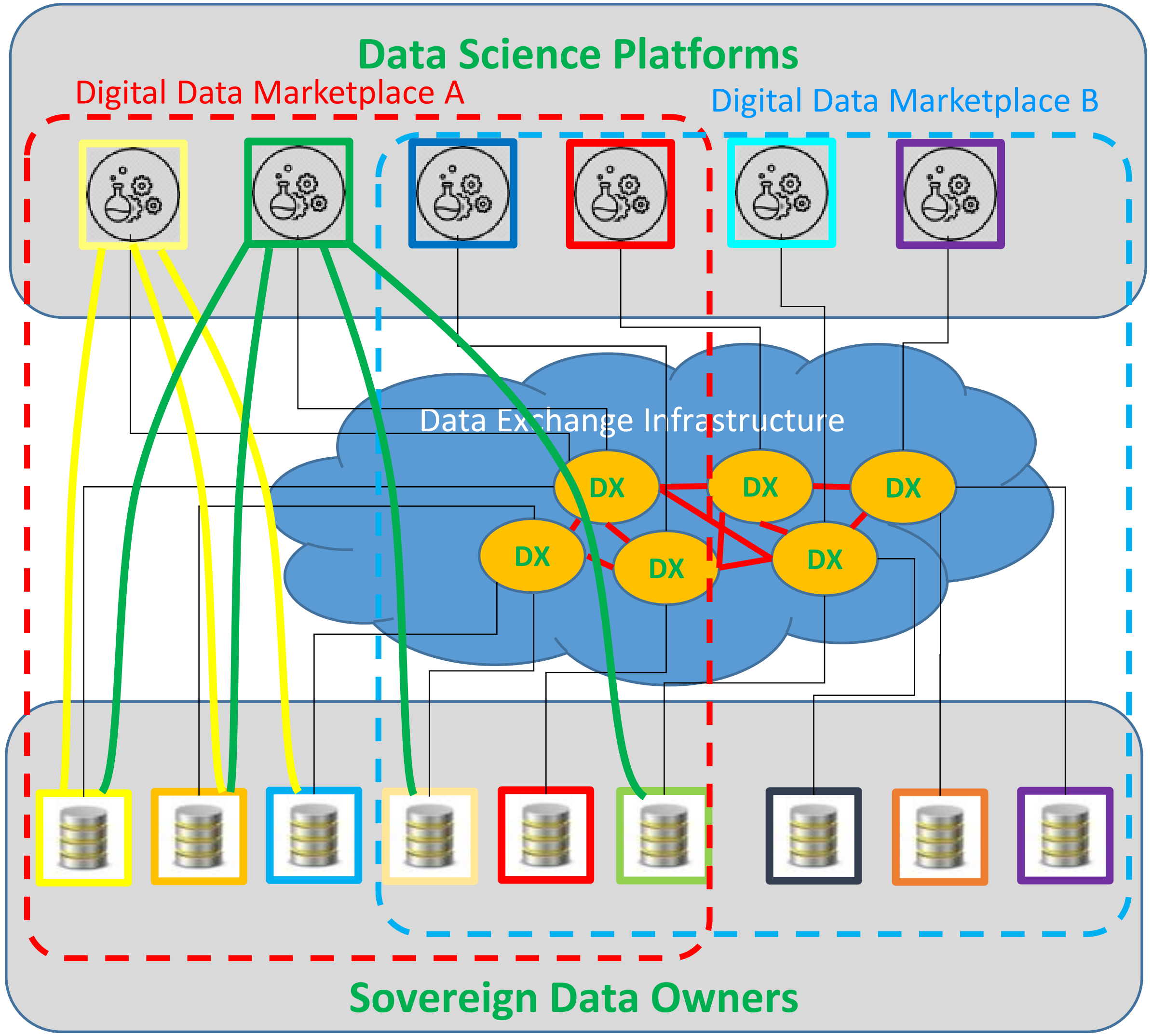
Digital Data Marketplace solution

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

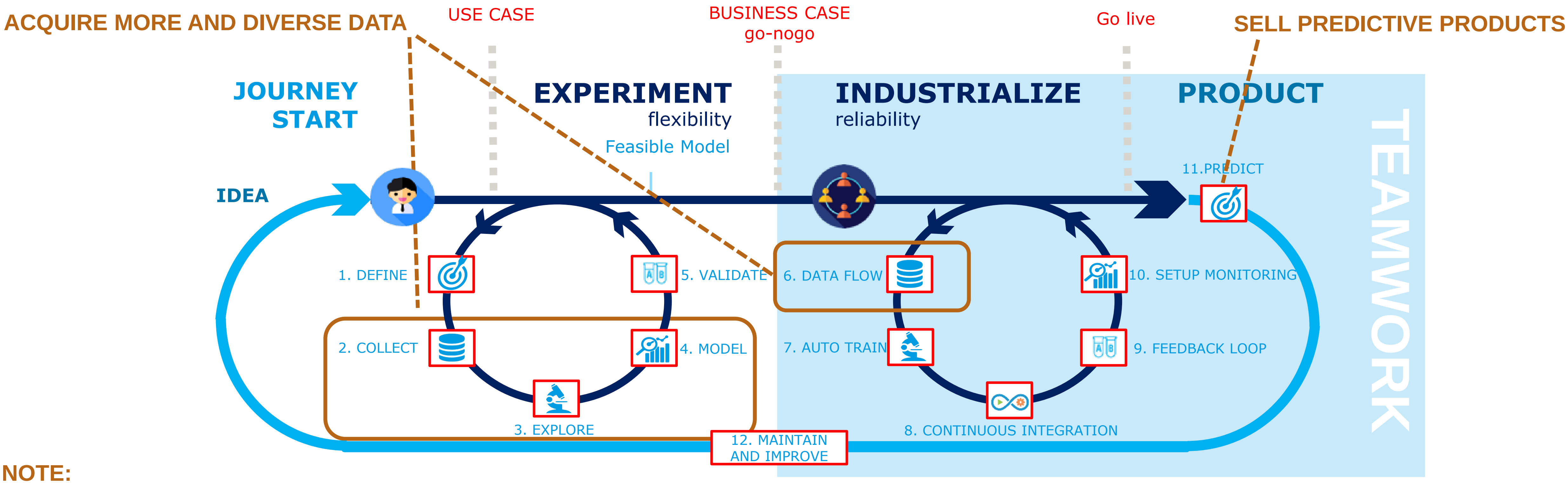
WHAT IS A DIGITAL MARKETPLACE ABOUT?

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



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

DEFINE (1-3)	EXPERIMENT (4-5)	INDUSTRIALIZE (6-10)	IMPROVE (11-12)	SHARE
What is the end purpose? How will it add value? Use case, data scope and stakeholders identification	**Collect and explore data, research data science model** Prototype, go/nogo to production	**Deliver the solution in production environment** Product GO live	**Feedback analysis, A/B testing, and performance monitoring** New product releases, business insights	

AIRFRANCE KLM

DIGITAL DATA MARKETPLACE GOVERNANCE

IMPLEMENTATION VIA A FOUR STEP APPROACH

Consortium | **Provider**

COMMON BENEFIT

Define and agree common benefit no single organization can achieve on its own.

GROUP RULES

Define consortium rules considering data use, access and benefit sharing

ORGANIZE TRUST

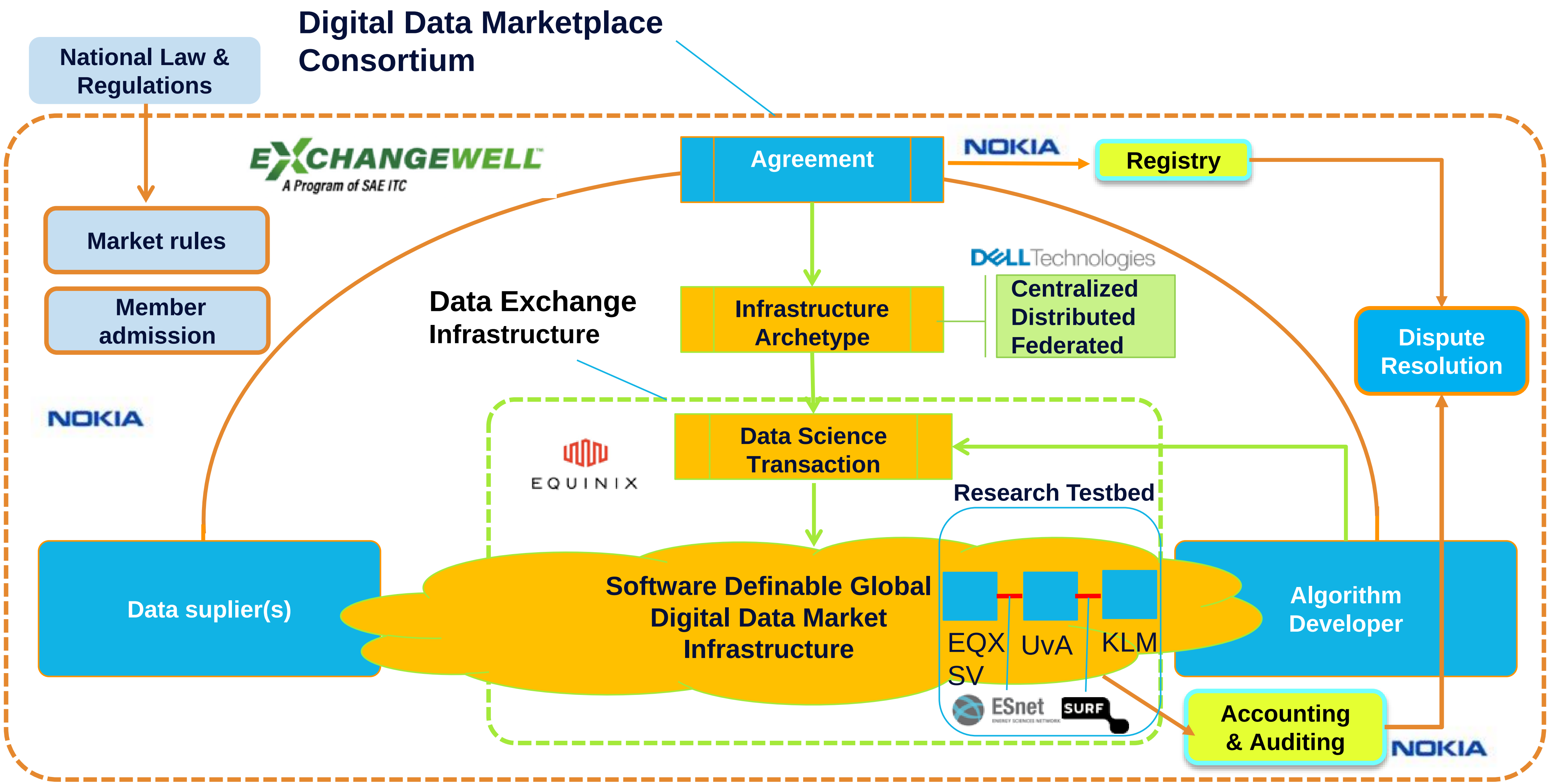
Organize power and trust as a **means to reduce risk** for participating members

IMPLEMENT INFRASTRUCTURE

Research operationalization of **Digital Data Marketplace** concepts

DIGITAL DATA MARKETPLACE ARCHITECTURE

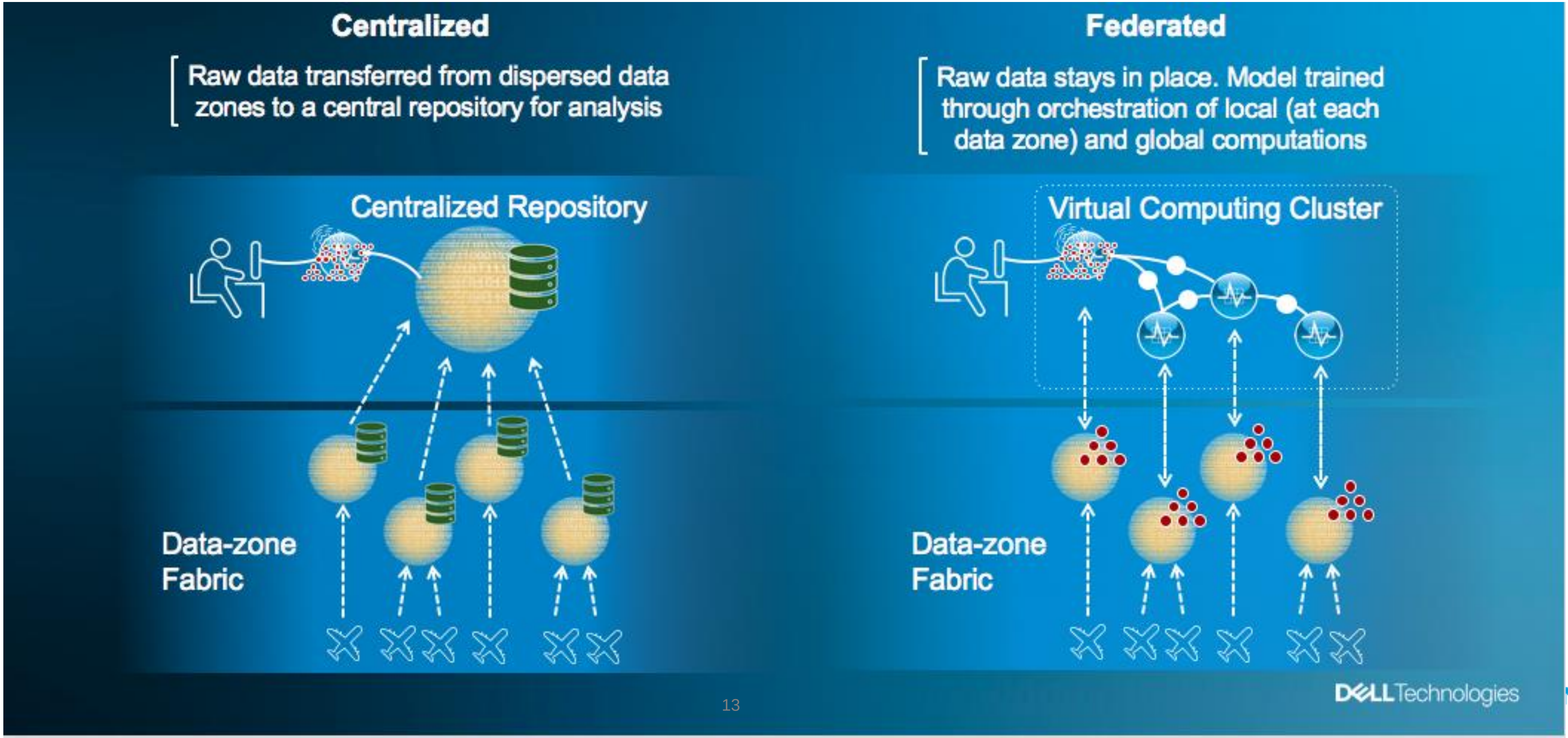
IMPLEMENTING ESSENTIAL ELEMENTS



AIRFRANCE KLM

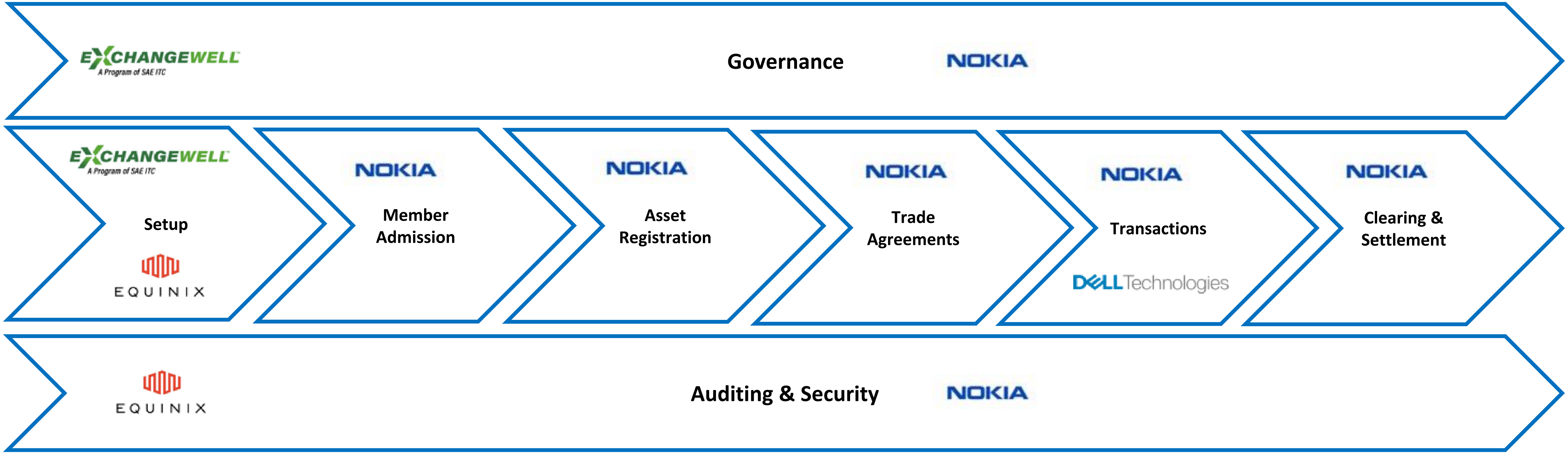
KEY COMPONENT: FEDERATED ANALYTICS

PREVENTS RAW DATA EXPOSURE AS ONLY THE ALGORITHM SEES THE DATA



MARKETPLACE WORKFLOW

IMPLEMENTING THE INDUSTRIALIZATION PHASE



NEXT: "EXPERIMENT PHASE" OF THE DATA SCIENTIST JOURNEY

AIRFRANCE KLM

QUESTIONS

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

AIRFRANCE KLM

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

A STAR ALLIANCE MEMBER

UNITED

Agenda

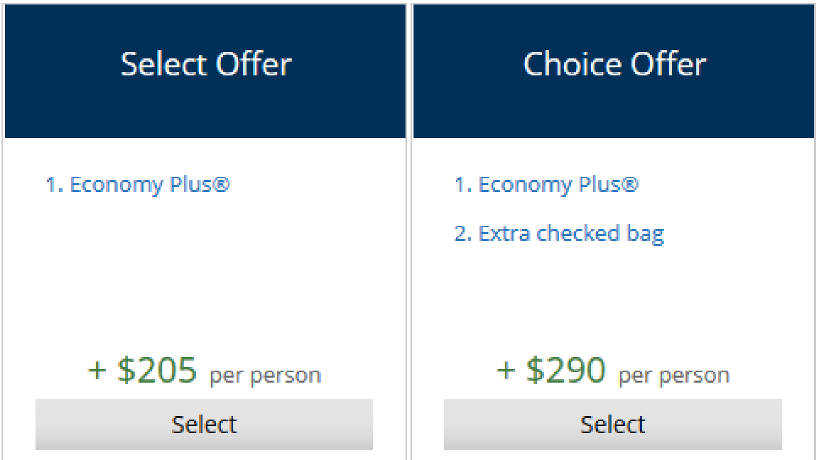
Where we were in 2018

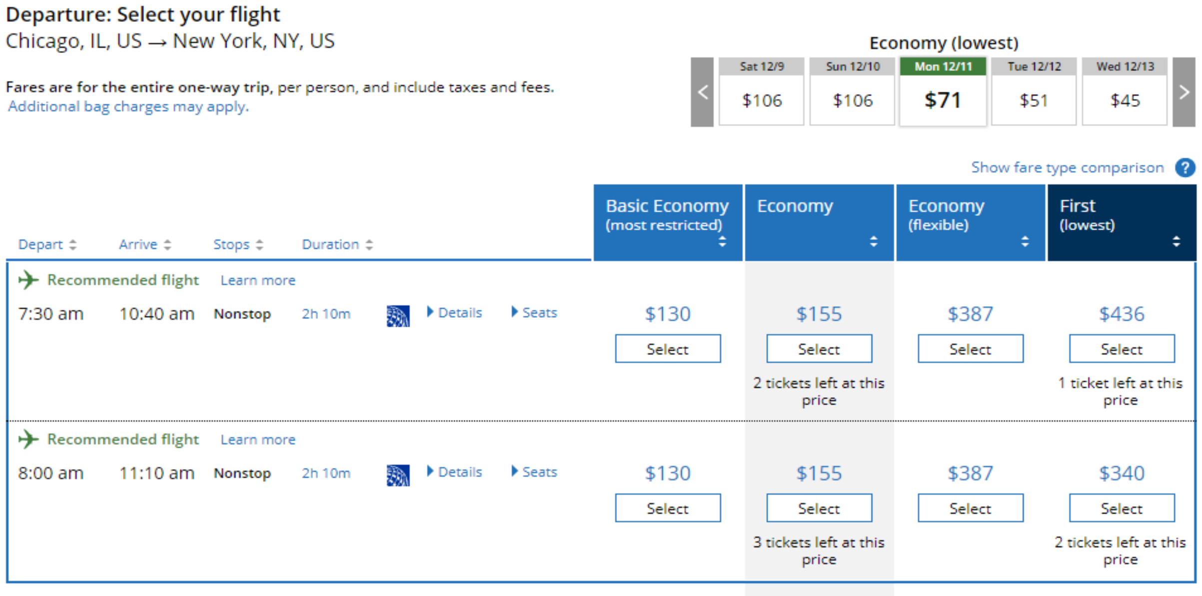
What we changed in 2019

What we're doing

Where we're headed

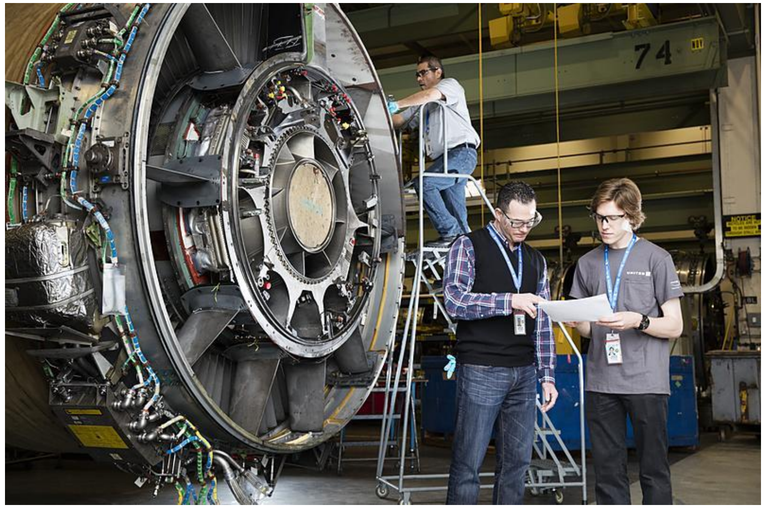
Last year I spoke about machine learning in the personalization context

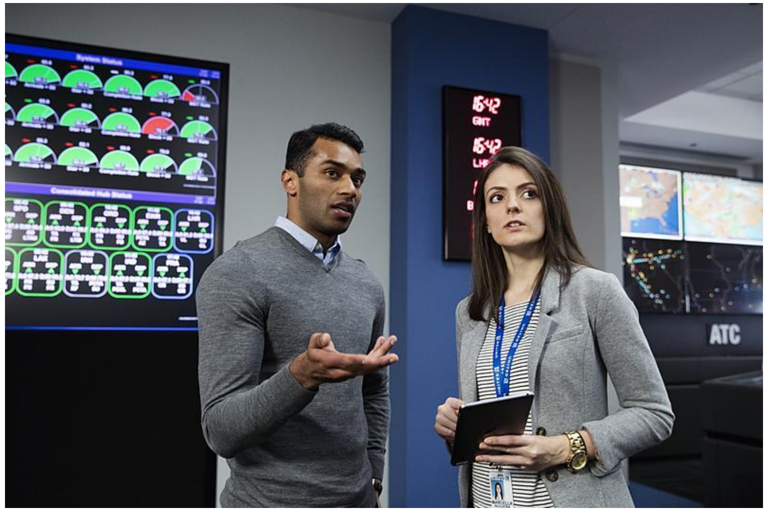




But something big was noticeably absent….

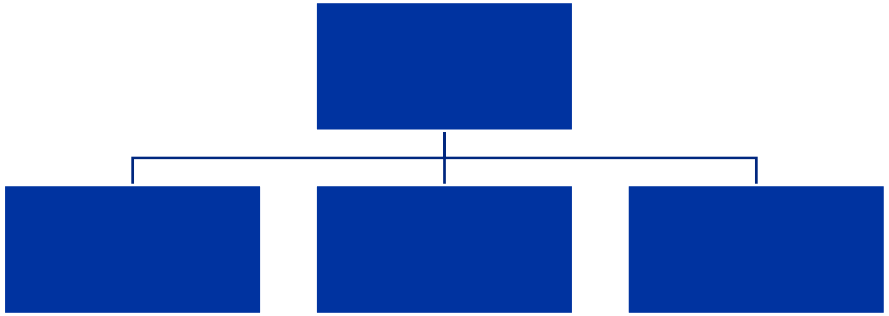
The Operation





After careful thought, we made a few changes

Team Alignment

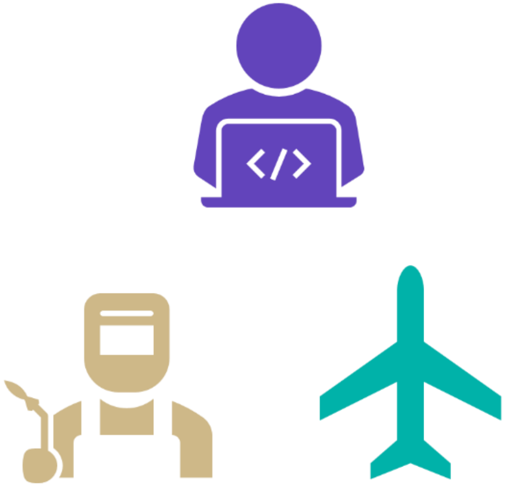


Technology

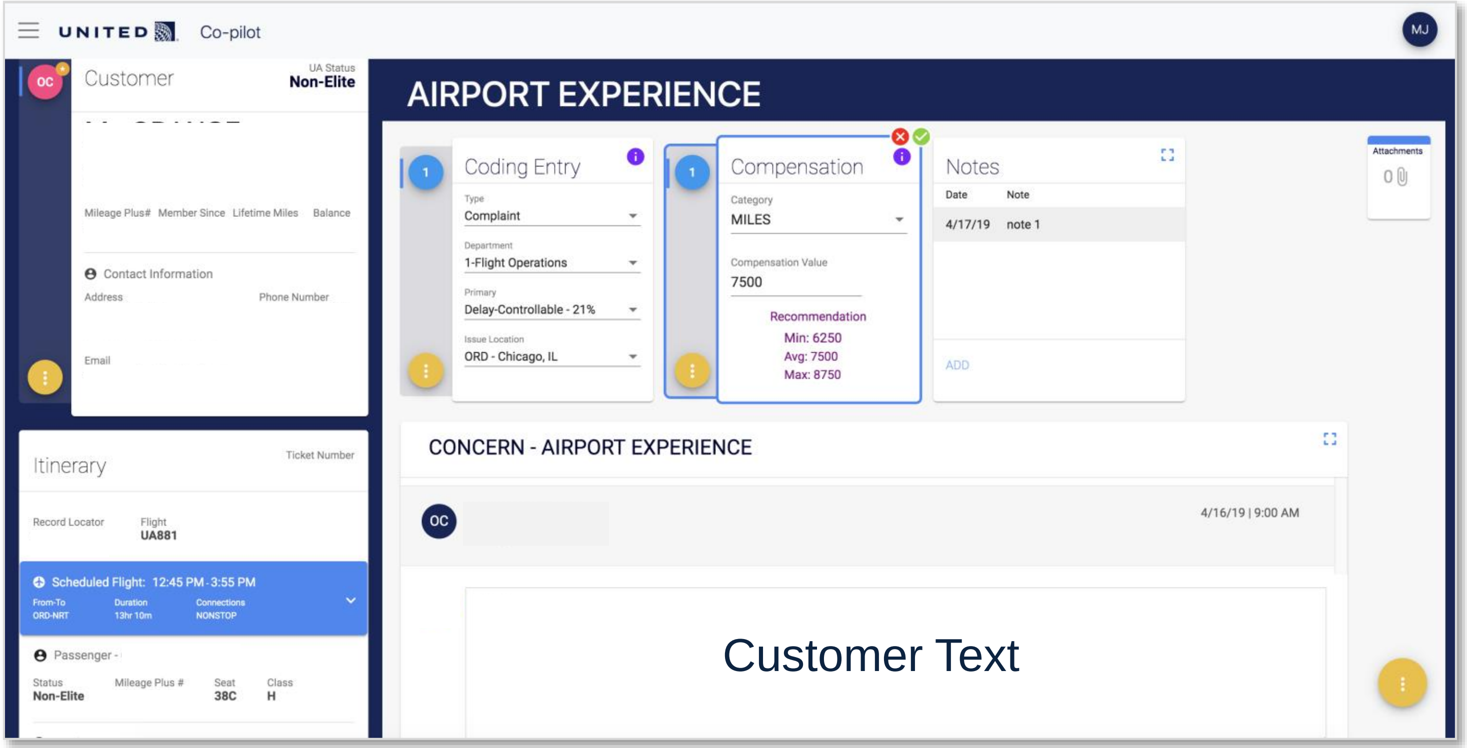
Palantir

skywise.

Domain Knowledge

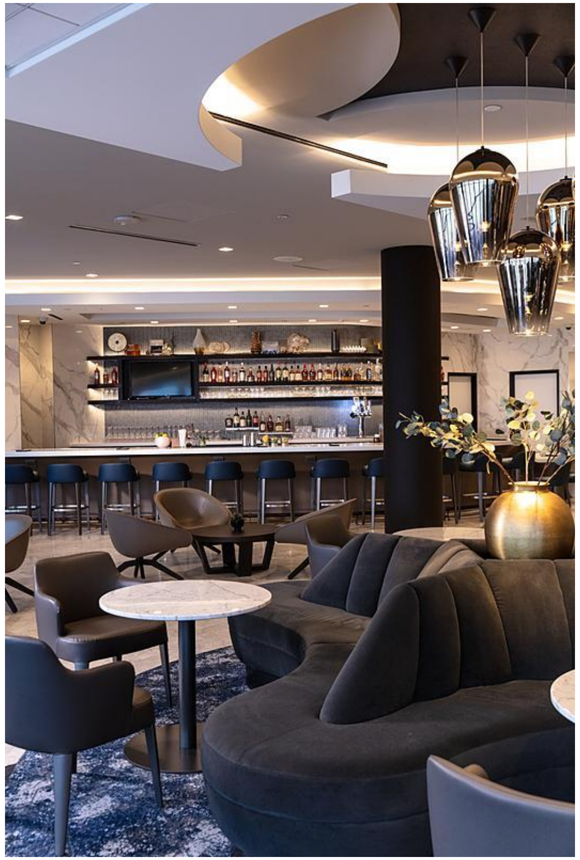


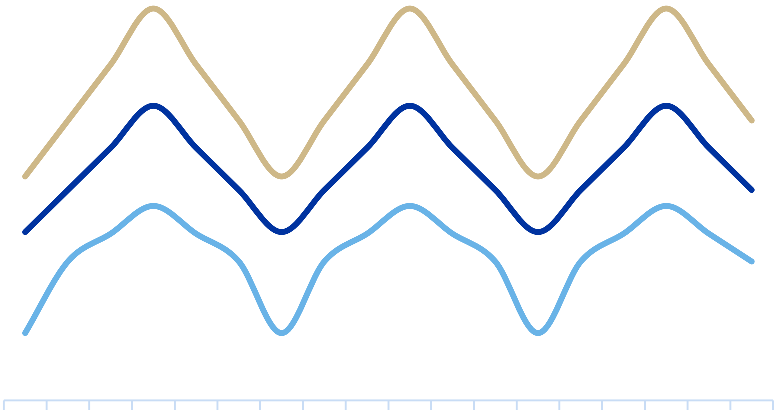
We used machine learning to drive quicker responses to our customers



- **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

UA Log Page

TAXI LIGHT IS OUT.

UA Log Page

TAXI LIGHT IS OUT.

Chapter 33

- **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

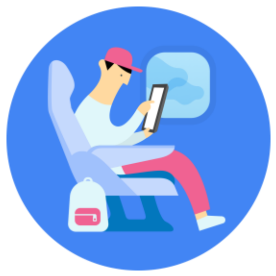
Mission

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

Google Flights Pillars

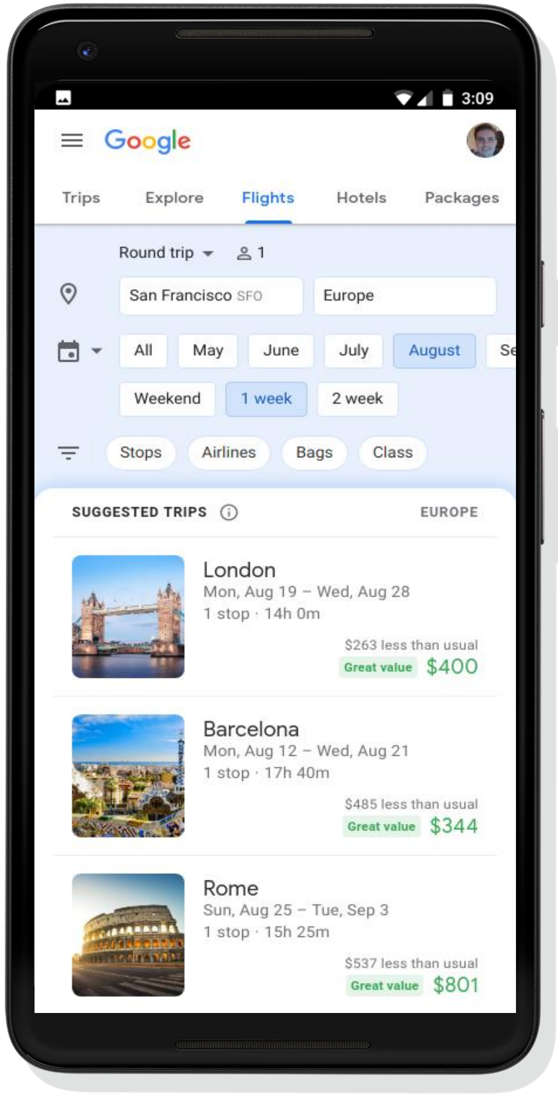
Flight Search

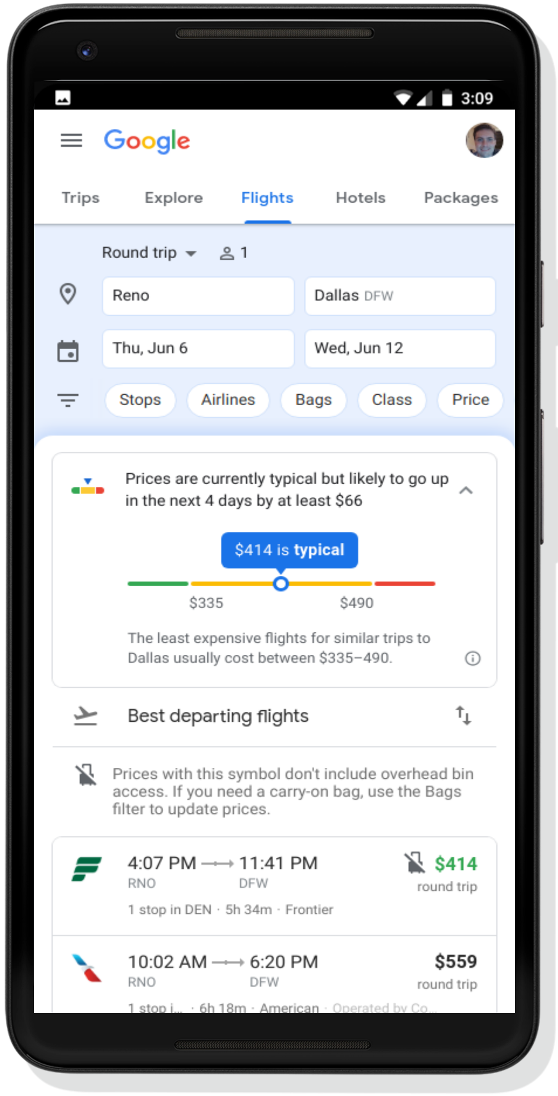
Airline Partners



Intelligent Assistance

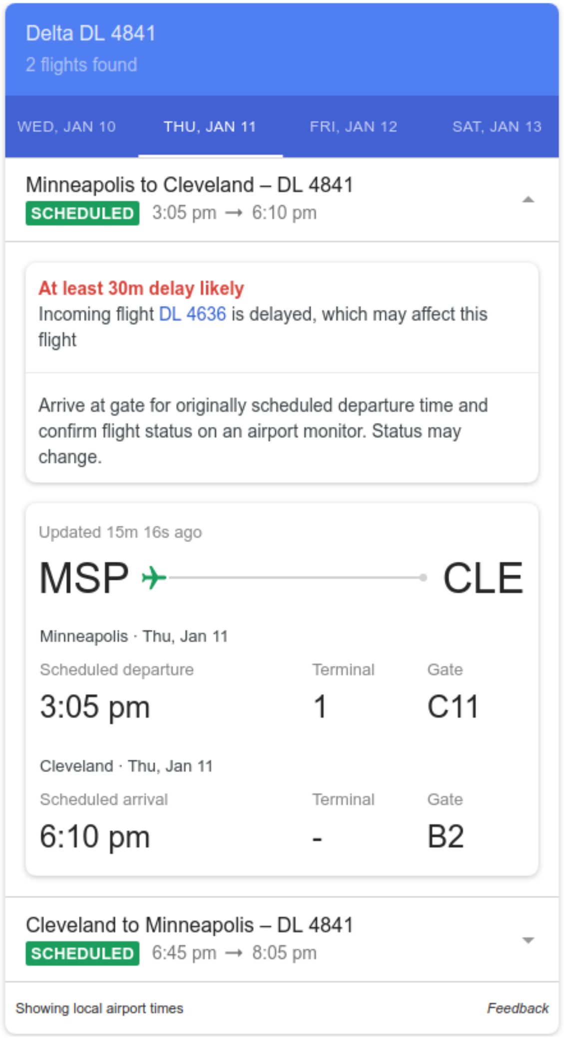
Flight Price Insights - Know when to book your flights





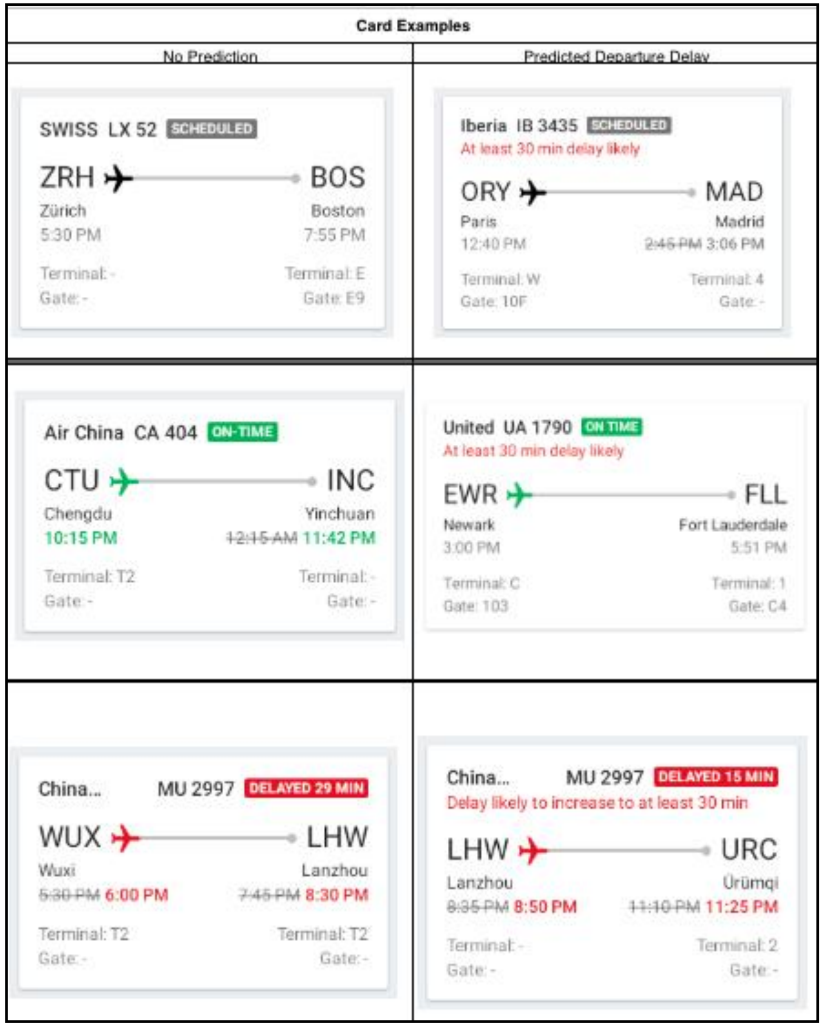
Flight Status - Know if your flight is on time

Search

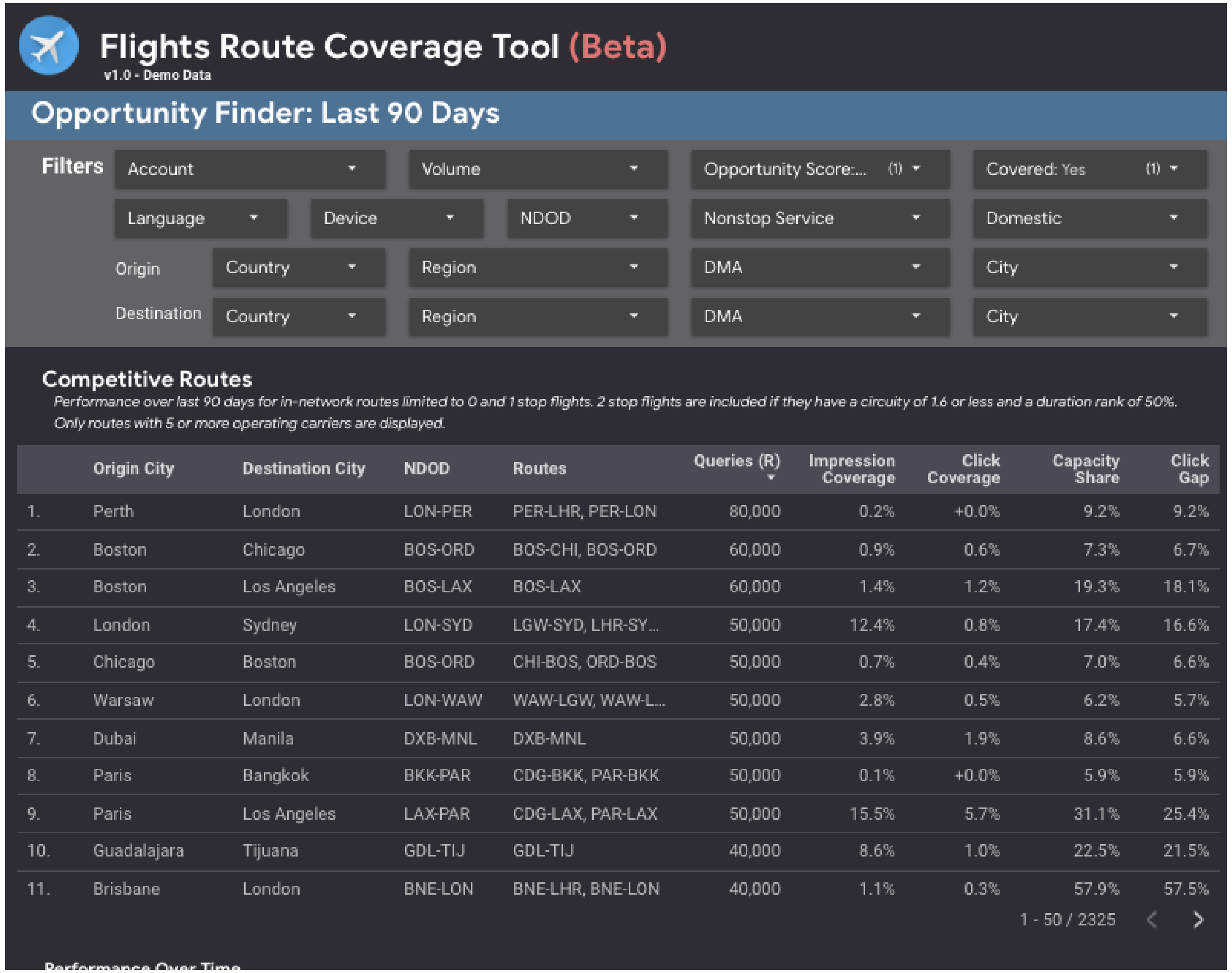


Assistant

Assistant



Route Coverage Tool - Leverage insights from user queries


Flights Route Coverage Tool (Beta)
v1.0 - Demo Data

Opportunity Finder: Last 90 Days

Filters: Account | Volume | Opportunity Score:... (1) | Covered: Yes (1)
Language | Device | NDOD | Nonstop Service | Domestic
Origin: Country | Region | DMA | City
Destination: Country | Region | DMA | City

Competitive Routes

Performance over last 90 days for in-network routes limited to 0 and 1 stop flights. 2 stop flights are included if they have a circuity of 1.6 or less and a duration rank of 50%. Only routes with 5 or more operating carriers are displayed.

	Origin City	Destination City	NDOD	Routes	Queries (R)	Impression Coverage	Click Coverage	Capacity Share	Click Gap
1.	Perth	London	LON-PER	PER-LHR, PER-LON	80,000	0.2%	+0.0%	9.2%	9.2%
2.	Boston	Chicago	BOS-ORD	BOS-CHI, BOS-ORD	60,000	0.9%	0.6%	7.3%	6.7%
3.	Boston	Los Angeles	BOS-LAX	BOS-LAX	60,000	1.4%	1.2%	19.3%	18.1%
4.	London	Sydney	LON-SYD	LGW-SYD, LHR-SY...	50,000	12.4%	0.8%	17.4%	16.6%
5.	Chicago	Boston	BOS-ORD	CHI-BOS, ORD-BOS	50,000	0.7%	0.4%	7.0%	6.6%
6.	Warsaw	London	LON-WAW	WAW-LGW, WAW-L...	50,000	2.8%	0.5%	6.2%	5.7%
7.	Dubai	Manila	DXB-MNL	DXB-MNL	50,000	3.9%	1.9%	8.6%	6.6%
8.	Paris	Bangkok	BKK-PAR	CDG-BKK, PAR-BKK	50,000	0.1%	+0.0%	5.9%	5.9%
9.	Paris	Los Angeles	LAX-PAR	CDG-LAX, PAR-LAX	50,000	15.5%	5.7%	31.1%	25.4%
10.	Guadalajara	Tijuana	GDL-TIJ	GDL-TIJ	40,000	8.6%	1.0%	22.5%	21.5%
11.	Brisbane	London	BNE-LON	BNE-LHR, BNE-LON	40,000	1.1%	0.3%	57.9%	57.5%

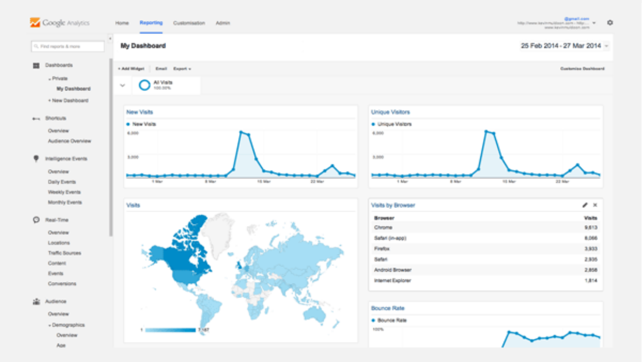
1 - 50 / 2325

Performance Over Time

Carriers May Apply Machine Learning to Gain Business Insights

Segmentation Data

Availability and Pricing Data

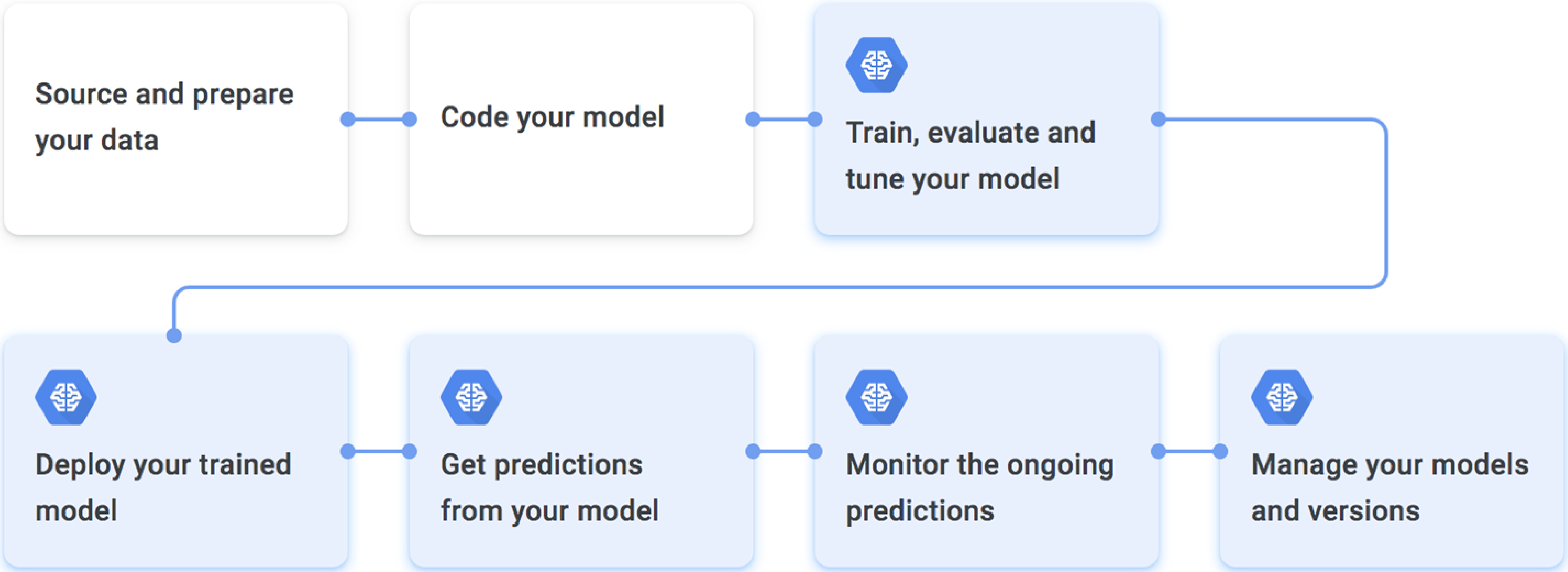


Revenue Management Data

Inventory Data

Booking Data

Google Cloud Machine Learning Workflow



Google

Flights Data & Google Cloud Infrastructure

Flight Data	• Fares, schedules, availability, pricing, flight status.
Big Query	• Enables storage of petabytes of data and slicing & dicing data across many dimensions.
Cloud Data Flow	• Fully managed service for developing and managing and executing a wide range of data patterns.
Cloud SQL	• 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.
Cloud ML	• Lets developers and data scientists build and run superior machine learning models in production.
Cloud AutoML	• Enables developers with limited machine learning expertise to train high-quality models specific to their business needs.

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

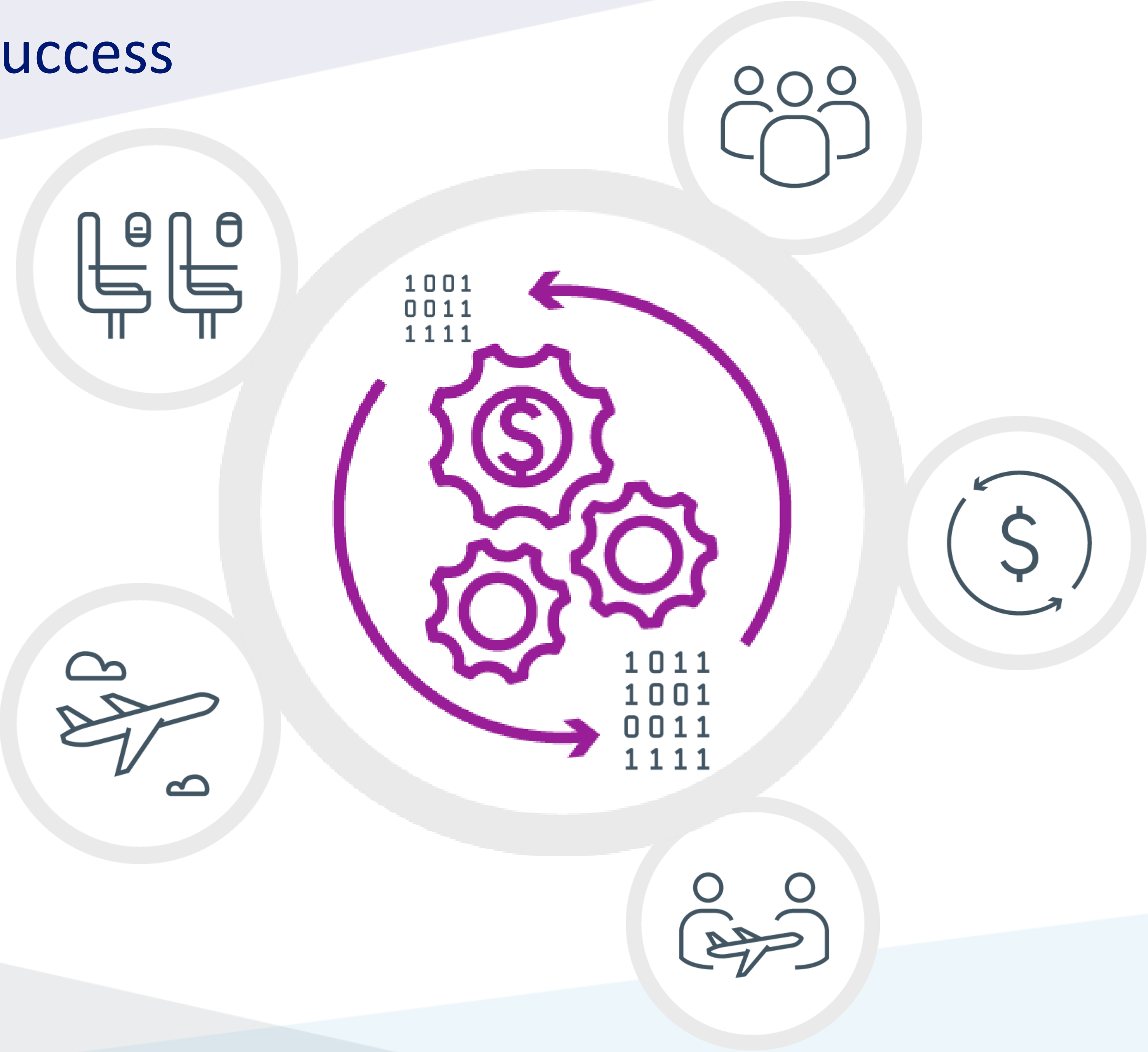
IATA ADS 2019

27 June 2019

accelya

Commercial Success

Commercial Success

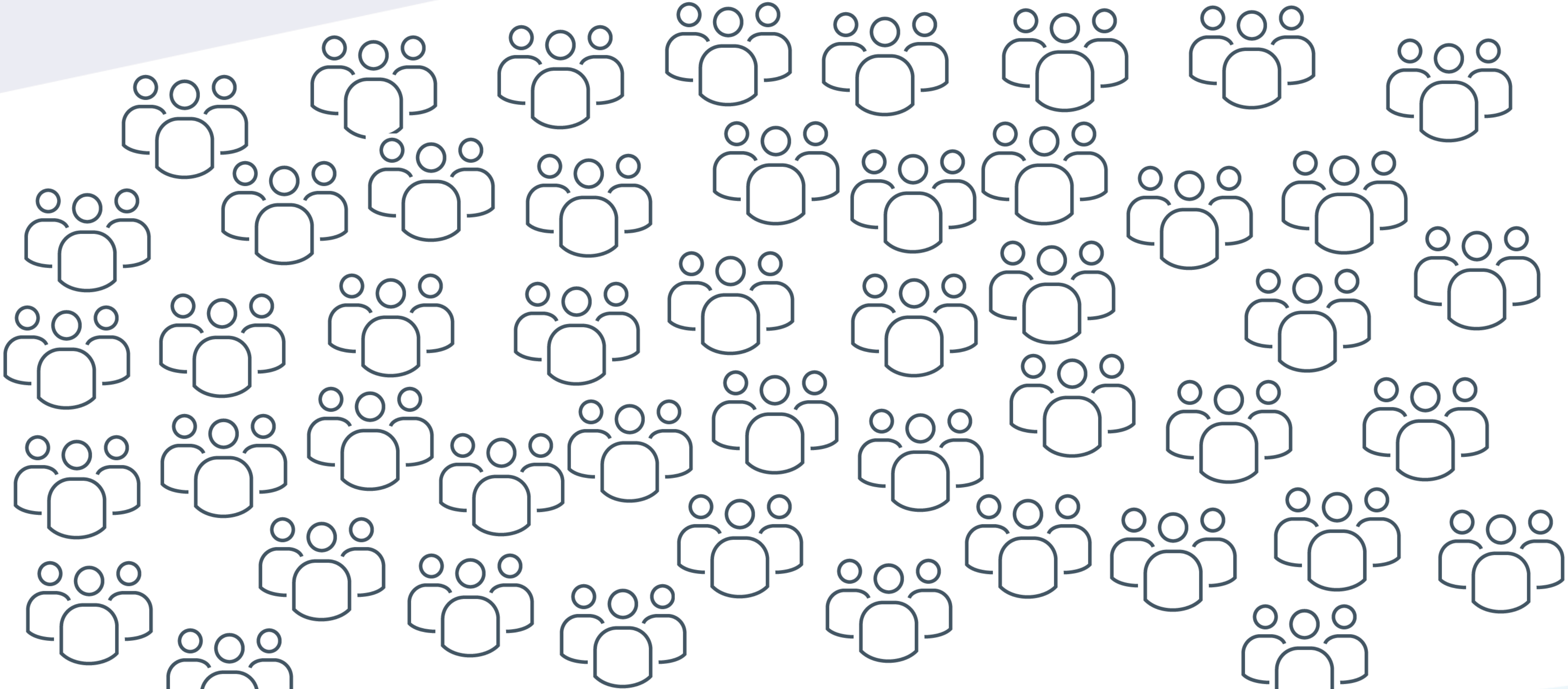


Know Your Customer

Know Your Customer?

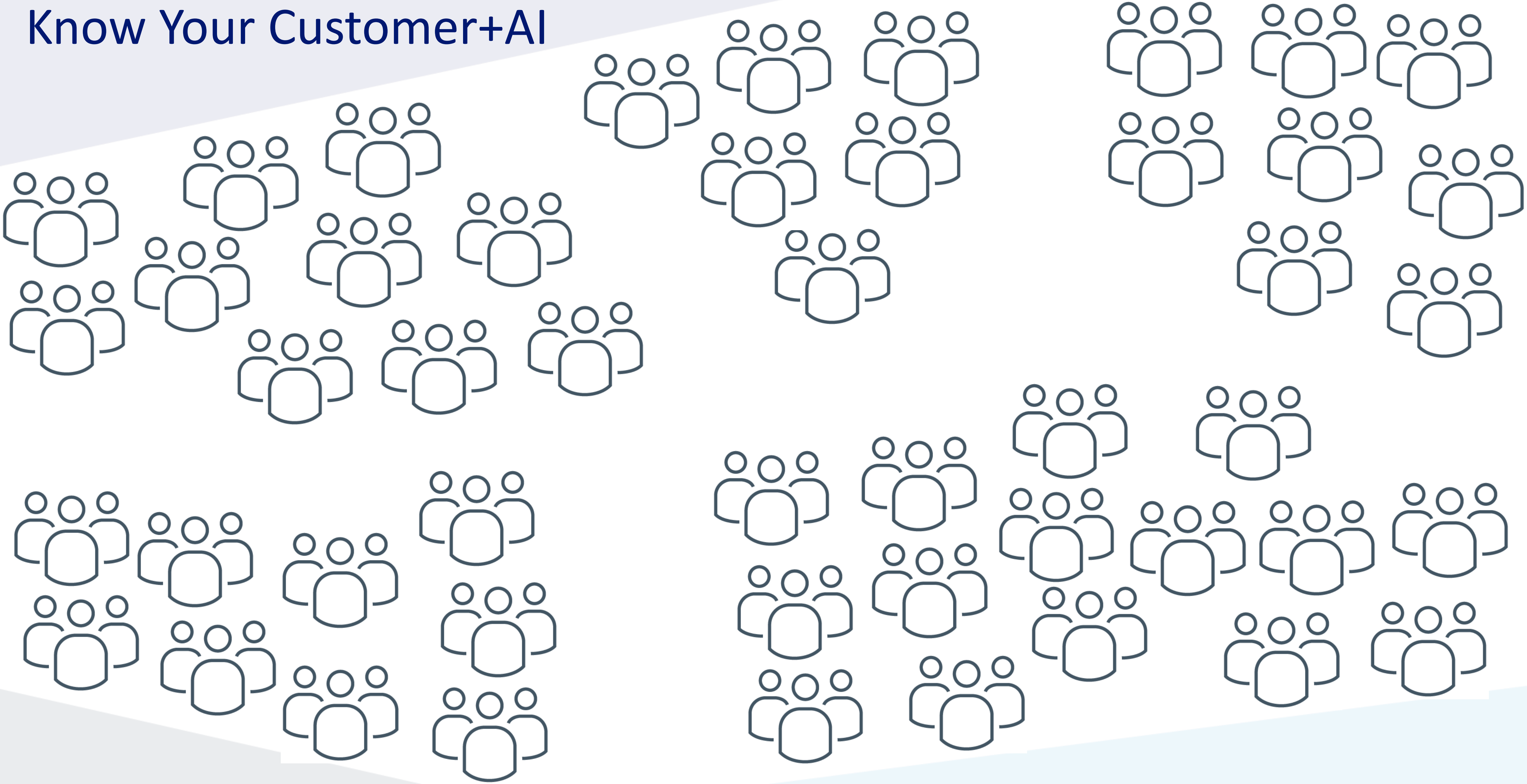
4.3 bn passengers 2018 worldwide

Know Your Customer?

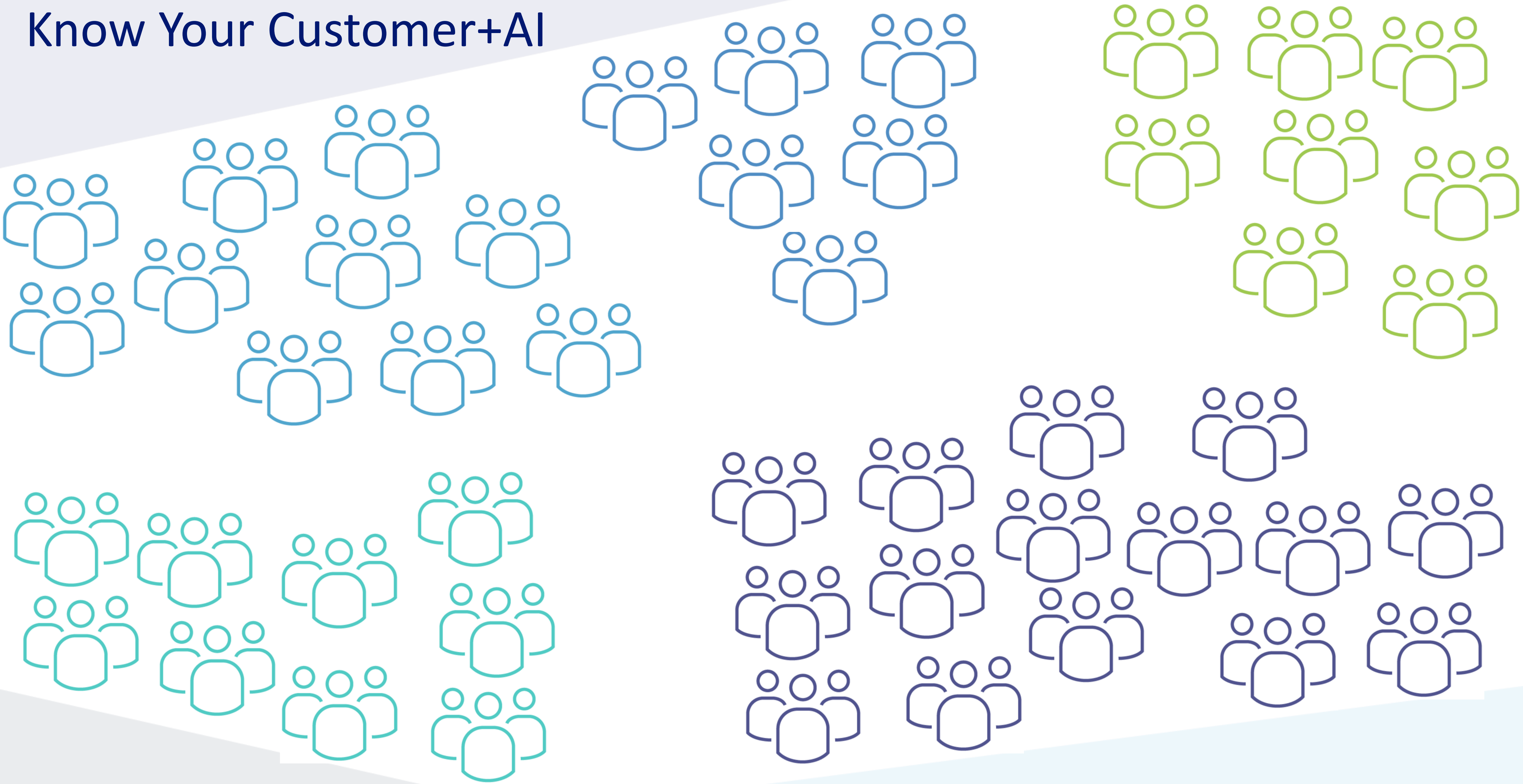


4.3 bn passengers 2018 worldwide

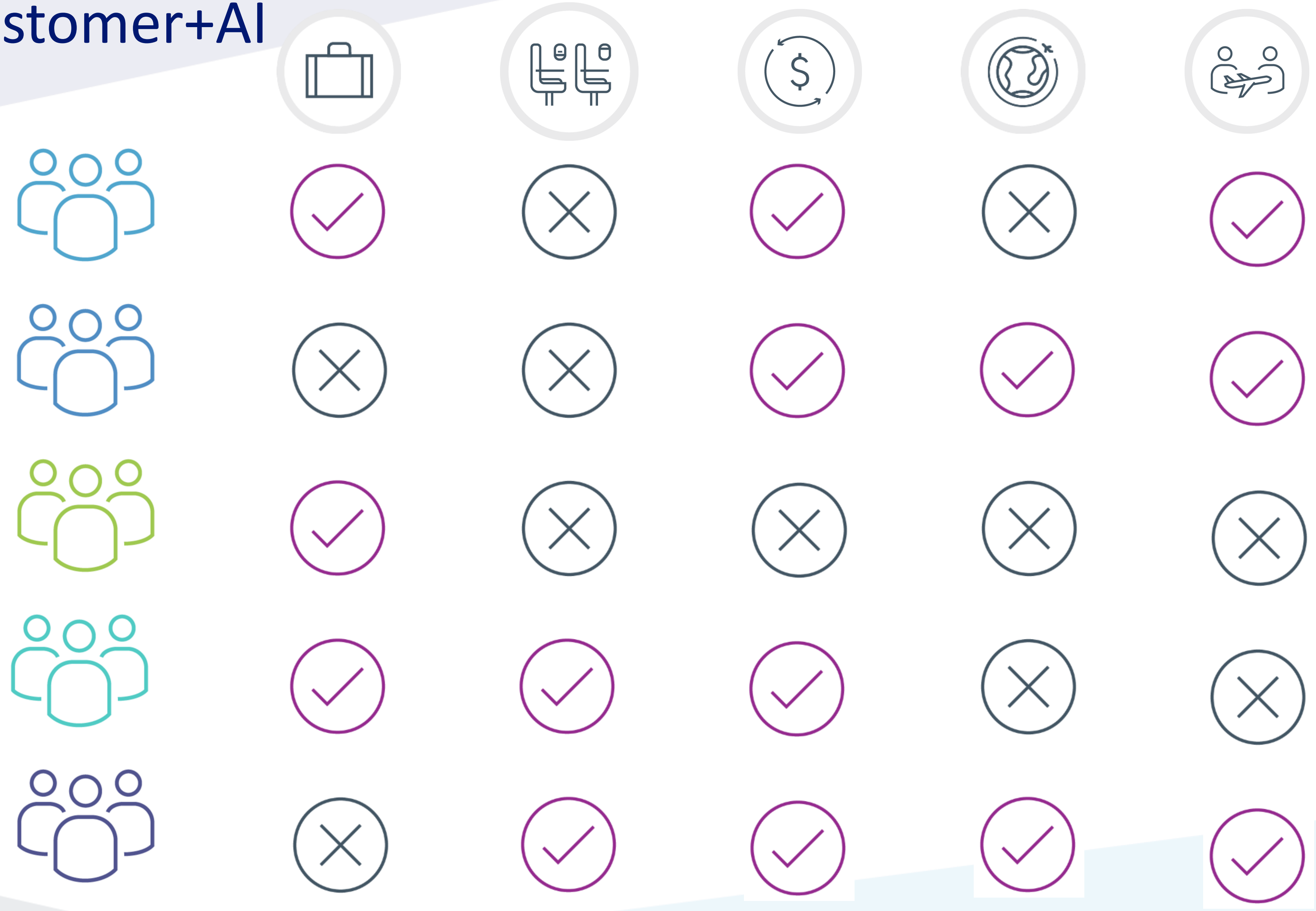
Know Your Customer+AI



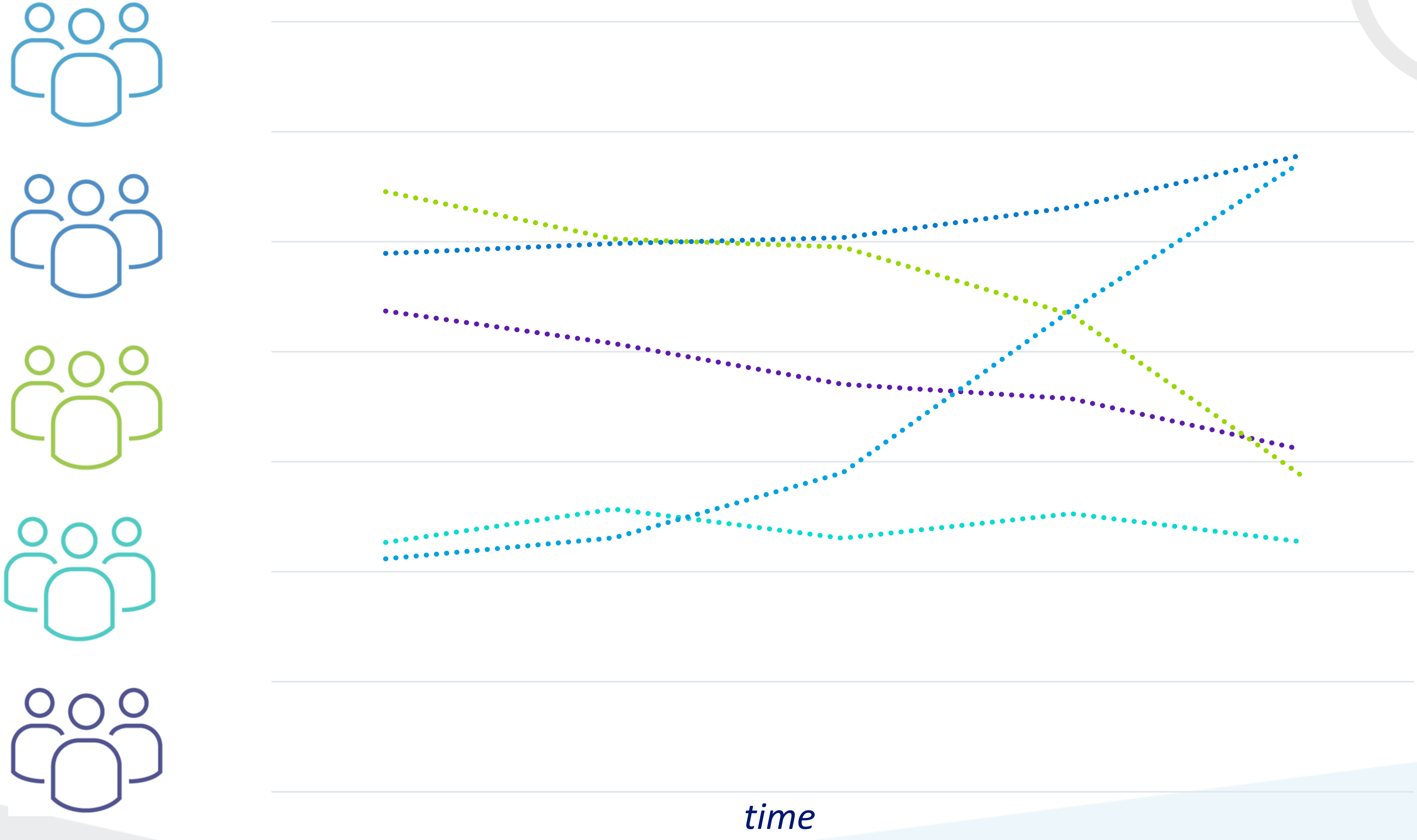
Know Your Customer+AI



Know Your Customer+AI

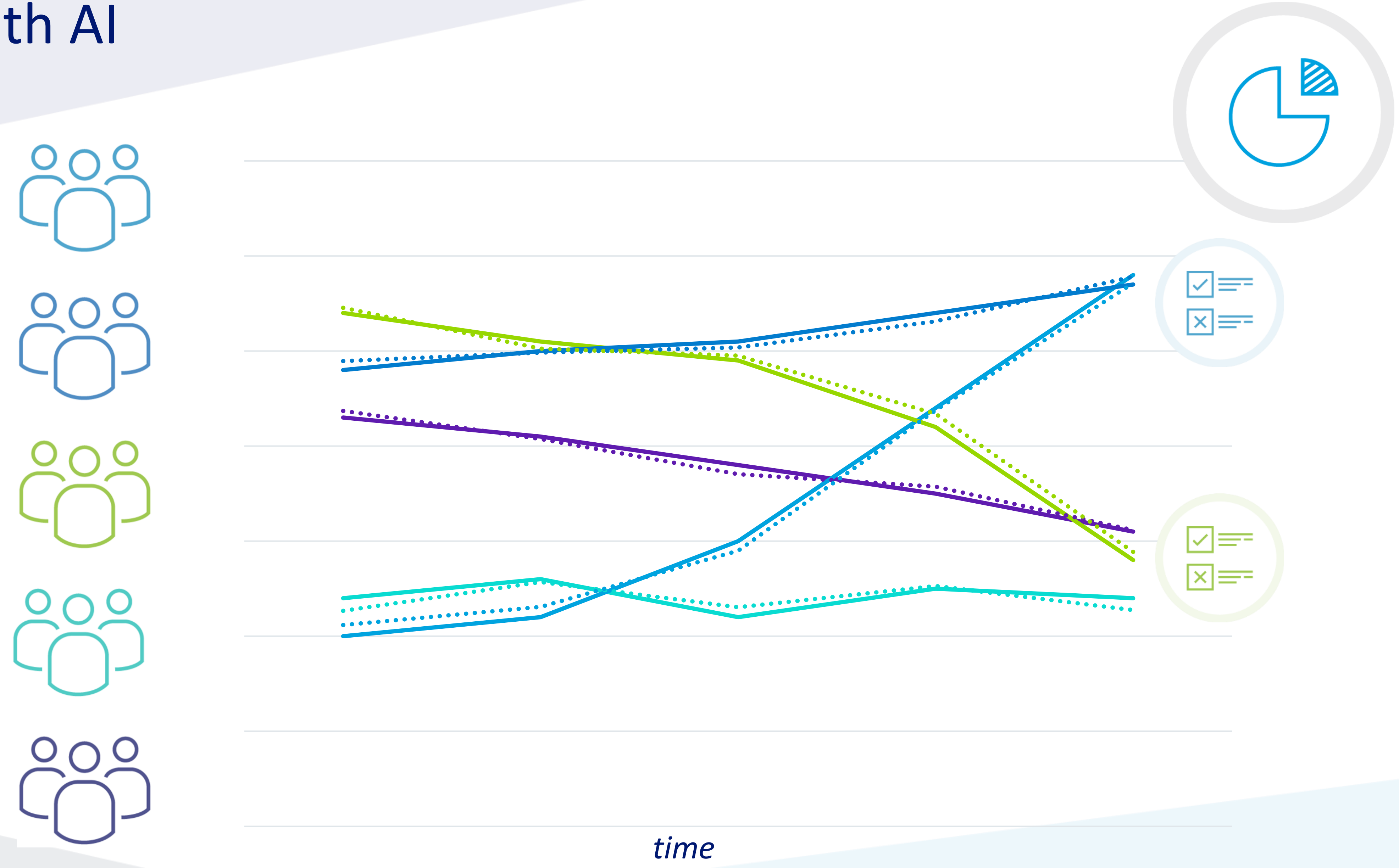


Predict with AI



accelya

Predict with AI



accelya

Commercial Success

Commercial Success

Thank you for your time

IATA AVIATION DATA SYMPOSIUM

ATHENS, GREECE 25 – 27 JUNE 2019

AI Lab

Sponsored by:

OpenJaw

IATA

High-performance Computing: Aviation Use Cases

Massimo Morin, Head, Worldwide Business Development, Travel, AWS

The Power of Data:
HPC & ML/AI 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

AI SERVICES	Easily add intelligence to applications without machine learning skills VISION | DOCUMENTS | SPEECH | LANGUAGE | CHATBOTS | FORECASTING | RECOMMENDATIONS	
ML SERVICES	Build, train and deploy machine learning models fast DATA LABELING | PRE-BUILT ALGORITHMS & NOTEBOOKS | ONE-CLICK TRAINING & DEPLOYMENT	
ML FRAMEWORKS & INFRASTRUCTURE	Flexibility and choice, high-performing infrastructure SUPPORT FOR ML FRAMEWORKS | COMPUTE OPTIONS PURPOSE-BUILT FOR ML	

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

AMAZON SAGEMAKER

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
- PYTORCH

INTERFACES
- GLUON
- Keras

INFRASTRUCTURE
- EC2 P3 & P3N
- EC2 C5
- FPGAs
- GREENGRASS
- ELASTIC INFERENCE

aws travel

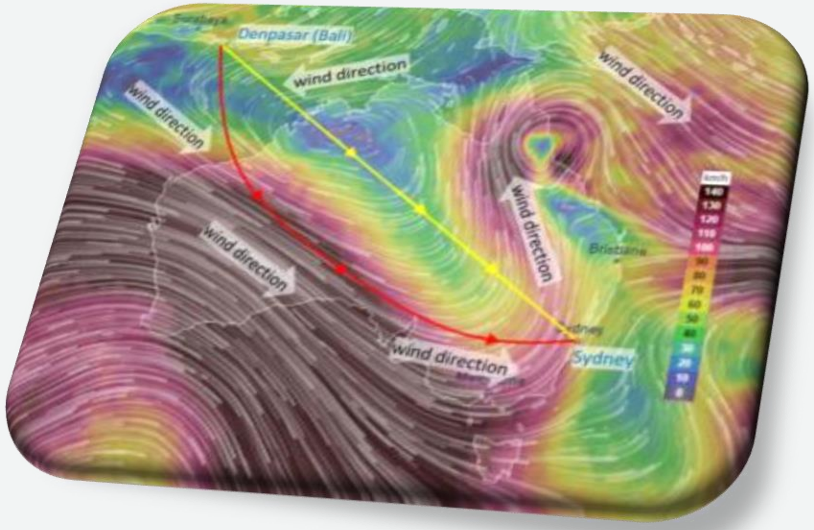
Qantas' Constellation

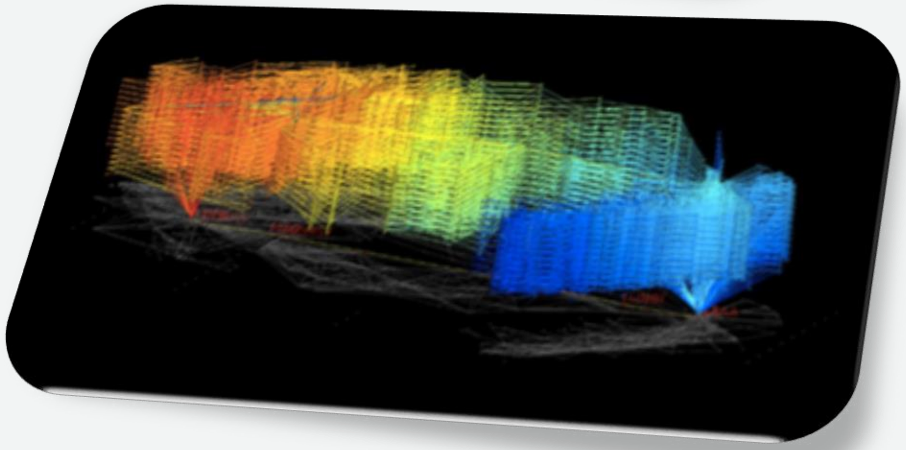
The ***scalability of cloud computing****, and ingestion of rich datasets from external sources, allows Qantas to continually assess and adjust planned paths en-route.*

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

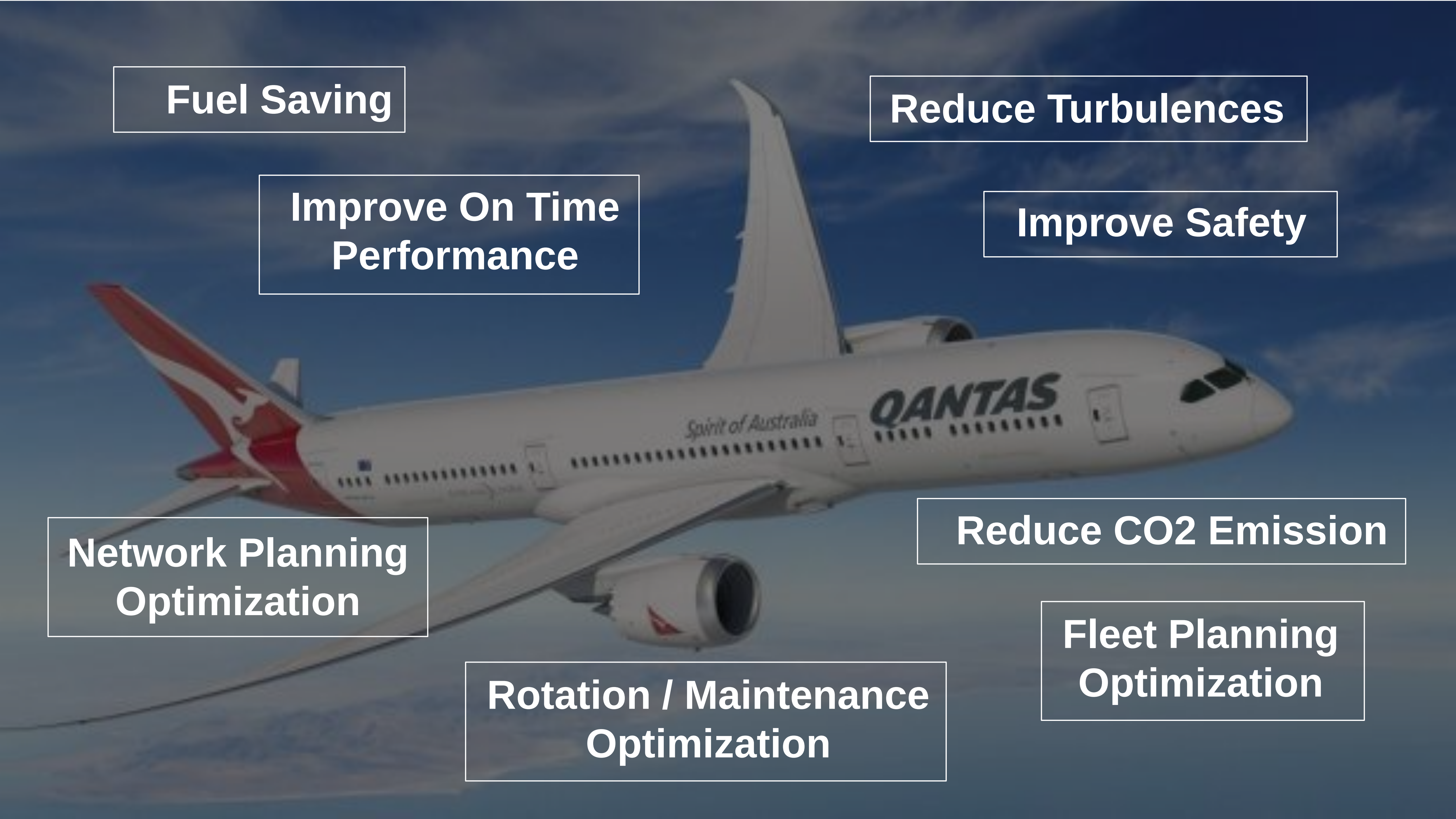




[Qantas' cloud-based flight sim saving millions in fuel]

[The results are in…the winners of the Jane's ATC Awards have been revealed]

aws travel



Fuel Saving

Reduce Turbulences

Improve On Time Performance

Improve Safety

Reduce CO2 Emission

Network Planning Optimization

Fleet Planning Optimization

Rotation / Maintenance Optimization

Air New Zealand's Carma

AIR NEW ZEALAND

> *… 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

https://www.linkedin.com/feed/update/activity:6473266710744039424/

- 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*

aws travel

Revenue increase by shipping more and being more efficient

Marketing and Promotions to shift demand

Forecasting and Planning

Delivery turn around

Capitalize on Your ML/AI R&D

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

aws travel


thank you
danke
謝謝
ngiyabonga
teşekkür ederim
gracias
рахмат
Баярлалаа
спасибо
faafetai lava
mersi
kia ora
barka
welalin
tack
spas
dank je
misaotra
matondo
paldies
grazzi
mahalo
vinaka
спасибі
blagodaram
kiitos
dankie
dhanyavad
nanni
nandri
bedankt
bayarlalaa
gràcie
hvala
mauruuru
köszönöm
enkosi
dziękuję
sobodi
děkuji
obrigado
mèsi
didi madloba
sagolun
sukriya
najis tuke
kam sah hamnida
rahmat
chnorakaloutioun
gratias ago
gràcies
kop khun
ありがとう
terima kasih
감사합니다
dankon
akun
хвала
manana
tenki
murakoze
Massimo Morin
Head Worldwide Business Development, Travel
AWS Enterprise and Industry Verticals Business Development
27 Melcher St, Boston, MA 02210, USA
morinmm@amazon.com

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 PASSENGE
RS

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

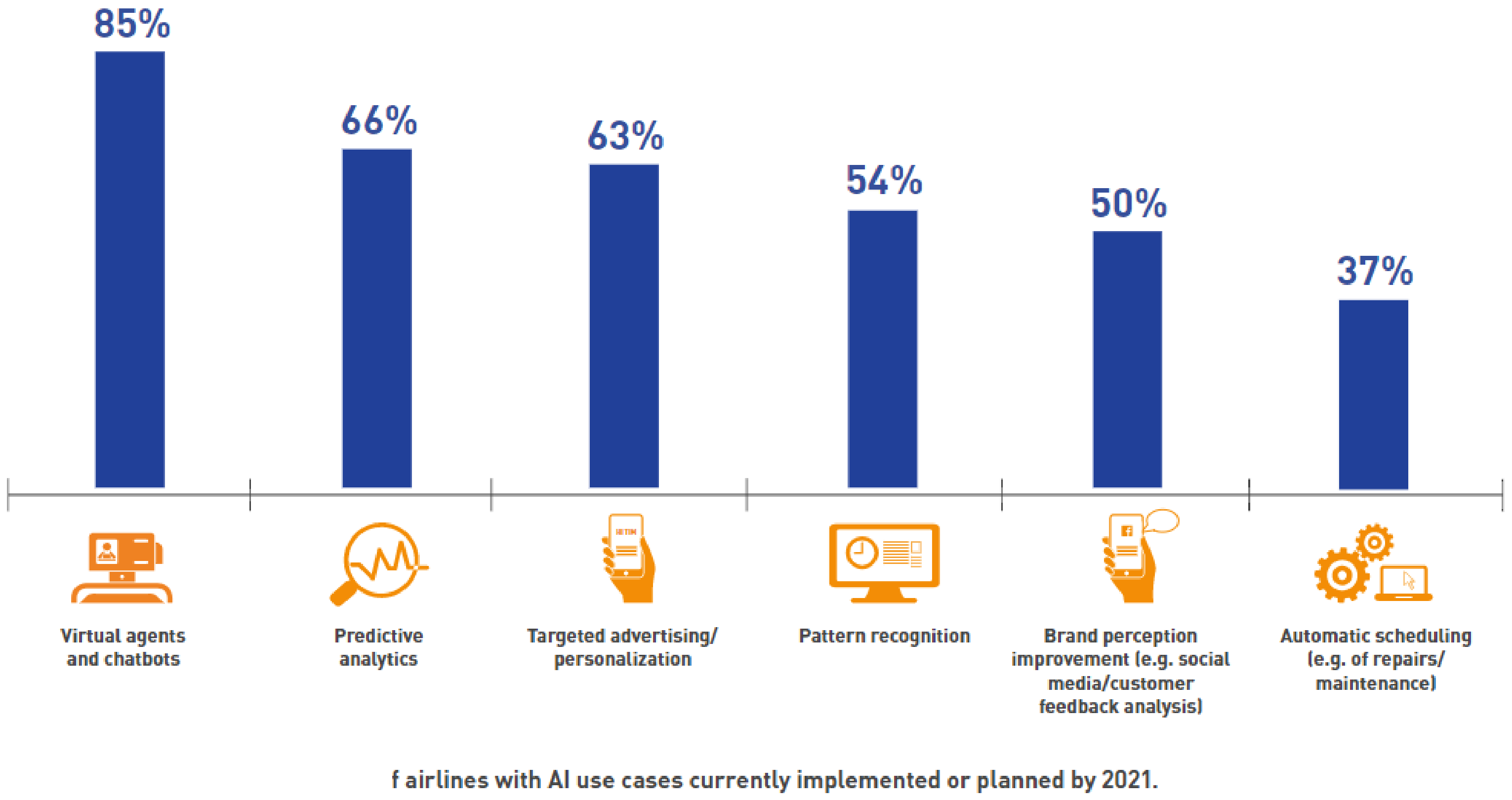
Awareness

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



SITA 2018: Air Transport IT insights

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

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

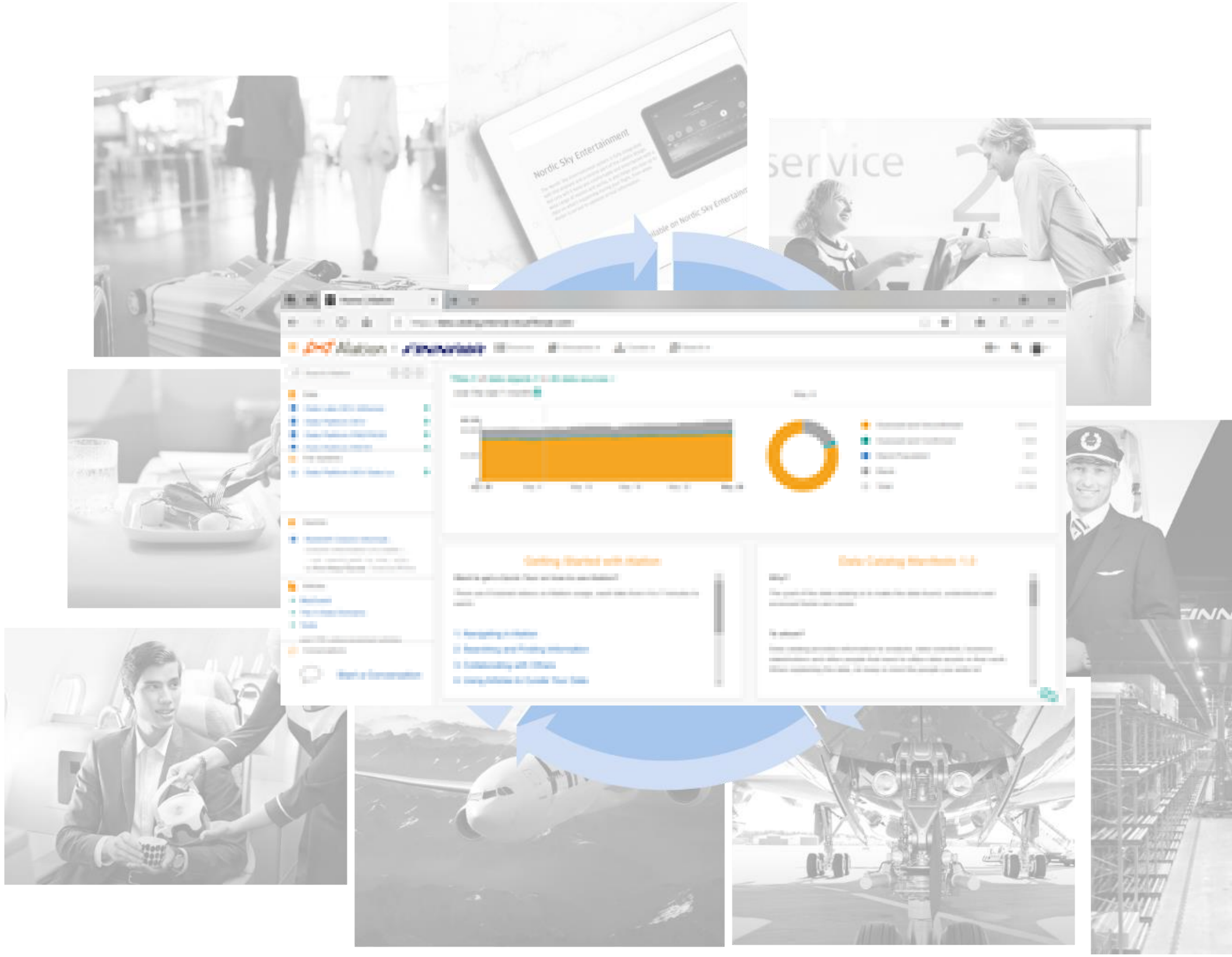
Data

Identifying **what data is** – it is more than the Data Warehouse

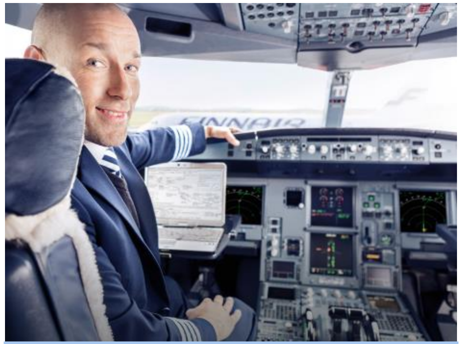
Knowing **the inventory** – what do we really have

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

Culture

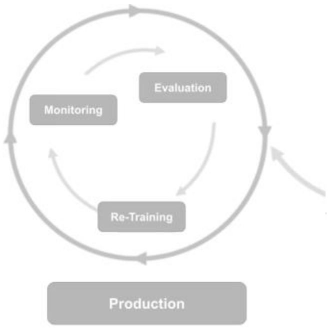
Data Science cannot be built in a separate ”Data Science” –silo. The **work needs to be embedded to the core business processes** – and **organization needs to be open for these new roles** (data scientists, data engineers, visual story tellers, service designers…) to invest on them – and to learn from them

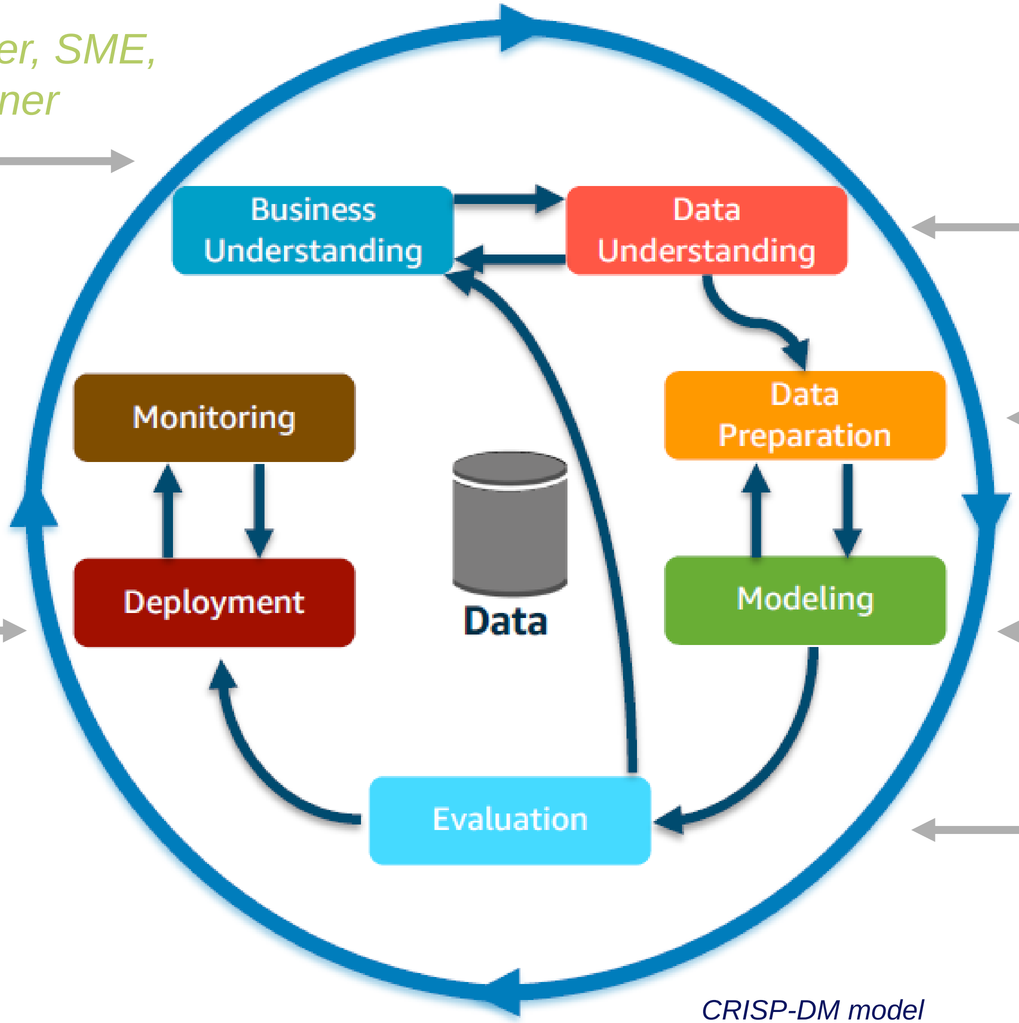
Data Science is a continuous, cross-functional journey – **company culture (and governance) needs to be ready for agile experimenting**

Reusability provides agility - Data Science community needs to also **collaborate across projects**

AI development lifecycle

Business/process owner, SME, Analyst, Service Designer





Business/data analyst

Data engineer

Data scientist, AI developer

SME, Analyst, Data scientist

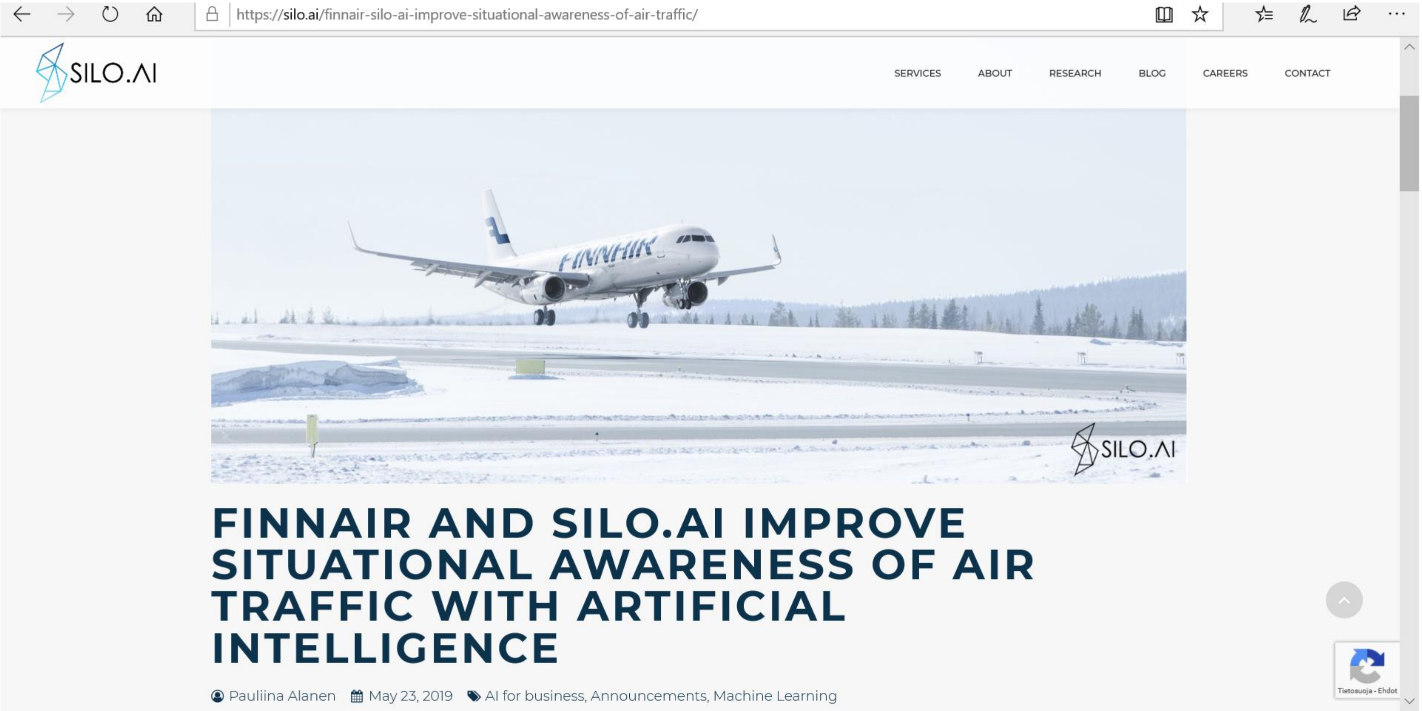
Business/process owner, SME, Analyst, Data Scientist, IT

CRISP-DM model

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 emloyees**…

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

AI Lab

Sponsored by:

OpenJaw

IATA

Predicting Passenger Choices considering Irrational Behavior

Rodrigo Acuna, Head of AI Research, Amadeus

IATA AVIATION DATA SYMPOSIUM

ATHENS, GREECE 25 – 27 JUNE 2019

Predicting Passenger Choices Considering Irrational Behavior

IATA ADS, June 26, 2019

Rodrigo Acuna-Agost

Head of AI Research, Amadeus

amadeus

Credits:

Collaboration Academy + Industry

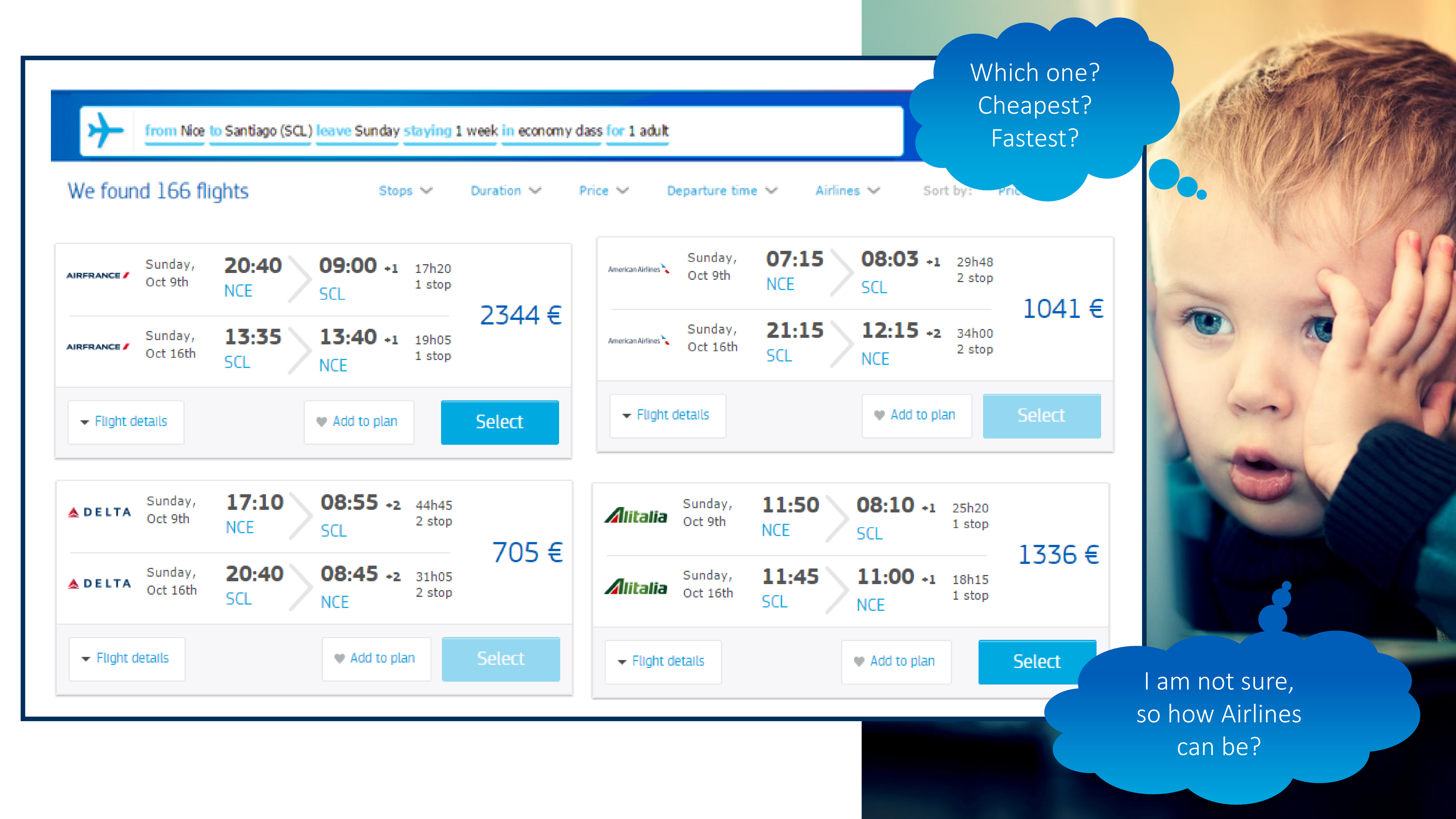
UNIVERSITÉ CÔTE D'AZUR

amadeus

Université Nice Sophia Antipolis

skema BUSINESS SCHOOL

NC STATE UNIVERSITY

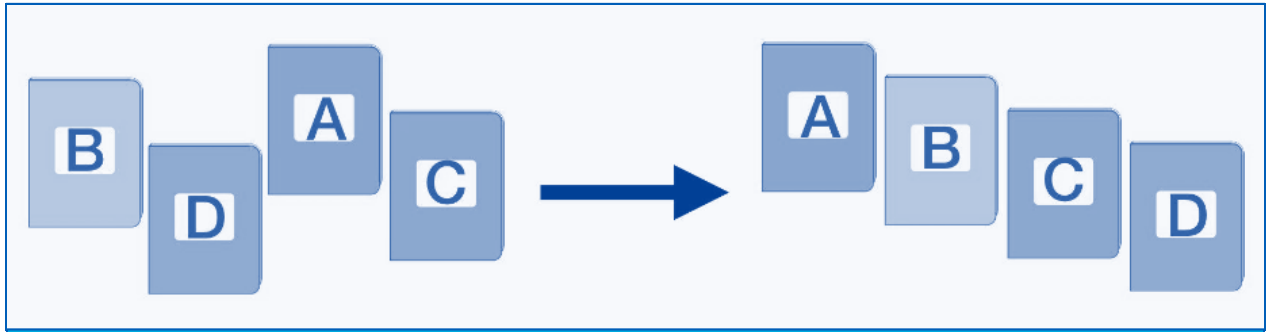

from Nice to Santiago (SCL) leave Sunday staying 1 week in economy class for 1 adult
We found 166 flights
Stops
Duration
Price
Departure time
Airlines
Sort by:
AIRFRANCE Sunday, Oct 9th 20:40 NCE 09:00 +1 SCL 17h20 1 stop
AIRFRANCE Sunday, Oct 16th 13:35 SCL 13:40 +1 NCE 19h05 1 stop
2344 €
Flight details
Add to plan
Select
American Airlines Sunday, Oct 9th 07:15 NCE 08:03 +1 SCL 29h48 2 stop
American Airlines Sunday, Oct 16th 21:15 SCL 12:15 +2 NCE 34h00 2 stop
1041 €
Flight details
Add to plan
Select
DELTA Sunday, Oct 9th 17:10 NCE 08:55 +2 SCL 44h45 2 stop
DELTA Sunday, Oct 16th 20:40 SCL 08:45 +2 NCE 31h05 2 stop
705 €
Flight details
Add to plan
Select
Alitalia Sunday, Oct 9th 11:50 NCE 08:10 +1 SCL 25h20 1 stop
Alitalia Sunday, Oct 16th 11:45 SCL 11:00 +1 NCE 18h15 1 stop
1336 €
Flight details
Add to plan
Select
Which one? Cheapest? Fastest?
I am not sure, so how Airlines can be?

imagine an airline’s **CEO** when we tell her

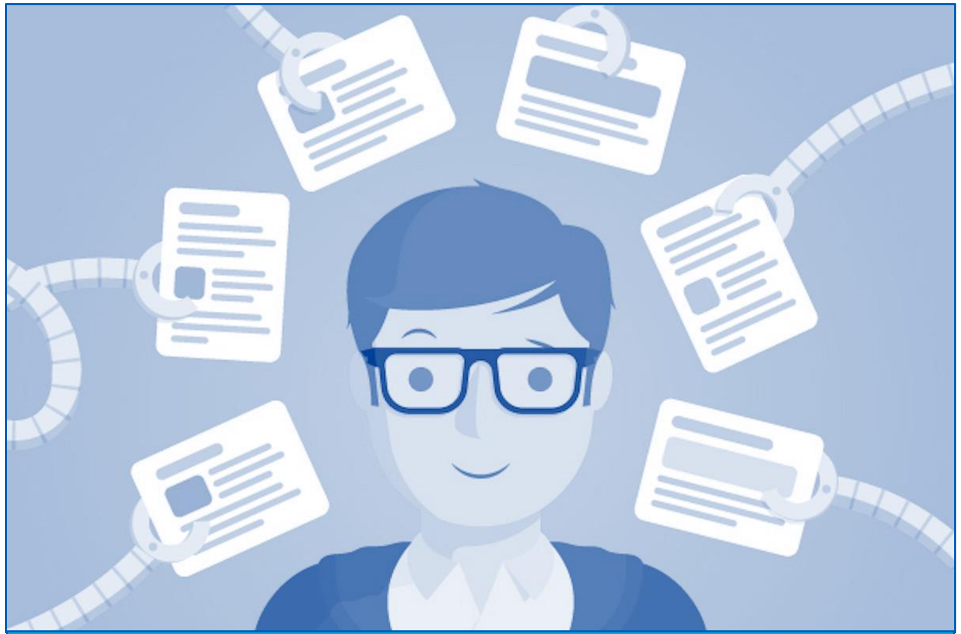
“we can predict travelers’ choices”

Some applications

dynamic offering

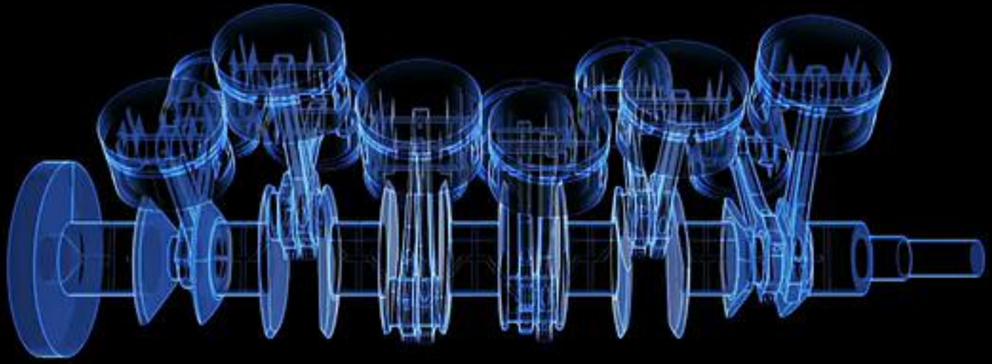


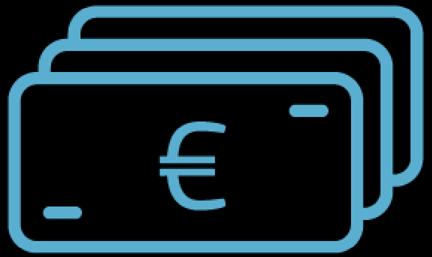
sorting



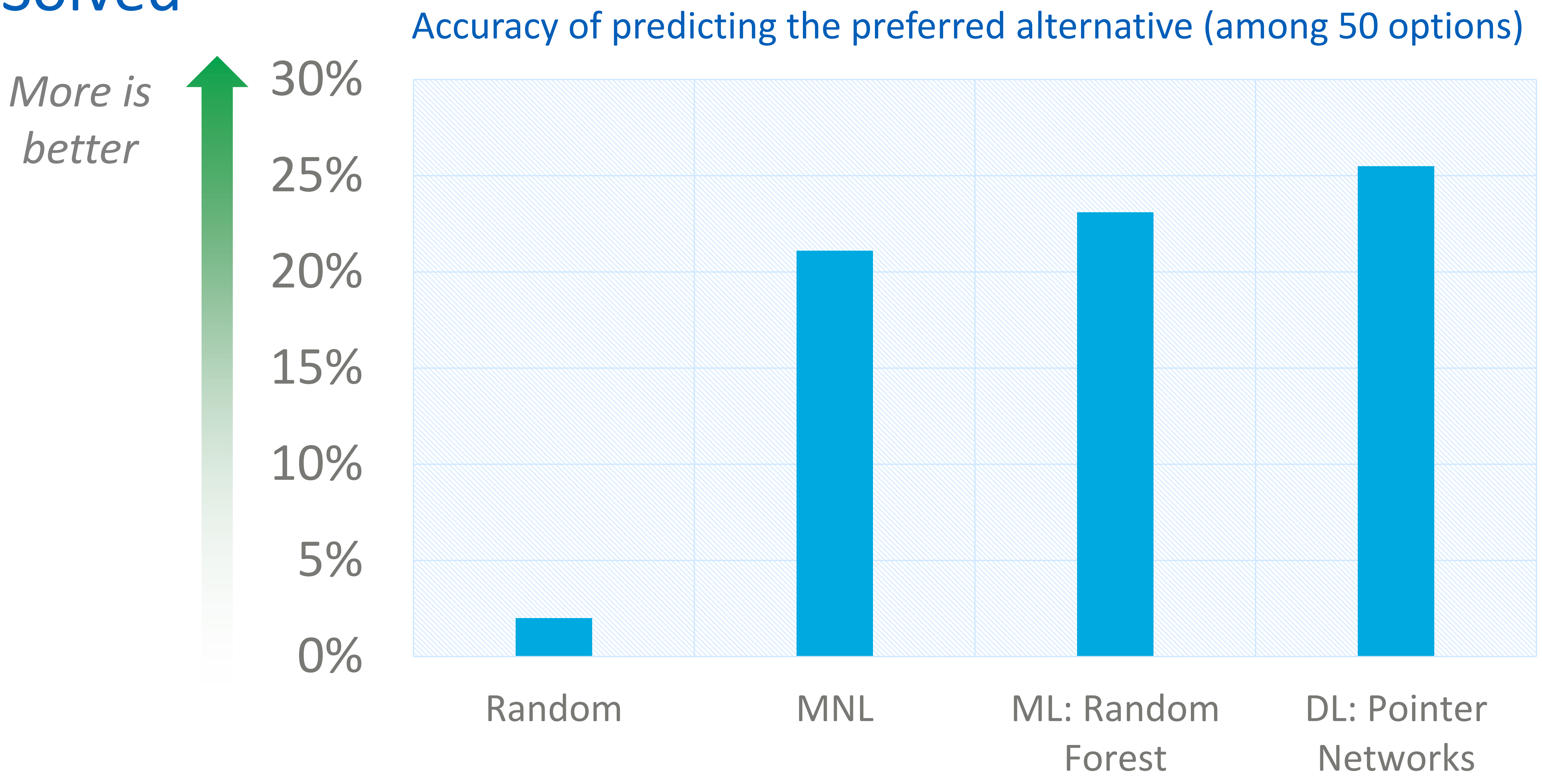
recommender systems

our engine



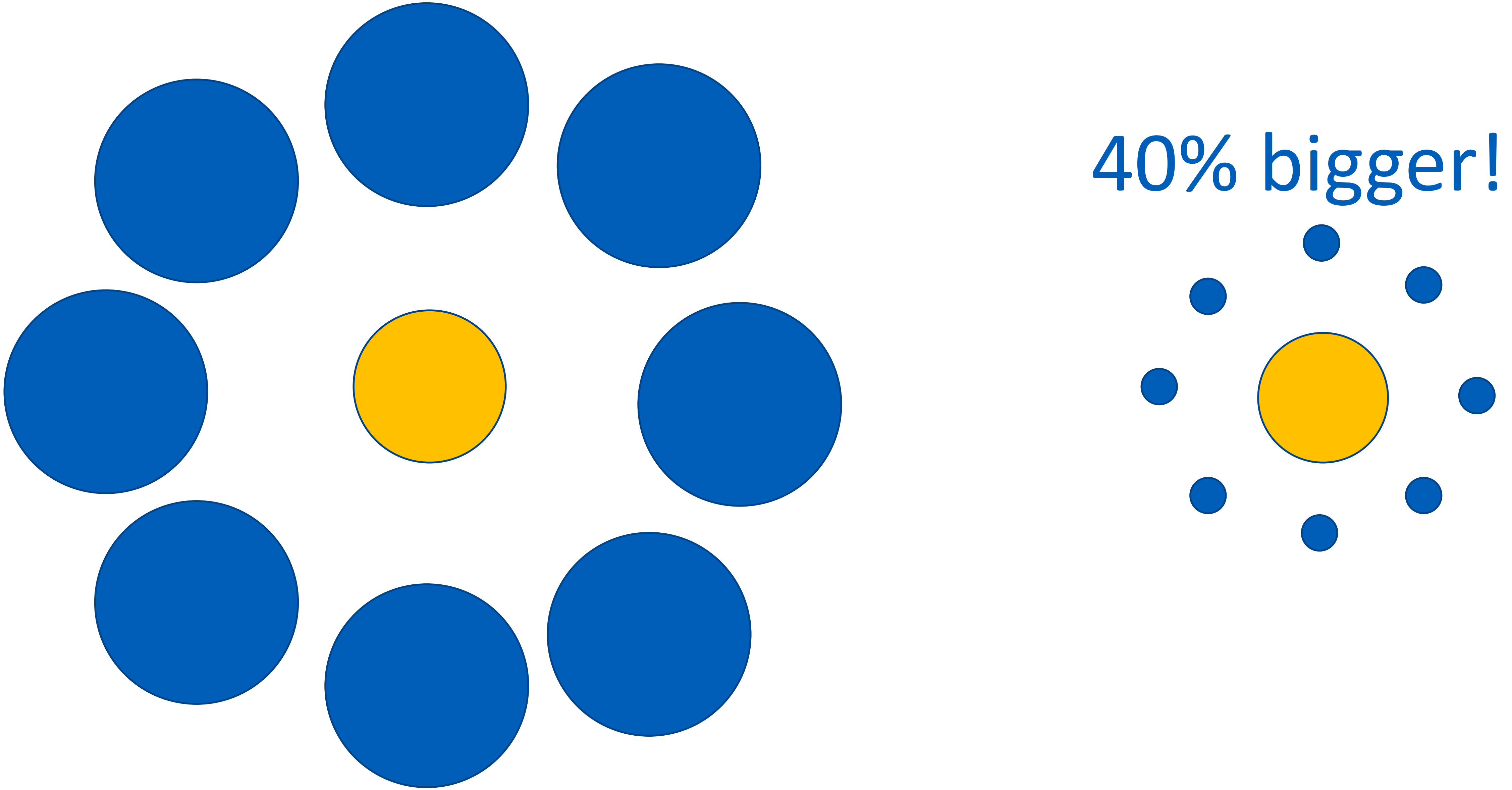


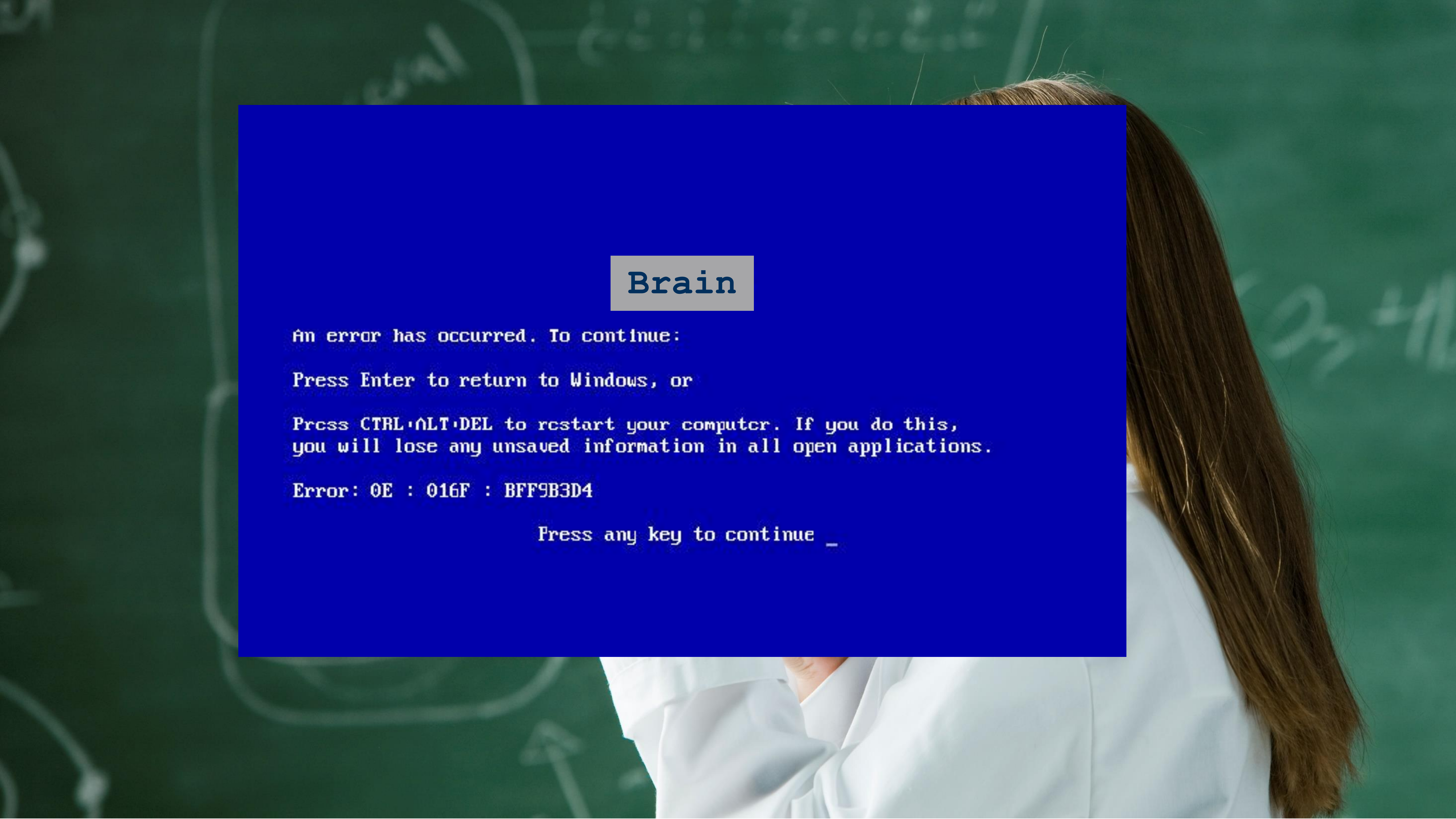
Solved

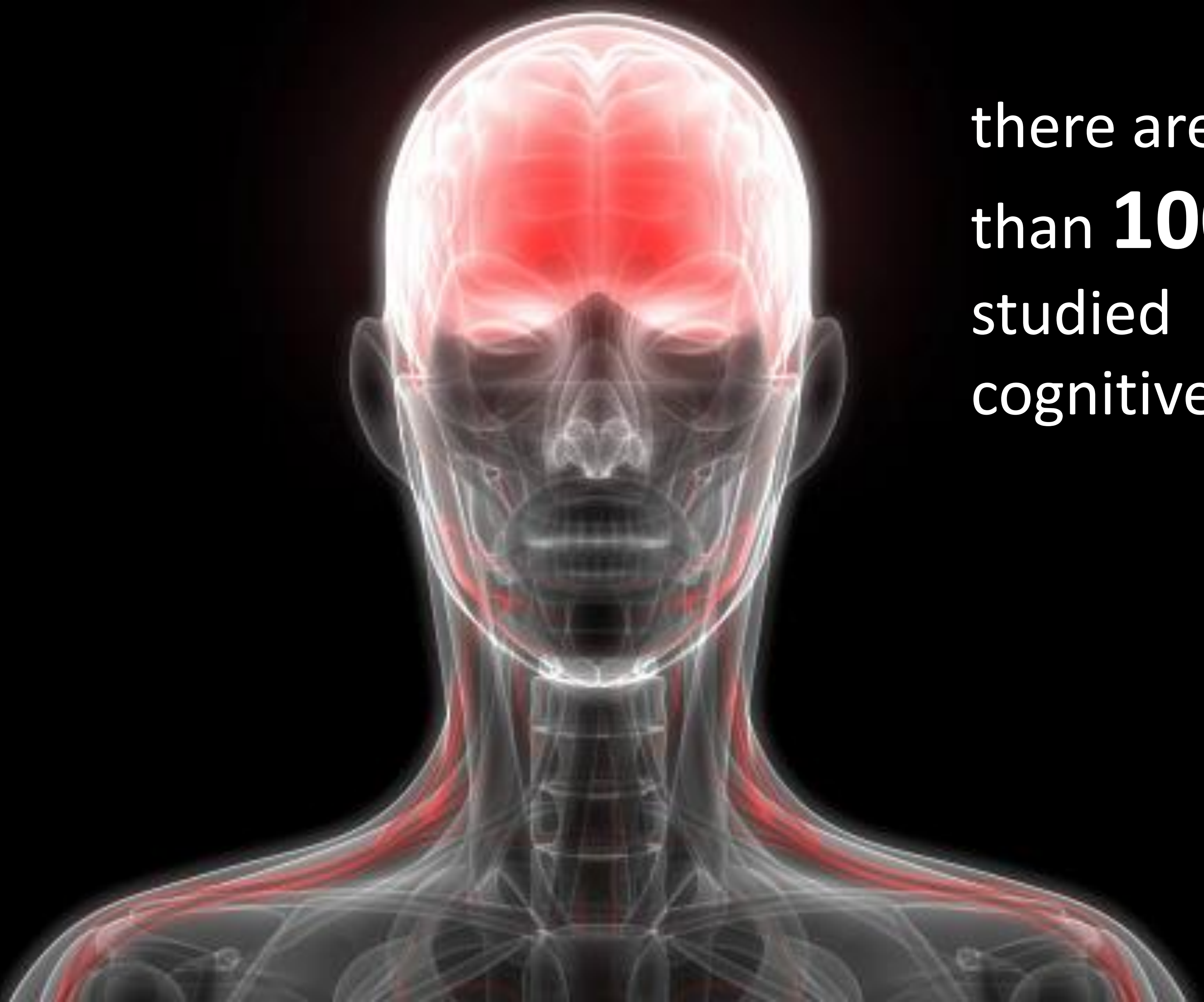


More is better
Accuracy of predicting the preferred alternative (among 50 options)
30%
25%
20%
15%
10%
5%
0%
Random
MNL
ML: Random Forest
DL: Pointer Networks

why we cannot
reach 100%
accuracy?

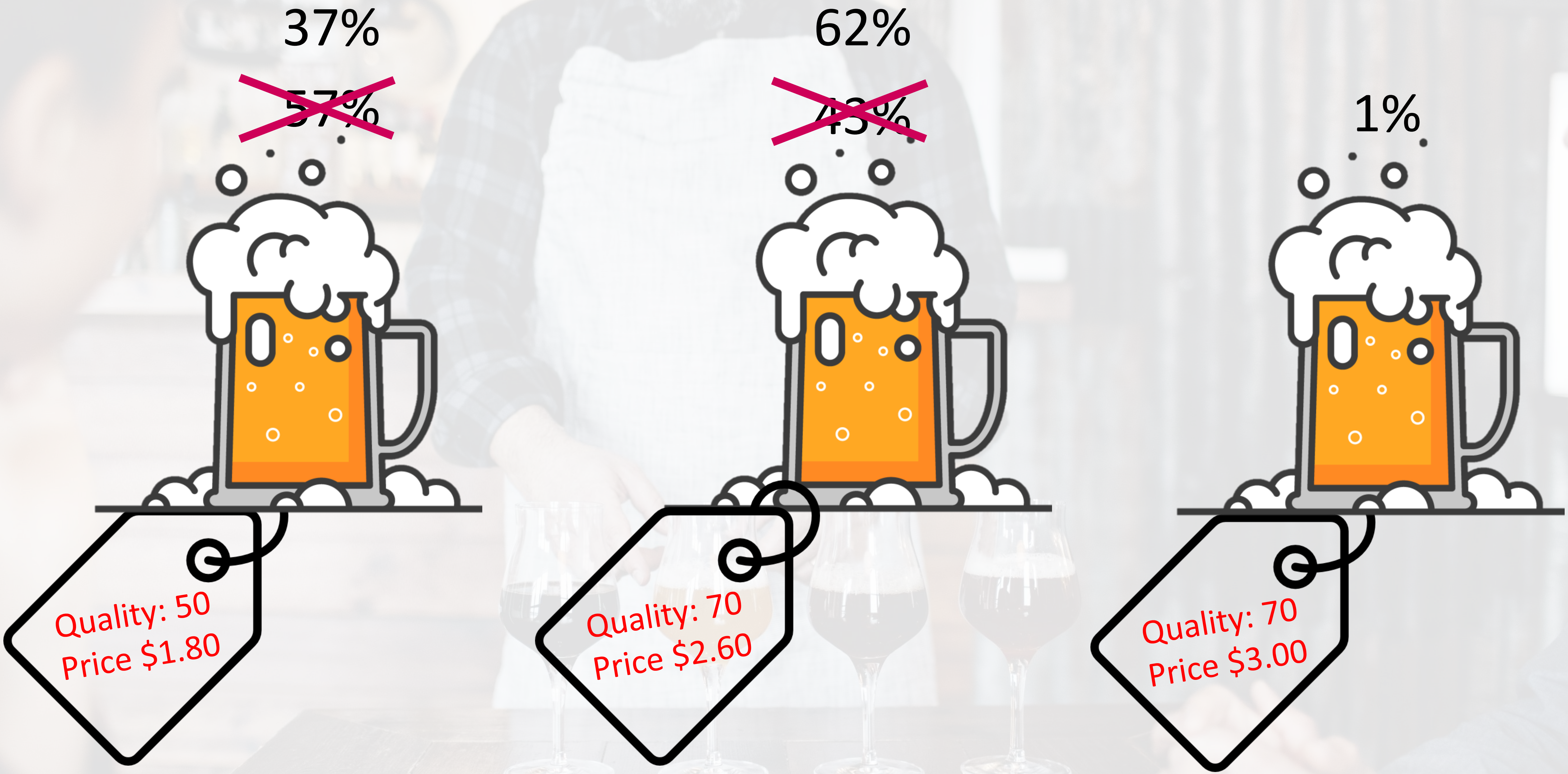

40% bigger!


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 _

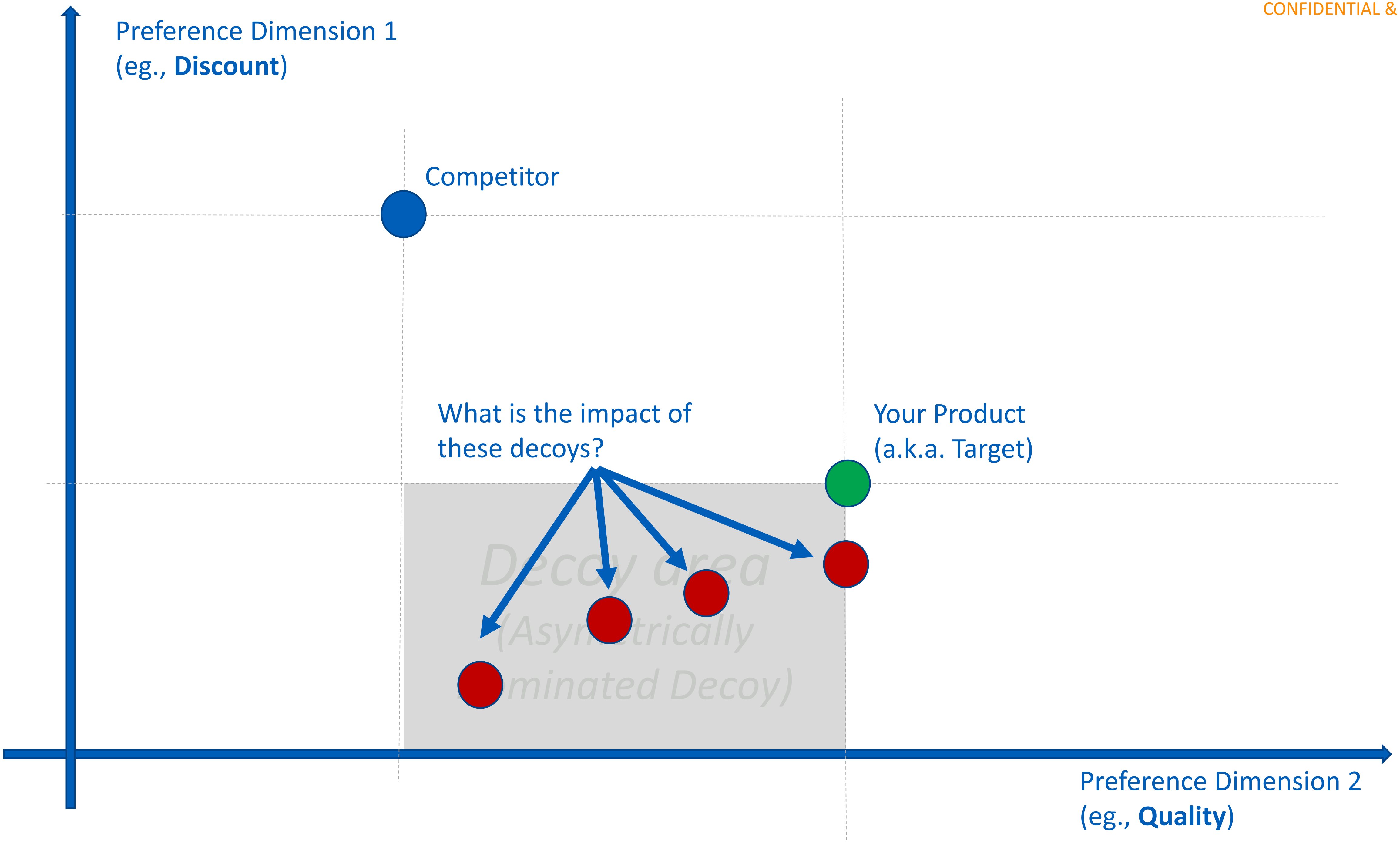


there are more than **100** studied cognitive biases

Decoy Effect



Reference: Adding Asymmetrically Dominated Alternatives: Violations of Regularity and the Similarity Hypothesis
Joel Huber, John W. Payne and Christopher Puto
Journal of Consumer Research, Vol. 9, No. 1 (Jun., 1982), pp. 90-98


Preference Dimension 1
(eg., **Discount**)
Competitor
What is the impact of
these decoys?
Your Product
(a.k.a. Target)
Decoy area
(Asymmetrically
Dominated Decoy)
Preference Dimension 2
(eg., **Quality**)

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

Impact in Conversion?

Online users
30000 user sessions

Live Lab:
Flight Choice

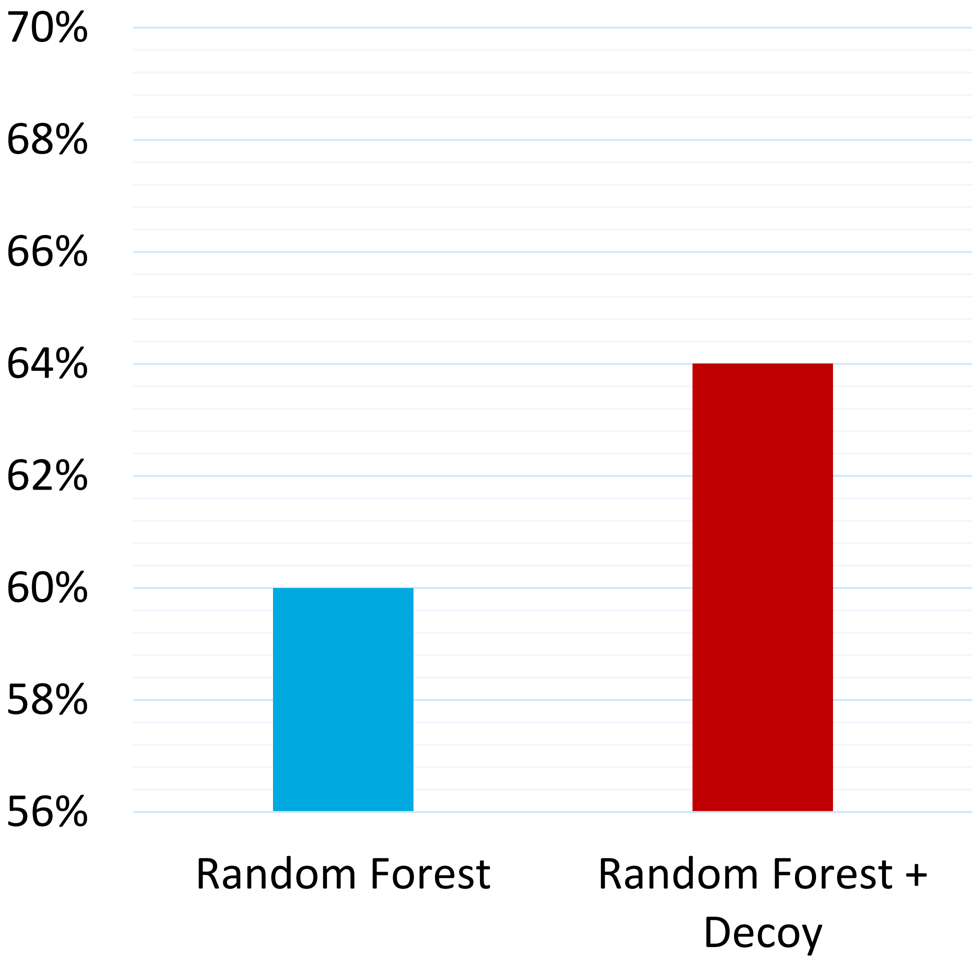
Understanding better:
Fully controlled experiment in the lab

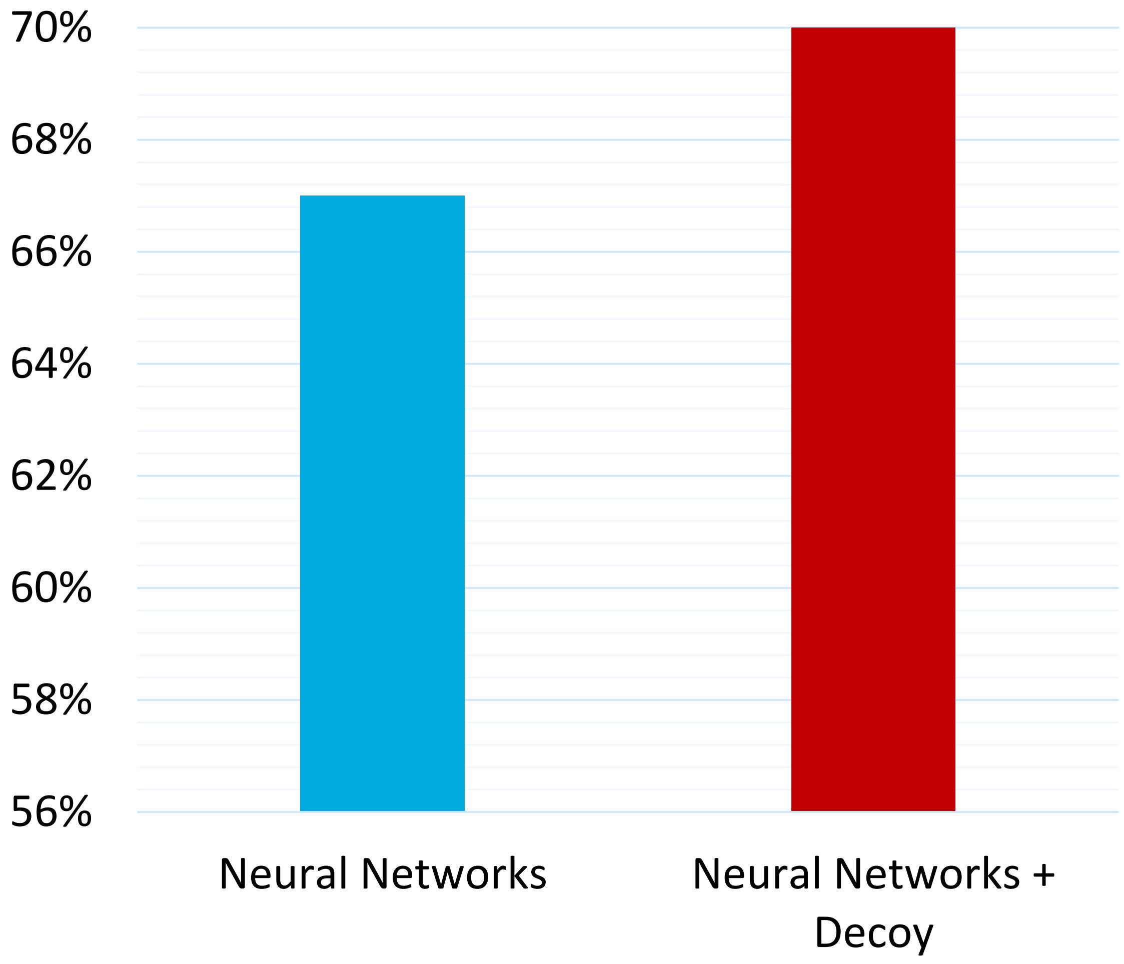
Experimental Economics laboratory
100 people

1) Fare Family Choice

Impact in Choice Prediction Accuracy?

Results: Classification Accuracy of Predictions





Three Experiments

Surveys: Fare Family Choice

Impact in Choice Prediction accuracy?

Survey Data
400k data points

Online users: Itinerary Choice

Impact in Conversion?

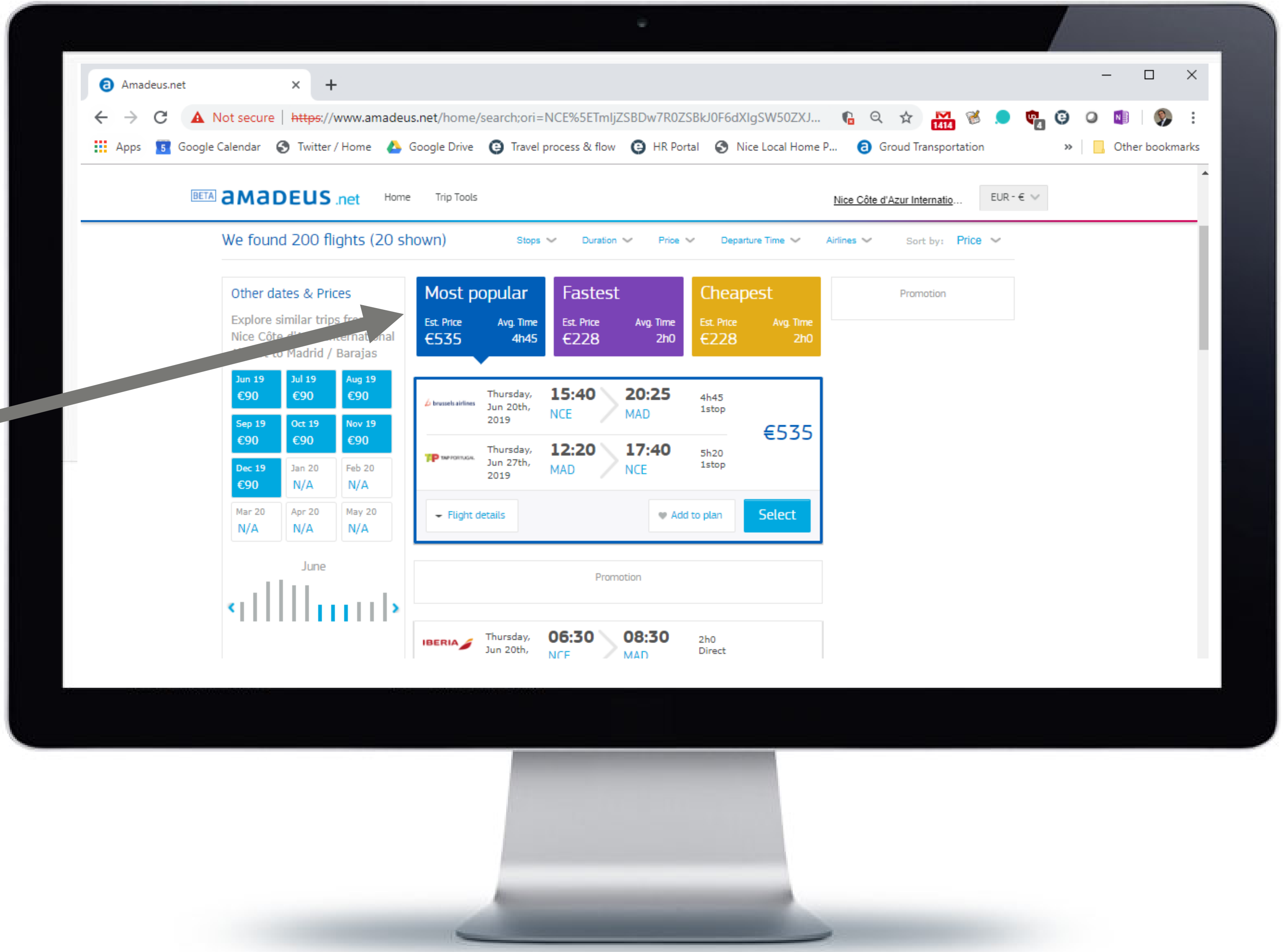
Online users
30000 user sessions

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

versus

A

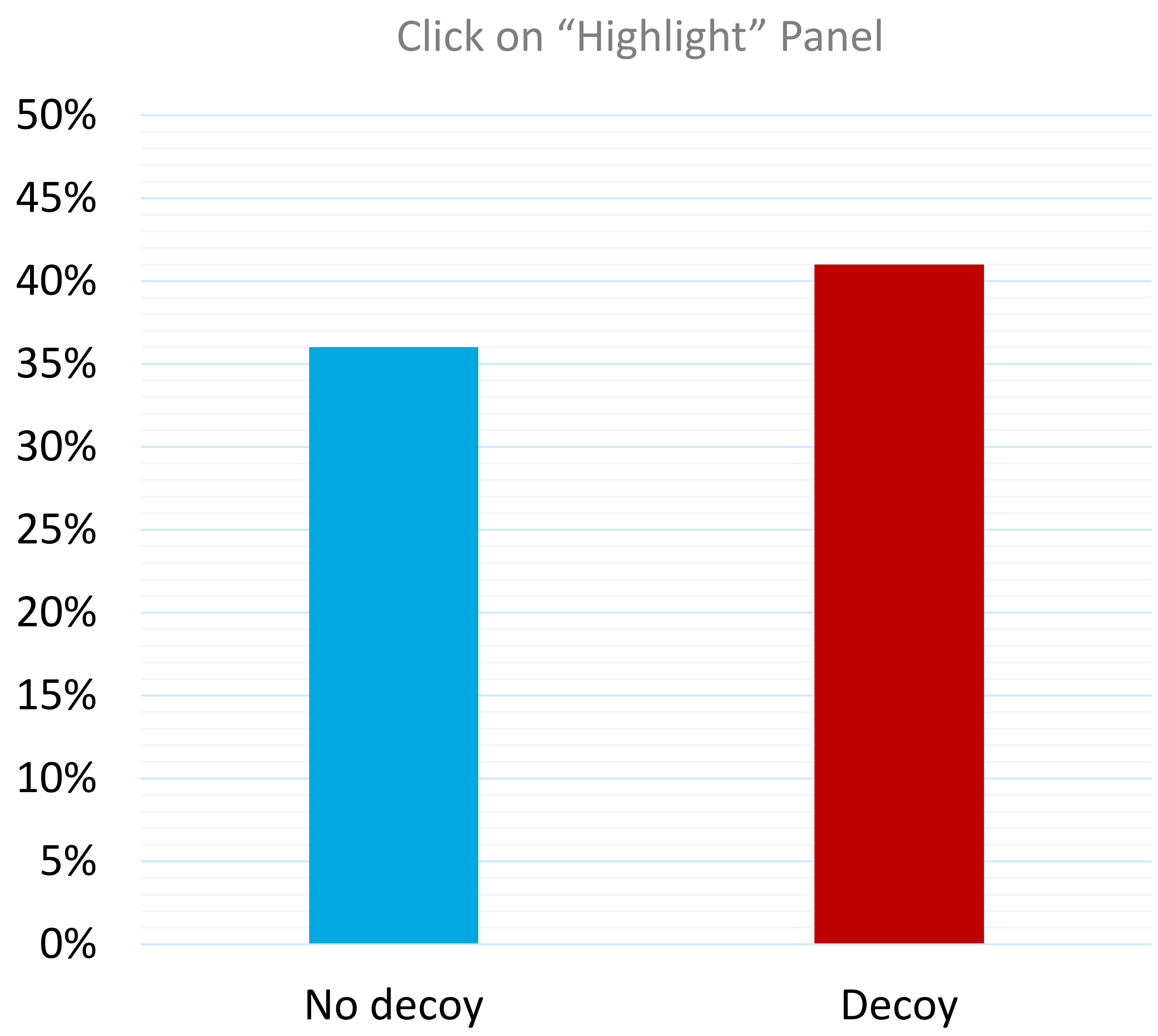
Cheapest	6h00	$ 200
Fastest	2h00	$ 350

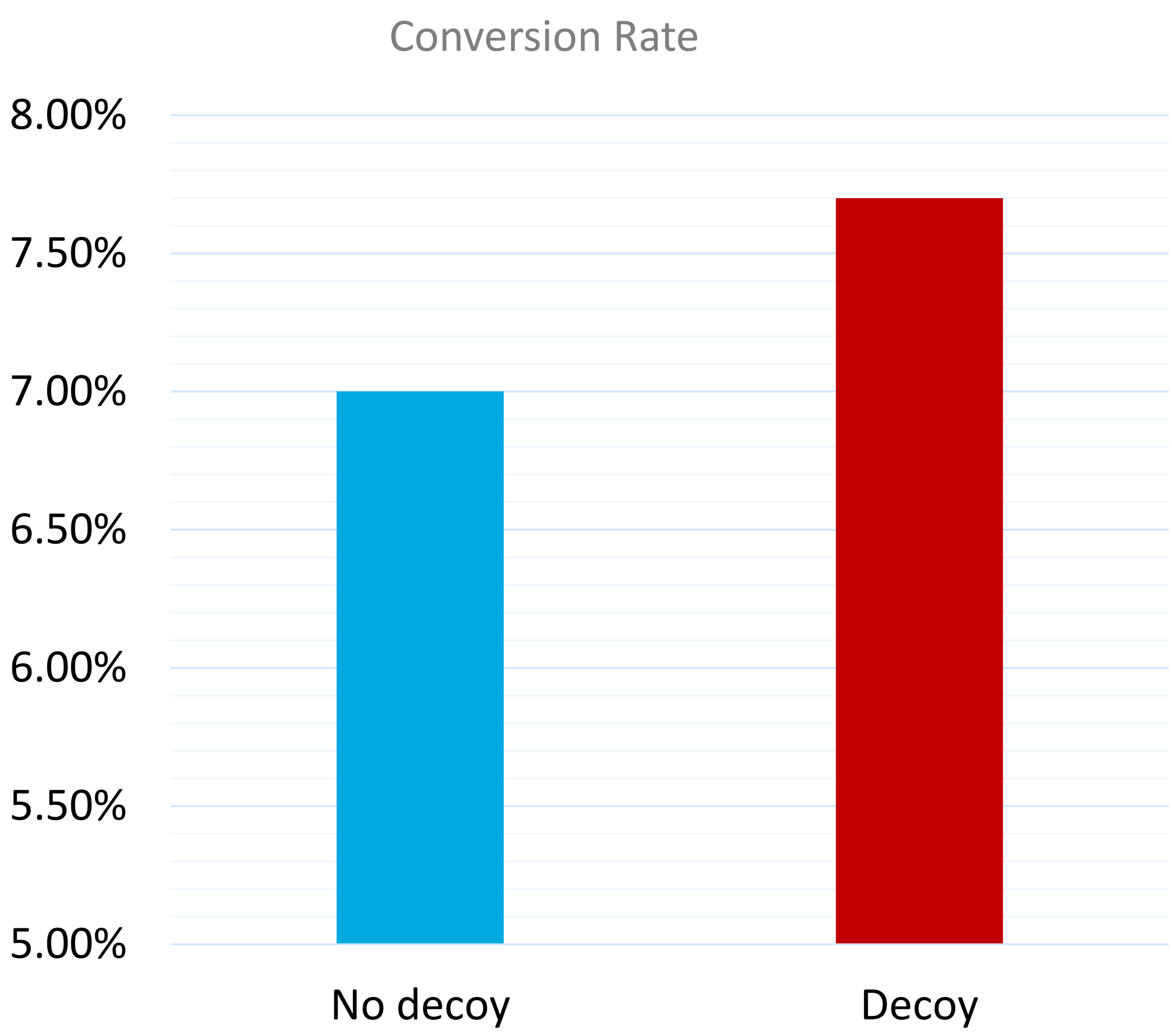
B

Cheapest	6h00	$ 200
Fastest	2h00	$ 350
Featured	2h00	$ 400

decoy

Results: does decoy improve conversion?





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:

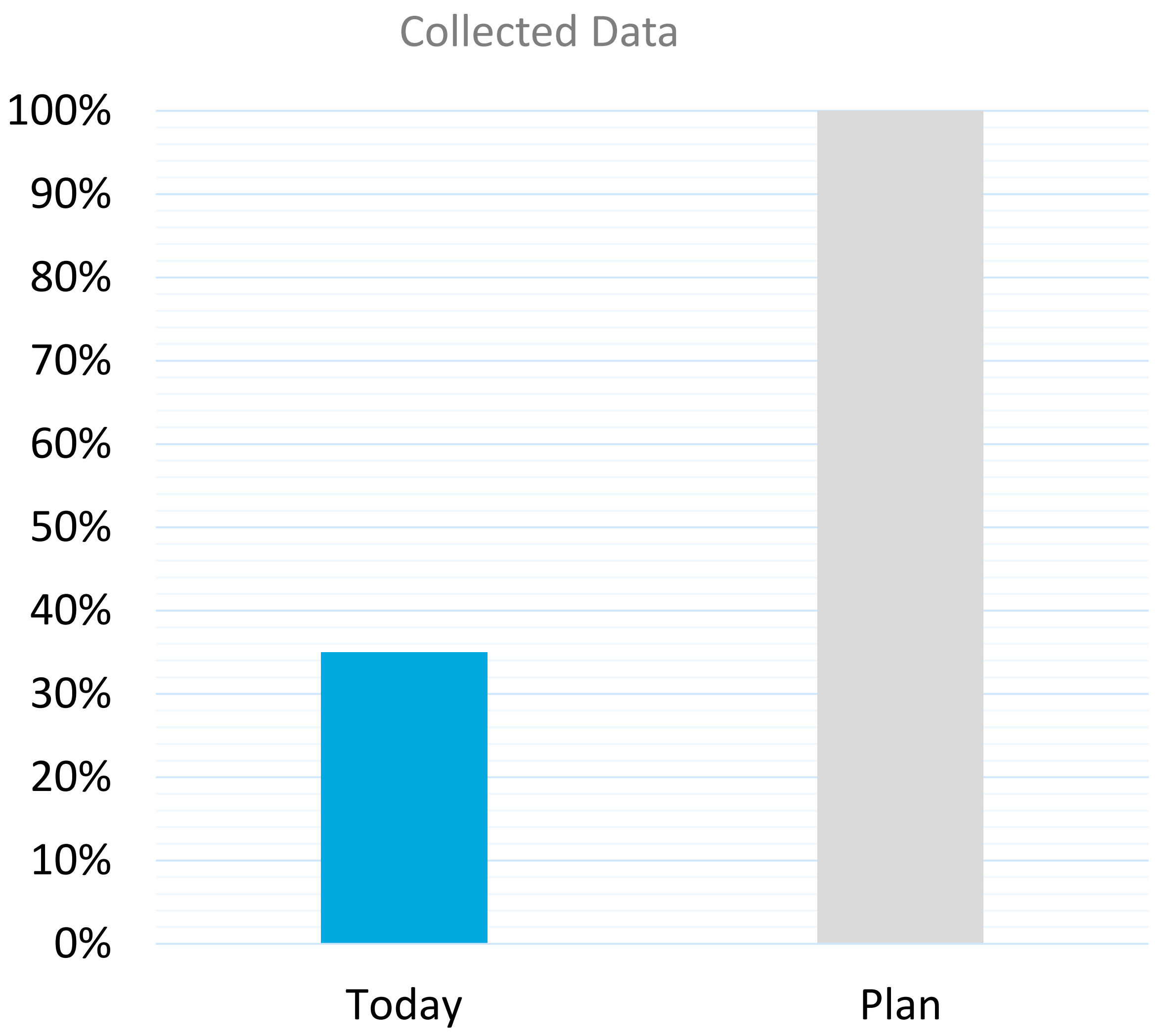
- 10 repeated choices x 100 people = 1000 observations mostly students

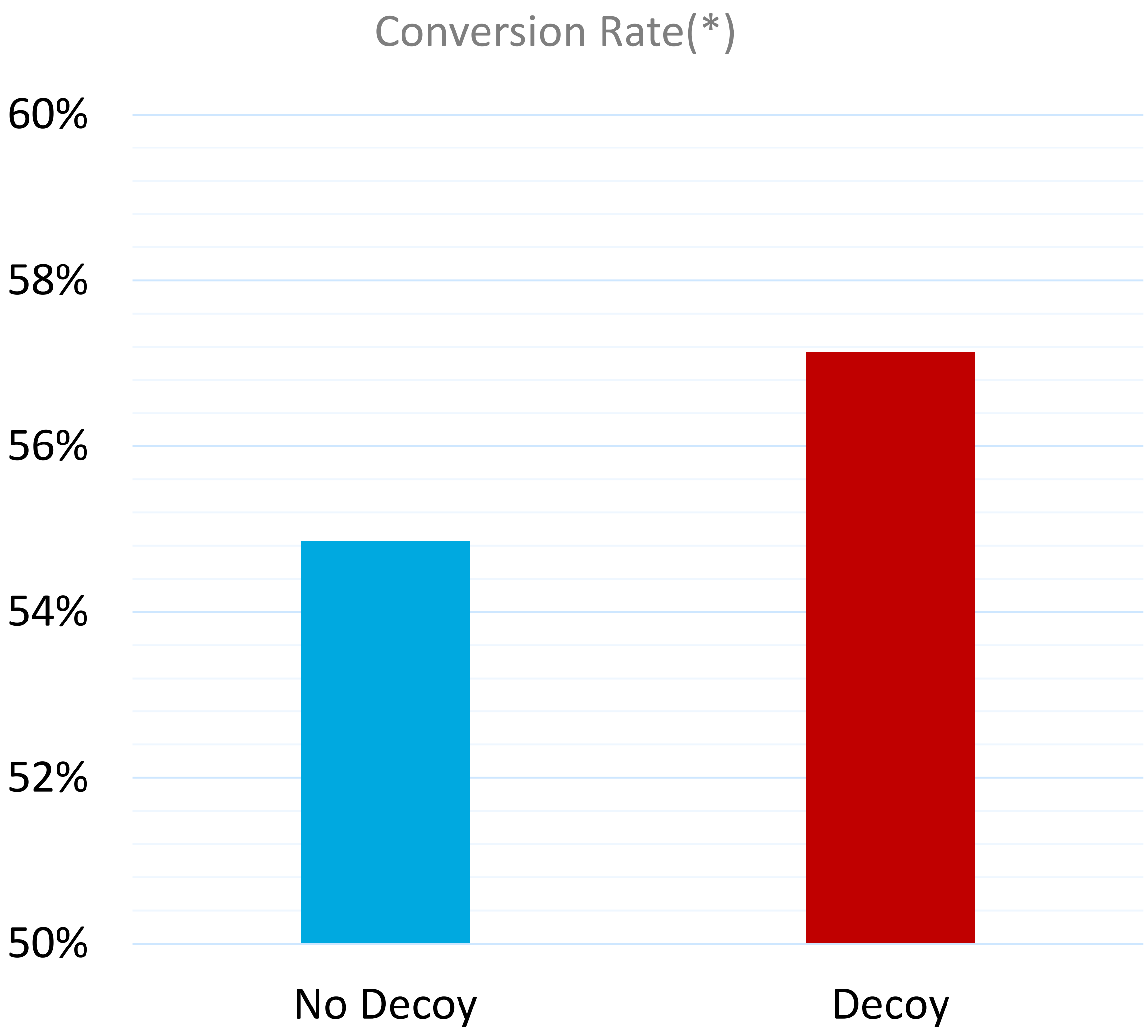
Incentives:

- 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)





(*): note that the experiment is calibrated to obtain relative high values of conversion rates.

AI RESEARCH

amadeus

Rodrigo ACUNA AGOST
Head of AI Research

Turnaround Management Optimization using AI

Stephane Cheikh, AI Program Director, SITA

Turnaround Management Optimization using AI

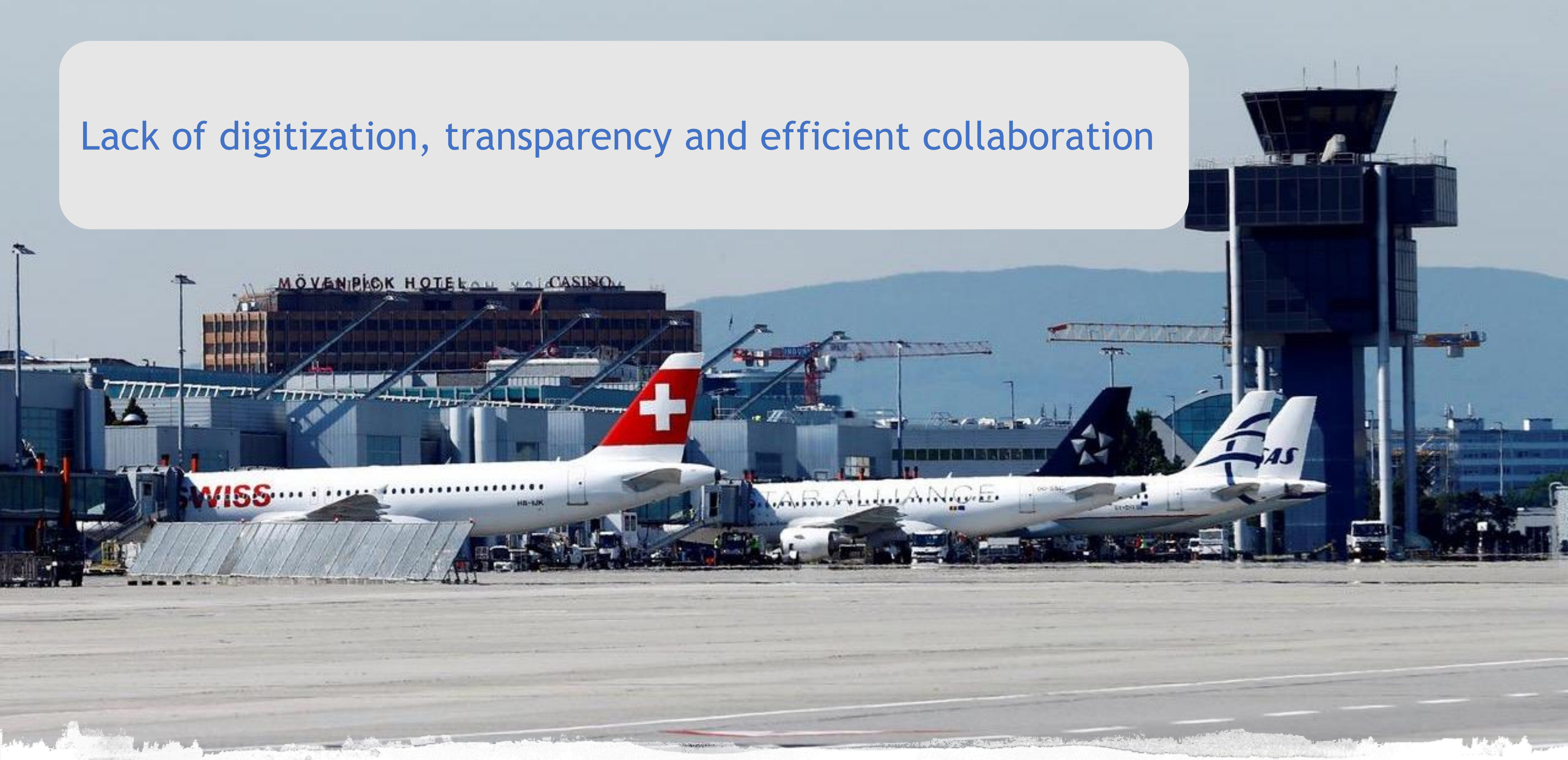
Stephane Cheikh
AI Program Director
SITA, Geneva

$39b = flight delays cost to airlines
$7.4b is related to turnaround
$420m saved directly by airlines, with technology & collaboration*

Turnaround Costs
Why should the industry care?

SITA

Lack of digitization, transparency and efficient collaboration



Turnaround Black Box

Where is the issue coming from?

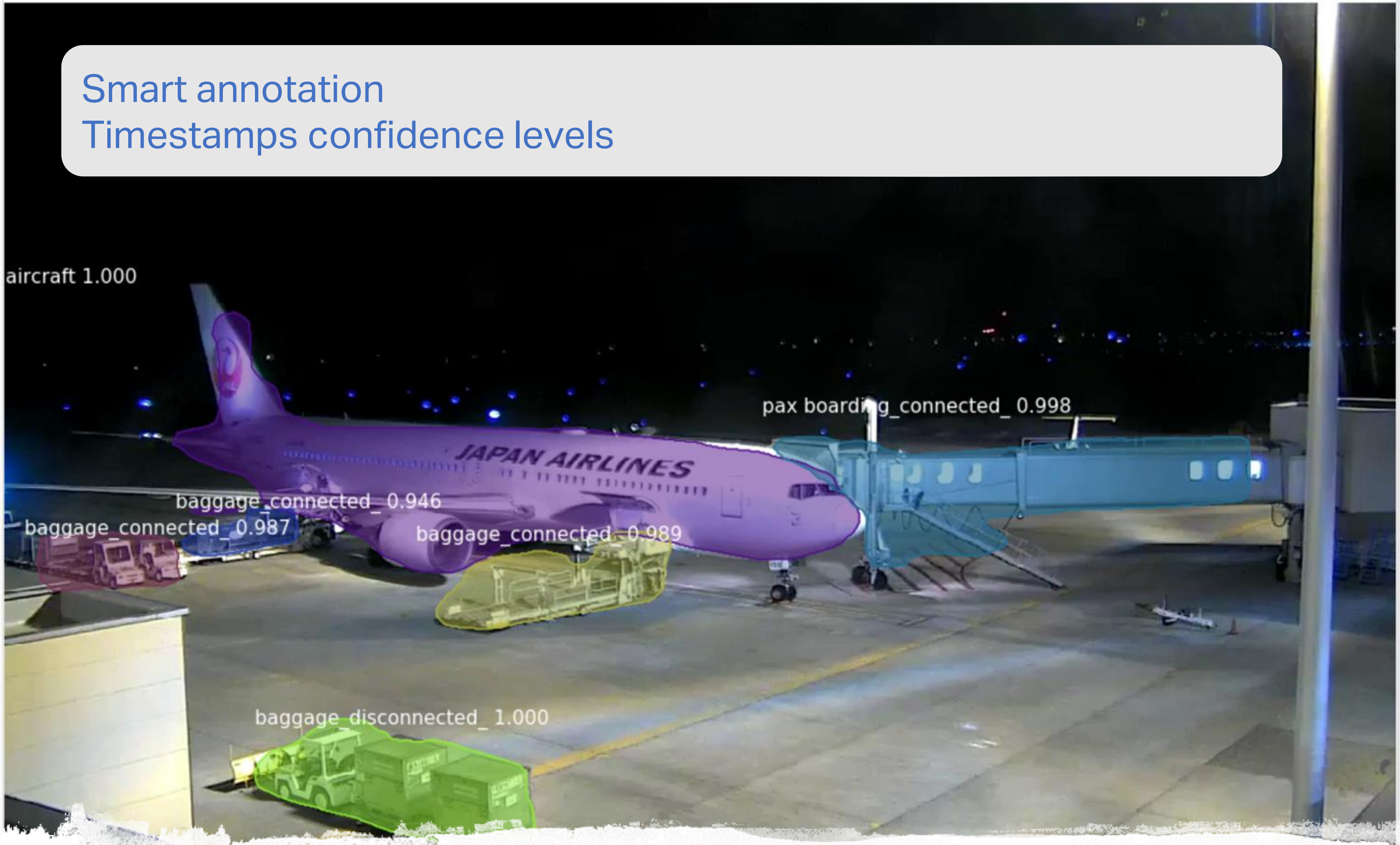
Baggage Loader 1
transports/loads single bags to/from
the airplane cargo hold
Water Supply Truck 2
supplies water to the aircraft
Cabin Cleaning Truck 3
used to clean passenger cabin and
replace blankets, soap etc.
De-Icing Truck 4
ansports and sprays de-icing
lution on leading and trailing edges
Lavatory Truck 5
used to pump waste from
aircraft lavatory tanks
Snow Plough 6
clears snow from the runway,
taxiways and terminal area (tarmac)
Catering Truck 7
transports and delivers food and
beverages to the aircraft
Container/Pallet Transporter 8
used for transporting freight containers
Container Loader 9
used to load/unload freight
Ground Power Unit 10
powers aircraft when engines are
shut down
Passenger Bus and VIP/Crew Transport Vehicl
transport passengers to/from the airplane
Push Back Tractor 12
pushes aircraft away from the gate
to the taxiway
Aircraft Taxi 13
directs airplanes to/from runway
and terminal
Ramp Supervisor Vehicle 14
transports ground support and
services supervisors
Tow Tractor 15
tows luggage/freight dollies and equipment,
and serves as general transportation
Fire Truck 16
is always on standby to fight fires
Fuel Truck 17
transports and delivers fuel
to the aircraft

Automate timestamps gathering
A single source of trustable data

Turnaround Timestamps

Using Computer Vision to extract “accurate” timestamps

SITA



Current Status:

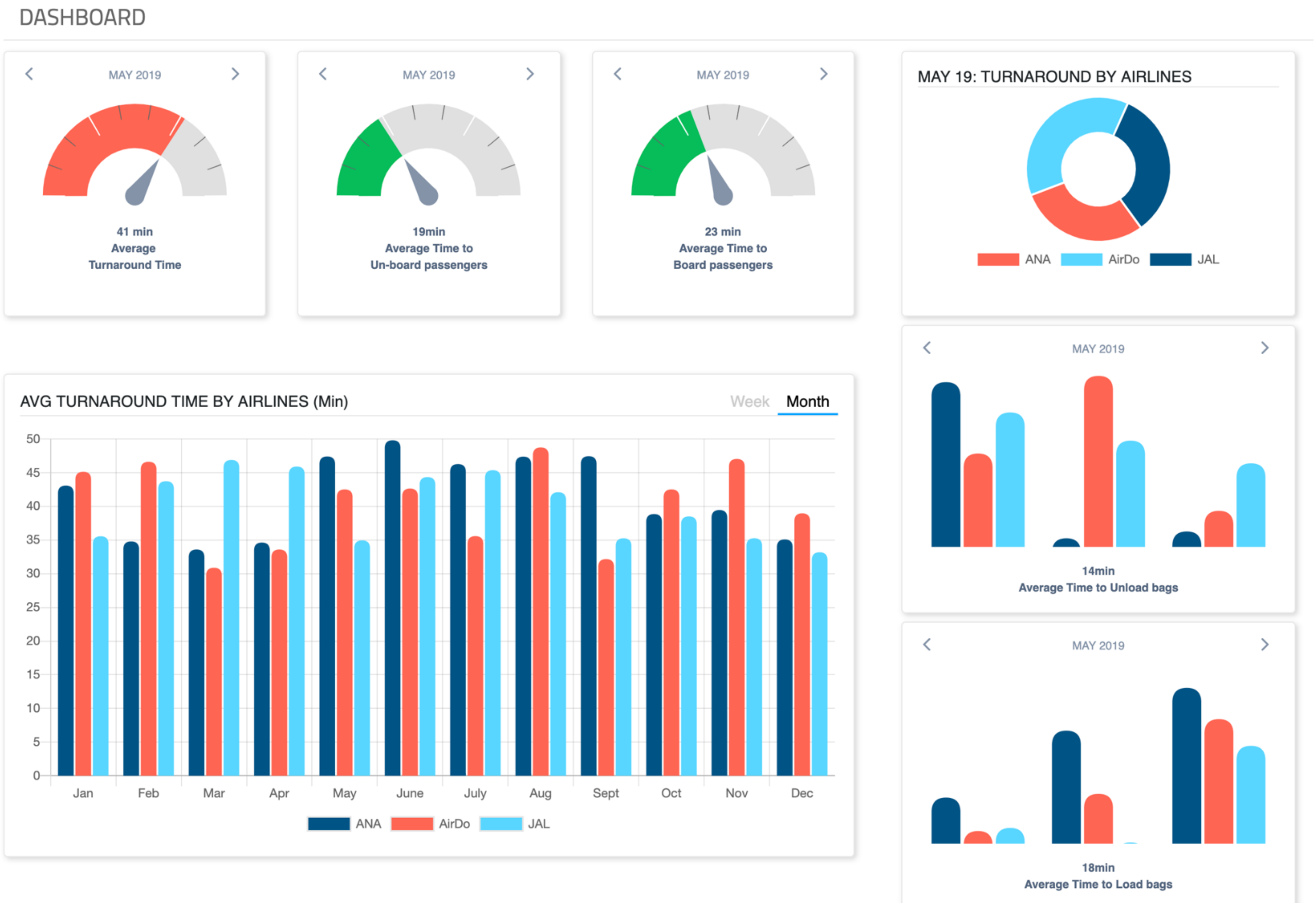
Aircraft	●
Pax Boarding Connected	●
Baggage Connected	●
Tug/Chocks Connected	●

Time Stamps

Aircraft	00:23:03
Pax Boarding Connected	00:23:03
Baggage Connected	00:23:03
Aircraft	00:43:03
Pax Boarding Connected	00:43:03
Baggage Connected	00:43:03
Aircraft	00:18:03
Pax Boarding Connected	00:18:03
Aircraft	00:17:03
Aircraft	00:26:03
Pax Boarding Connected	00:26:03

Turnaround Timestamps

Using Computer Vision to extract "accurate" timestamps


DASHBOARD
MAY 2019
41 min
Average
Turnaround Time
MAY 2019
19min
Average Time to
Un-board passengers
MAY 2019
23 min
Average Time to
Board passengers
MAY 19: TURNAROUND BY AIRLINES
ANA
AirDo
JAL
AVG TURNAROUND TIME BY AIRLINES (Min)
Week
Month
50
45
40
35
30
25
20
15
10
5
0
Jan
Feb
Mar
Apr
May
June
July
Aug
Sept
Oct
Nov
Dec
ANA
AirDo
JAL
MAY 2019
14min
Average Time to Unload bags
MAY 2019
18min
Average Time to Load bags

- Aircraft movement (AODB)
- Passenger journey at airport (check-in, security, boarding)
- Baggage tracking (bag check-in, processing & loading)
- Fix and mobile resource allocation (AMS)
- Air traffic control messages

Turnaround Timestamps

SITA is well positioned – access to diverse data to be meshed with timestamps

SITA

Turnaround Digital Twin

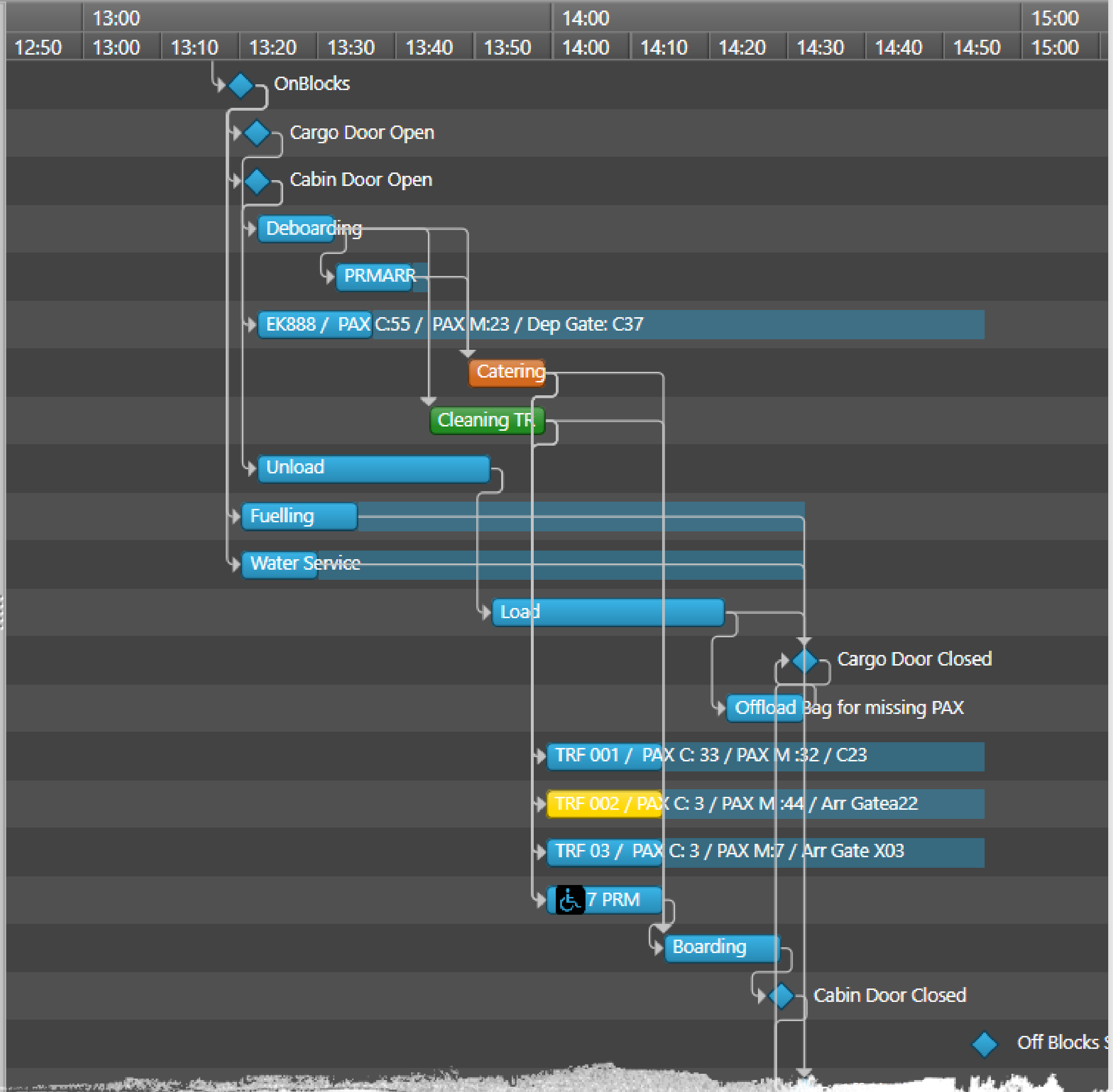
Ability to view live turnaround via an immersive platform

SITA

Remove PRM | Cancel Offload Bag | Start Offload Bag

Overview | Transfer | Baggage

ID	Dependencies	Service	Duration	Start	End
3	2	OnBlocks	0 mins	02Sep16 13:20	02Sep16 13:20
4	3FS+2 mins	Cargo Door Open	0 mins	02Sep16 13:22	02Sep16 13:22
5	3FS+2 mins	Cabin Door Open	0 mins	02Sep16 13:22	02Sep16 13:22
6	5	Deboarding	10 mins	02Sep16 13:22	02Sep16 13:32
7	6	PRMARR	10 mins	02Sep16 13:32	02Sep16 13:42
8	5	EK888 / PAX C:55 / PAX M:23 /	15 mins	02Sep16 13:22	02Sep16 13:37
9	6,7	Catering	10 mins	02Sep16 13:49	02Sep16 13:59
10	6,7	Cleaning TR	15 mins	02Sep16 13:44	02Sep16 13:59
11	4	Unload	30 mins	02Sep16 13:22	02Sep16 13:52
12	3	Fuelling	15 mins	02Sep16 13:20	02Sep16 13:35
13	3	Water Service	10 mins	02Sep16 13:20	02Sep16 13:30
14	11	Load	30 mins	02Sep16 13:52	02Sep16 14:22
15	14,16	Cargo Door Closed	0 mins	02Sep16 14:32	02Sep16 14:32
16	14	Offload Bag for missing PAX	10 mins	02Sep16 14:22	02Sep16 14:32
17	9,10	TRF 001 / PAX C: 33 / PAX M :3	15 mins	02Sep16 13:59	02Sep16 14:14
18	9,10	TRF 002 / PAX C: 3 / PAX M :44	15 mins	02Sep16 13:59	02Sep16 14:14
19	9,10	TRF 03 / PAX C: 3 / PAX M:7 / /	15 mins	02Sep16 13:59	02Sep16 14:14
20	10,9	7 PRM	15 mins	02Sep16 13:59	02Sep16 14:14
21	9,10,20	Boarding	15 mins	02Sep16 14:14	02Sep16 14:29
22	21	Cabin Door Closed	0 mins	02Sep16 14:29	02Sep16 14:29
23		Off Blocks Scheduled	0 mins	02Sep16 14:55	02Sep16 14:55
24	12,13,15,22FS+2 m	Off Blocks	0 mins	02Sep16 14:32	02Sep16 14:32



Turnaround Manager – Activity Flow

Delivers aircraft operation overview for Airlines operating a Hub or FS GH

SITA

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?

SITA

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

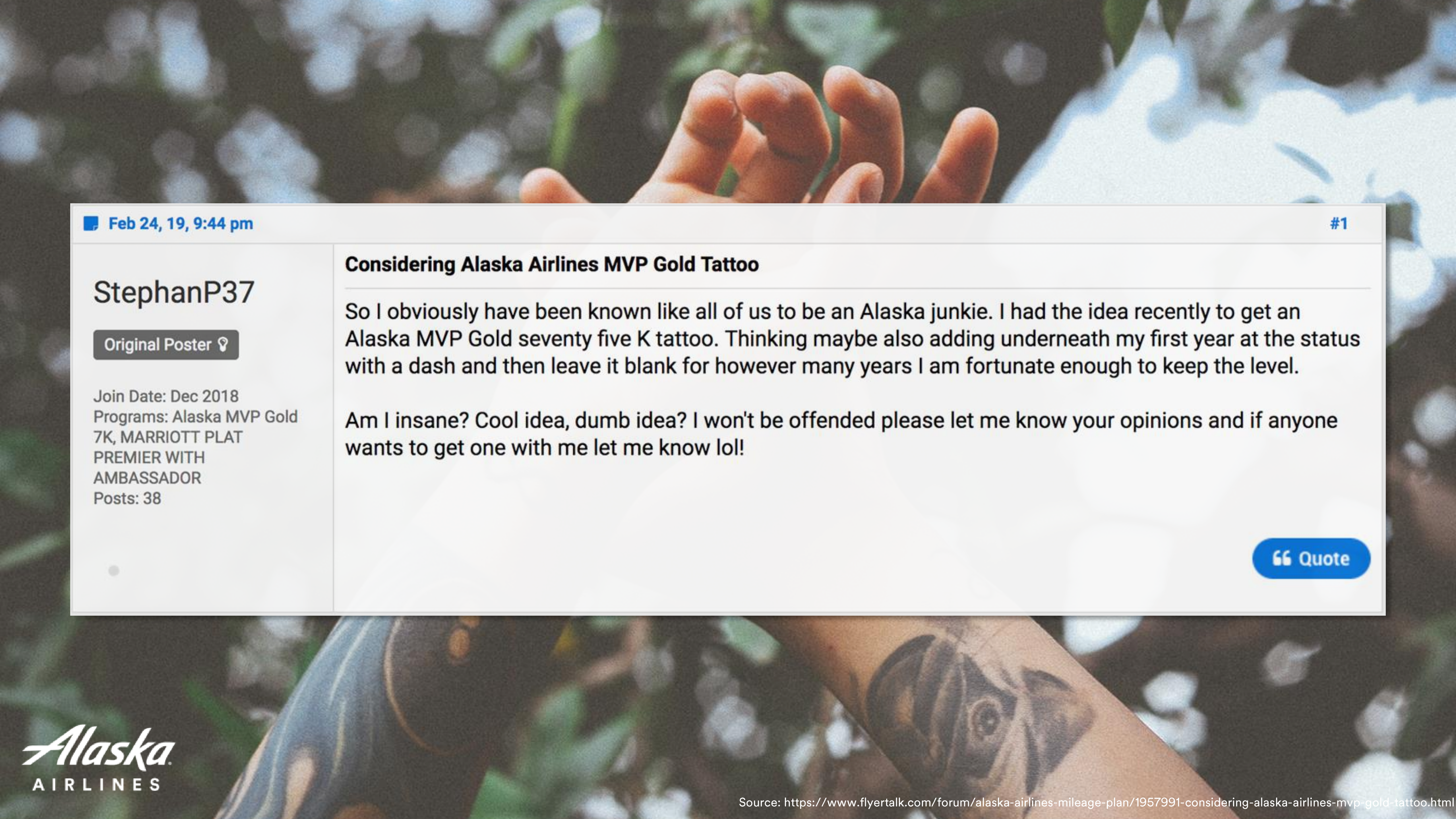
Matt Hahnfeld, Software Engineering Manager

Xavier Lucas, Software Engineer III

June 27, 2019

Alaska AIRLINES

Highest in Customer Satisfaction Among Traditional Carriers in North America, Twelve Years in a Row.



Feb 24, 19, 9:44 pm #1

StephanP37

Original Poster

Join Date: Dec 2018
Programs: Alaska MVP Gold 7K, MARRIOTT PLAT PREMIER WITH AMBASSADOR
Posts: 38

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!

Quote

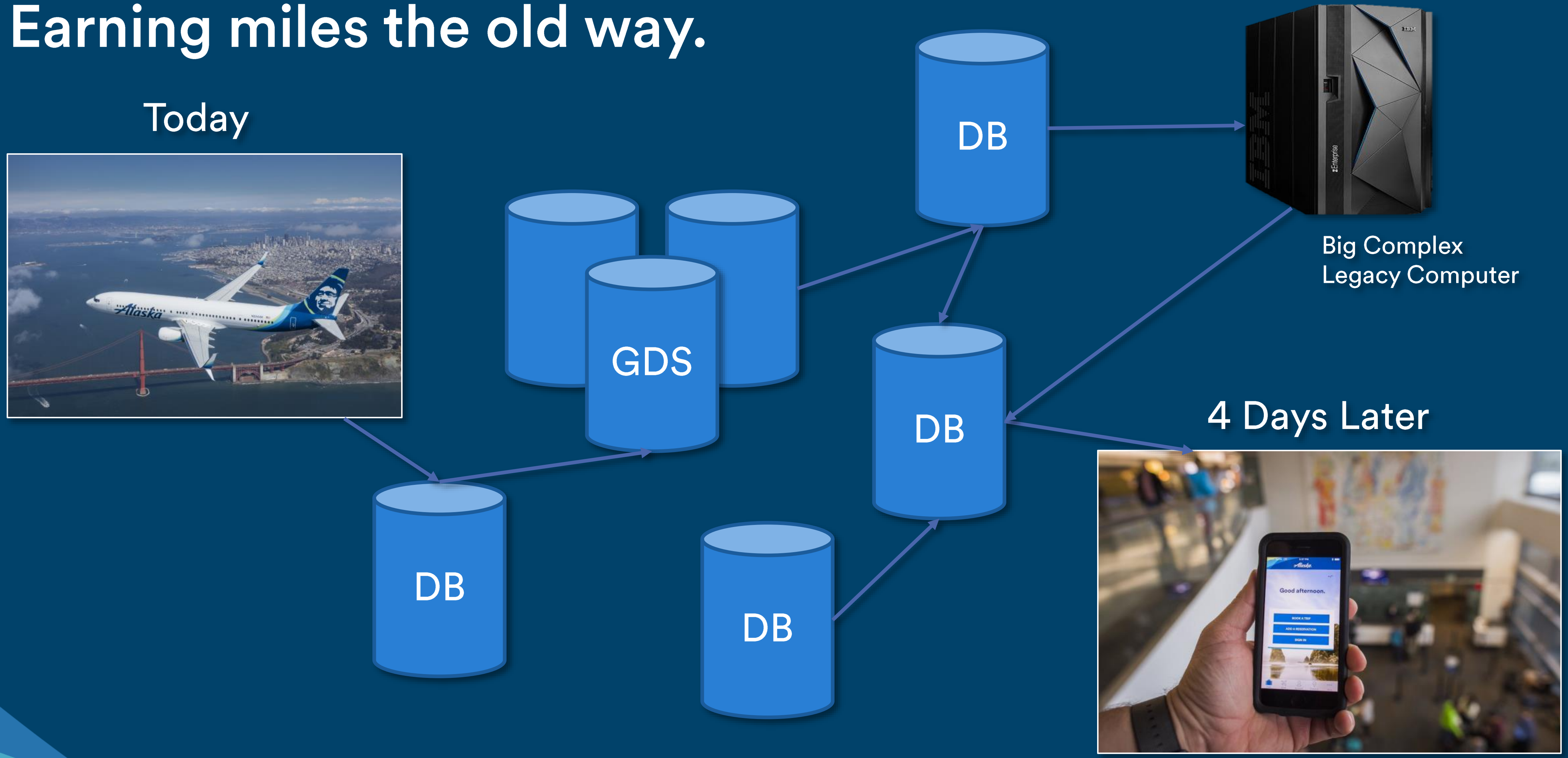
Alaska AIRLINES

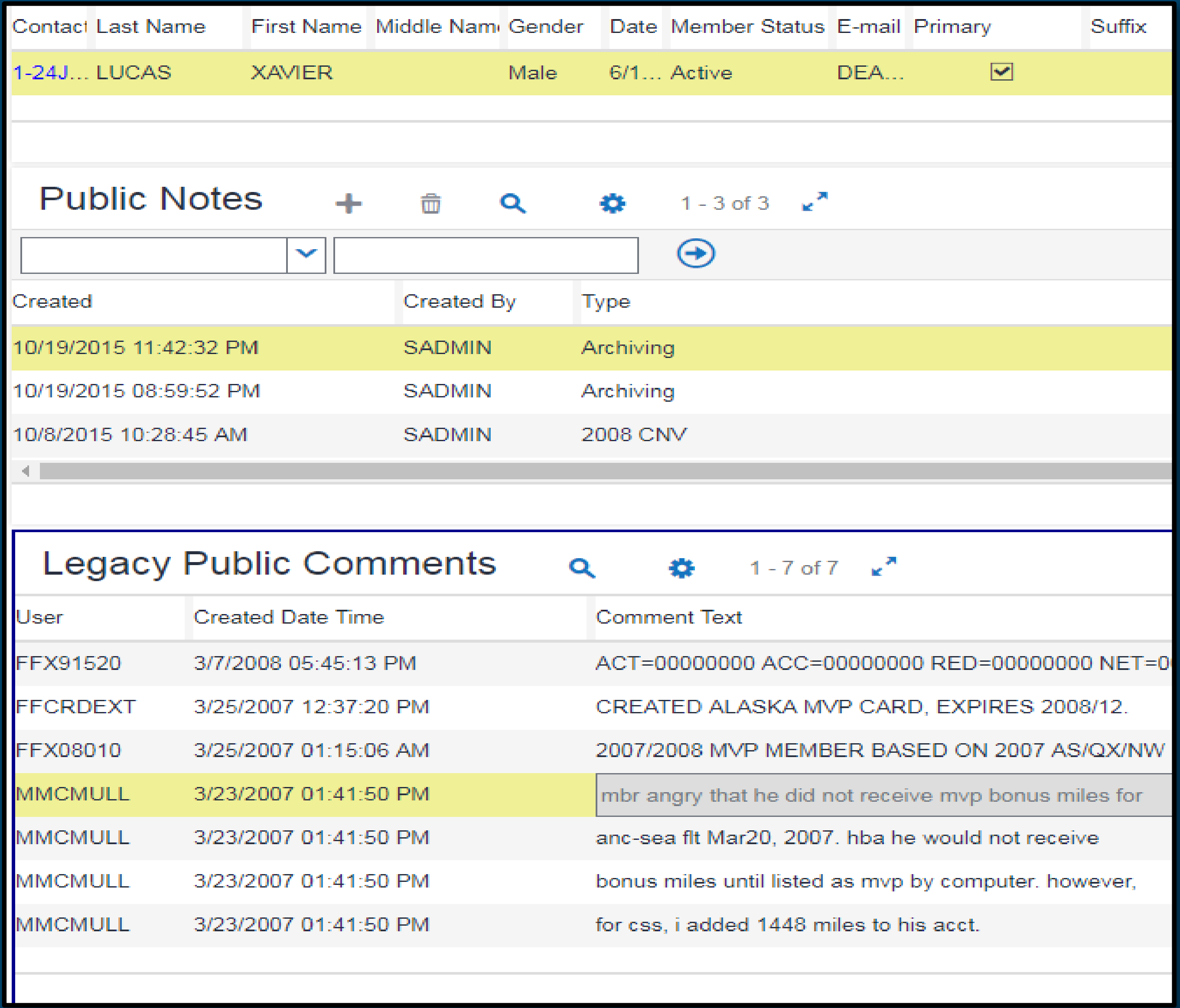
Source: https://www.flyertalk.com/forum/alaska-airlines-mileage-plan/1957991-considering-alaska-airlines-mvp-gold-tattoo.html

Tech at Alaska is...

Alaska
AIRLINES

Earning miles the old way.





Contact	Last Name	First Name	Middle Name	Gender	Date	Member Status	E-mail	Primary	Suffix
1-24J...	LUCAS	XAVIER		Male	6/1...	Active	DEA...	☑	

Public Notes

1 - 3 of 3

Created	Created By	Type
10/19/2015 11:42:32 PM	SADMIN	Archiving
10/19/2015 08:59:52 PM	SADMIN	Archiving
10/8/2015 10:28:45 AM	SADMIN	2008 CNV

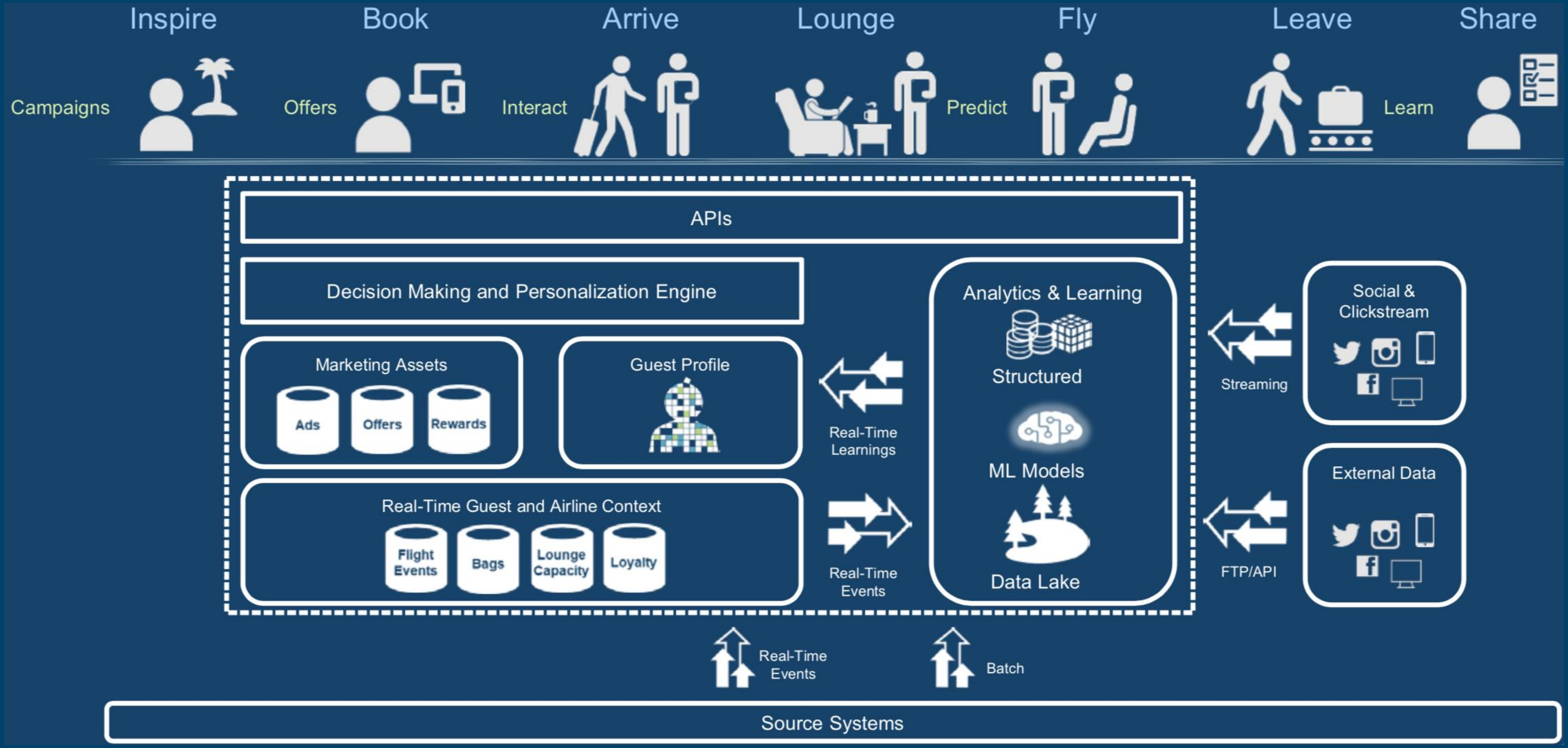
Legacy Public Comments

1 - 7 of 7

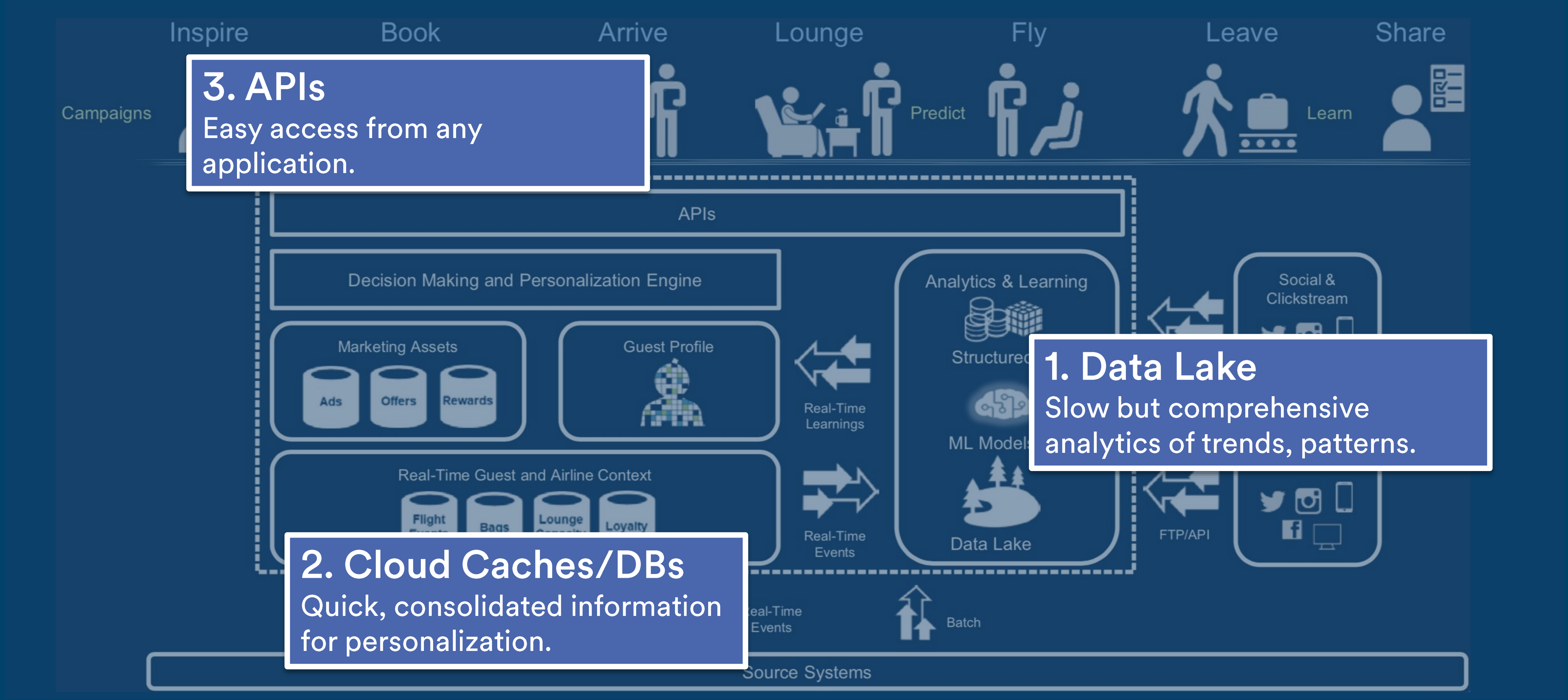
User	Created Date Time	Comment Text
FFX91520	3/7/2008 05:45:13 PM	ACT=00000000 ACC=00000000 RED=00000000 NET=0
FFCRDEXT	3/25/2007 12:37:20 PM	CREATED ALASKA MVP CARD, EXPIRES 2008/12.
FFX08010	3/25/2007 01:15:06 AM	2007/2008 MVP MEMBER BASED ON 2007 AS/QX/NW
MMCMULL	3/23/2007 01:41:50 PM	mbr angry that he did not receive mvp bonus miles for
MMCMULL	3/23/2007 01:41:50 PM	anc-sea flt Mar20, 2007. hba he would not receive
MMCMULL	3/23/2007 01:41:50 PM	bonus miles until listed as mvp by computer. however,
MMCMULL	3/23/2007 01:41:50 PM	for css, i added 1448 miles to his acct.

From the archives.

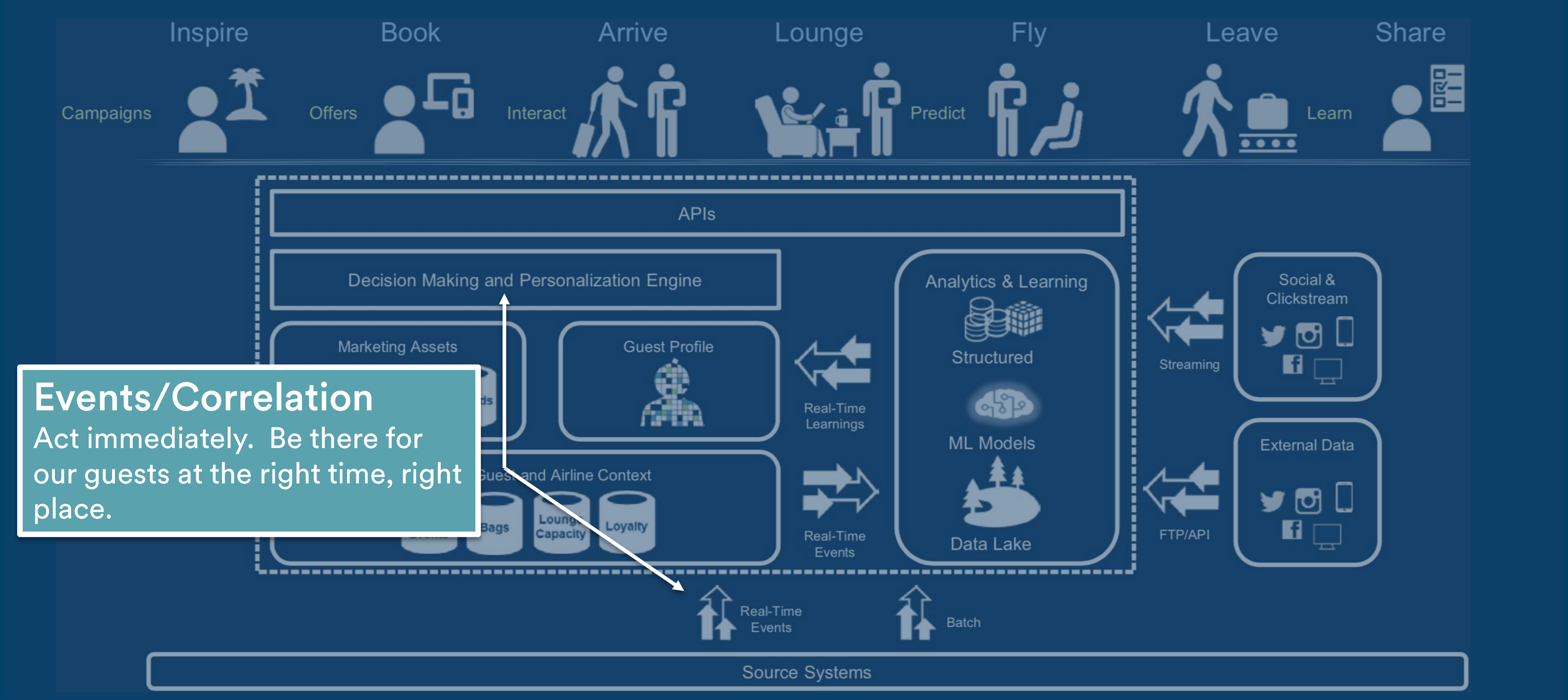
Two years ago in Miami.



On-demand personalization.



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

Home > News & Press Information > Press Releases > 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

Alaska AIRLINES

Source: https://helloworld.com/article/2019-merkle-helloworld-loyalty-report-reveals-54-consumers-want-swifter-reward-redemption

Instant Gratification Requires Thinking Differently


MONEY

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

Share

Alexandria White

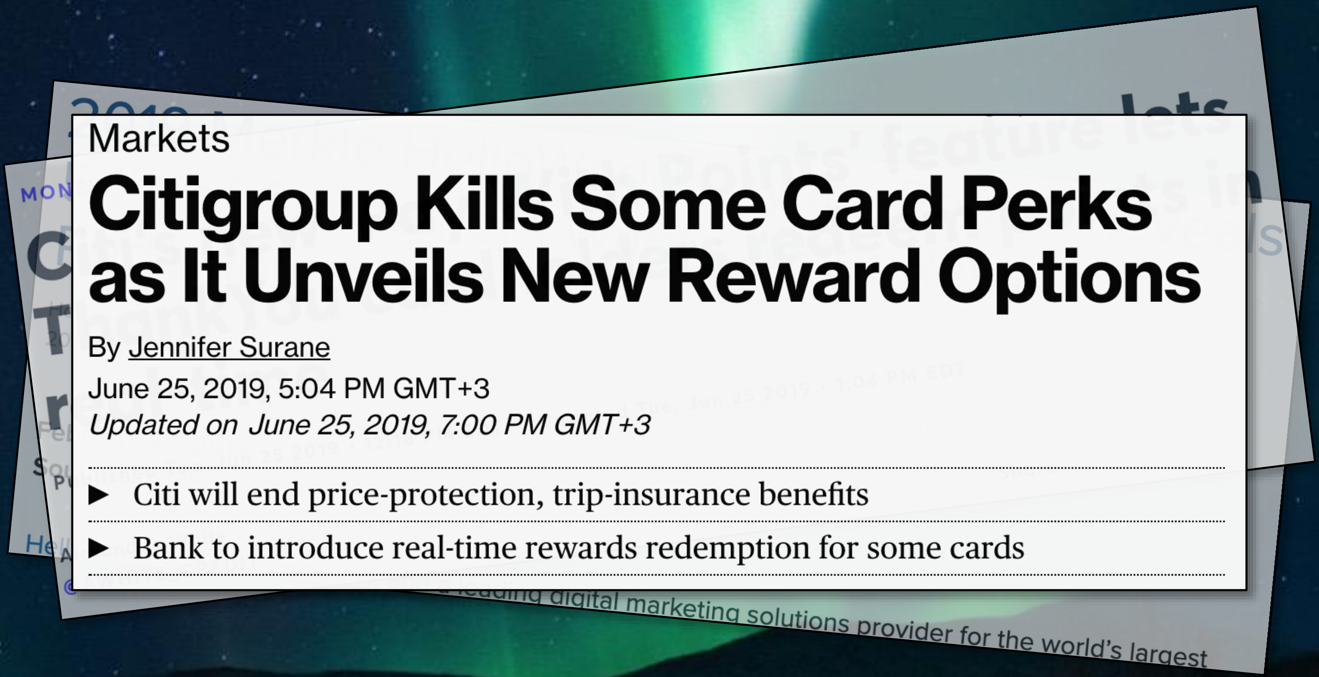
@AWHITE_CREDIT

and a leading digital marketing solutions provider for the world's largest

Alaska AIRLINES

Source: https://www.cnbc.com/2019/06/25/citi-pay-with-points-allows-cardmembers-to-redeem-points-in-real-time.html

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."

Alaska AIRLINES

Source: https://www.bloomberg.com/news/articles/2019-06-25/citi-ends-card-perks-including-trip-insurance-price-protection

Real-Time
Requires Thinking Differently

Alaska
AIRLINES

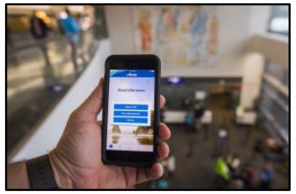
Earning miles the new way.

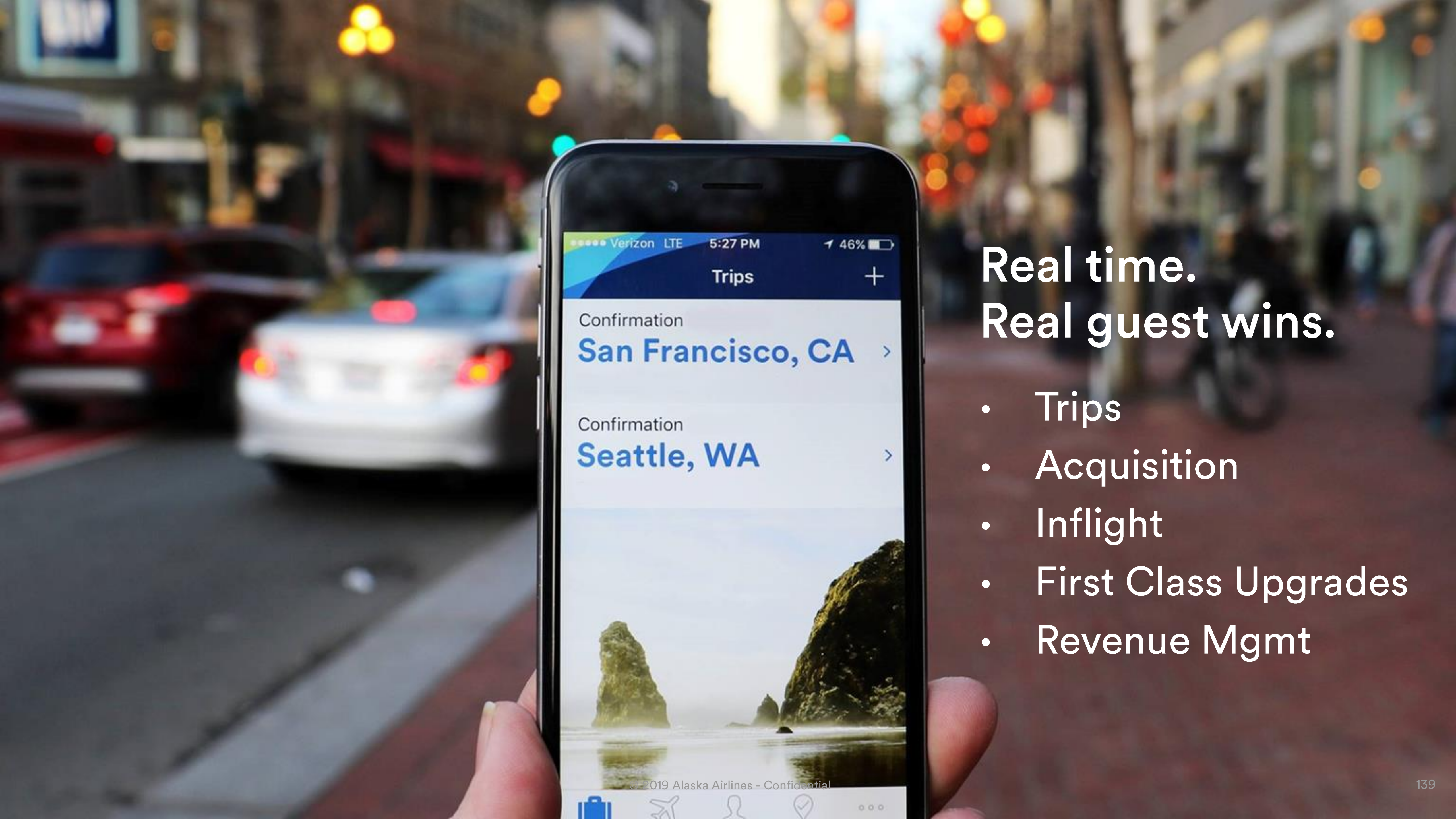





Correlate

Validate / Post





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

Alaska AIRLINES

The future is bright.

Alaska AIRLINES

Thank you.

Matt Hahnfeld, Software Engineering Manager
Xavier Lucas, Software Engineer III
Loyalty and Non-Flight Partners

Alaska AIRLINES

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
A TravelSky Company

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

OpenJaw
A TravelSky Company

Global Customer Base

ANA
BRITISH AIRWAYS
CATHAY PACIFIC
成都航空 CHENGDU AIRLINES
Comair Limited
中国联航 CHINA UNITED AIRLINES CUA
AIR MILES

深圳航空 Shenzhen Airlines
FOUR SEASONS
IAG
kulula
Discovery
海南航空 HAINAN AIRLINES
aeroplan
IBERIA

四川航空 SICHUAN AIRLINES
山东航空公司 SHANDONG AIRLINES
Travelport
AVIS
CATHAY DRAGON 國泰港龍航空
Color Line
桂林航空 Air Guilin
西藏航空 TIBET AIRLINES

POSADAS
VIAJES El Corte Inglés
HONGKONG AIRLINES 香港航空
ASIA MILES
NORTHROP GRUMMAN

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

3 Stages of Maturity

#1 Interaction	#2 Intelligence	#3 Integration
Model: Standard FAQ	Model: Inference & Intent	Model: Augment + Combine
'What time do I need to be at the airport? '	*'I want to sit in an exit row'*	*I'm flying to London, can I change my flight to tomorrow"*
Source: FAQ, hard coded, decision tree or rules based	Source: NLP, AI, Machine Learning	Source: NLP, AI, Machine Learning, PSS, Booking, DCS, CRM data

#1 Interaction

Feature	Value to Organisation	Value to Passenger
General Advisory (FAQ) Agent w. Escalation	Decrease volume to call centre	Quicker response time
Flying with Us	Brand experience	Quicker response times to common questions
MMB	Decrease call centre volumes	Quicker response times to common questions
Help FAQs	Decrease call centre volumes	Quicker response times to common questions
Contact Us	Route calls to appropriate agents, cut down wastage	Find correct agent more quickly.

#2 Intelligence

Feature	Value to Organisation	Value to Passenger
Deep linking system to generate URLs to link to MMB, Check-in and Flight Sales	Increase conversion by directing to correct web page.	Precise answers
MMB Conversational Flow	MMB handled via a conversation interface	Friction reduction; fast results
Online Check-in Conversational Flow	Check-in via conversation interface	Faster and easier to find complete check-in experience
Flight Selling Conversational Flow	Enable flight selling with specific offer page	Engage customer with natural language in a private message flow

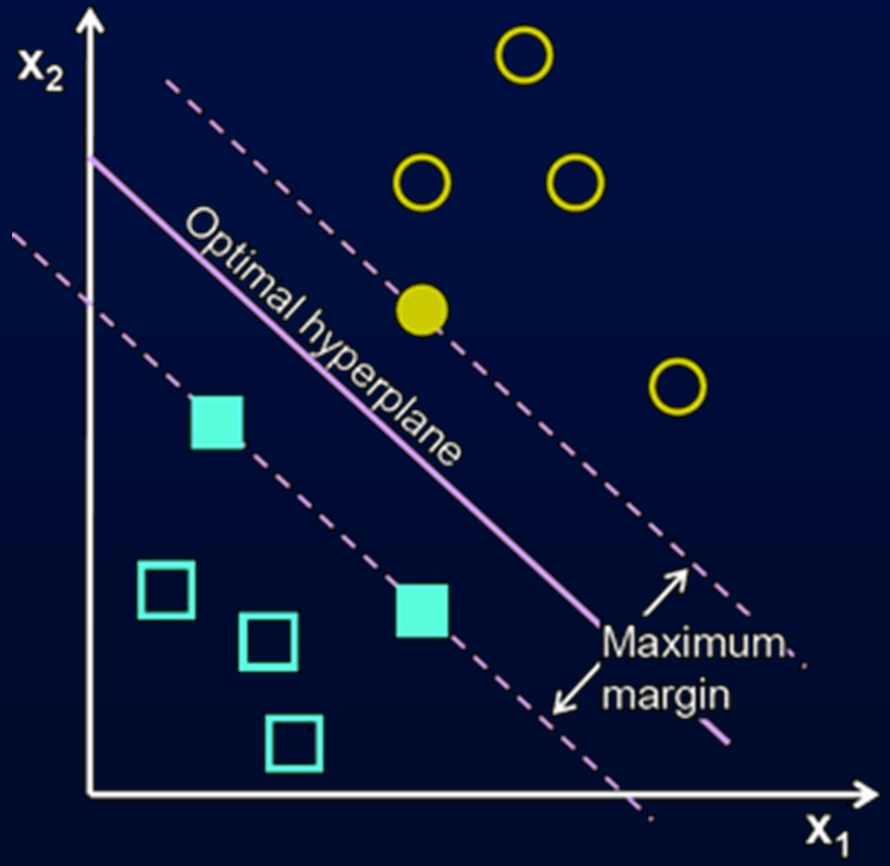
#3 Integration

Feature	Value to Organisation	Value to Passenger
Check-in w/ Ancillary Sales	Decrease volume to call centre, provide conversational opportunity for upsell	Ability to check-in online via Facebook Messenger or WhatsApp
Flights Status, FIFO, and Regulatory Details	Reduce call centre volumes	Quicker response to queries.
MMB Baggage and Seat Upsell	Decrease call centre volumes and increase baggage and seat sales	Reduce friction in seat sales bag sales

How do we use AI?

Teach not tell

Machine Learning

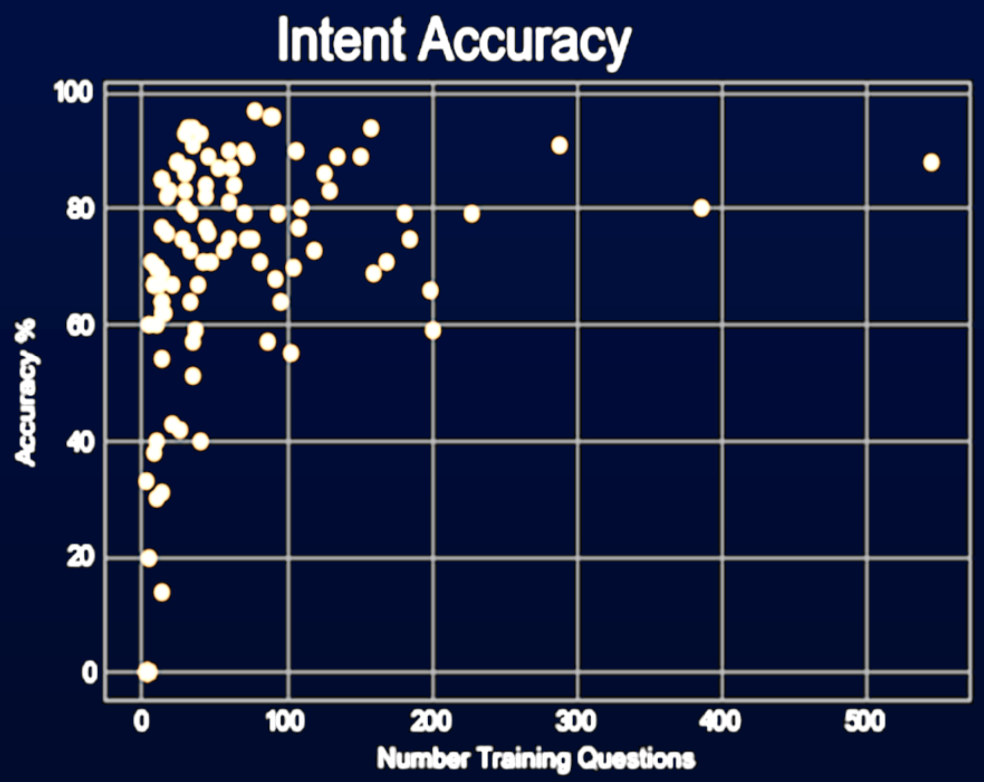


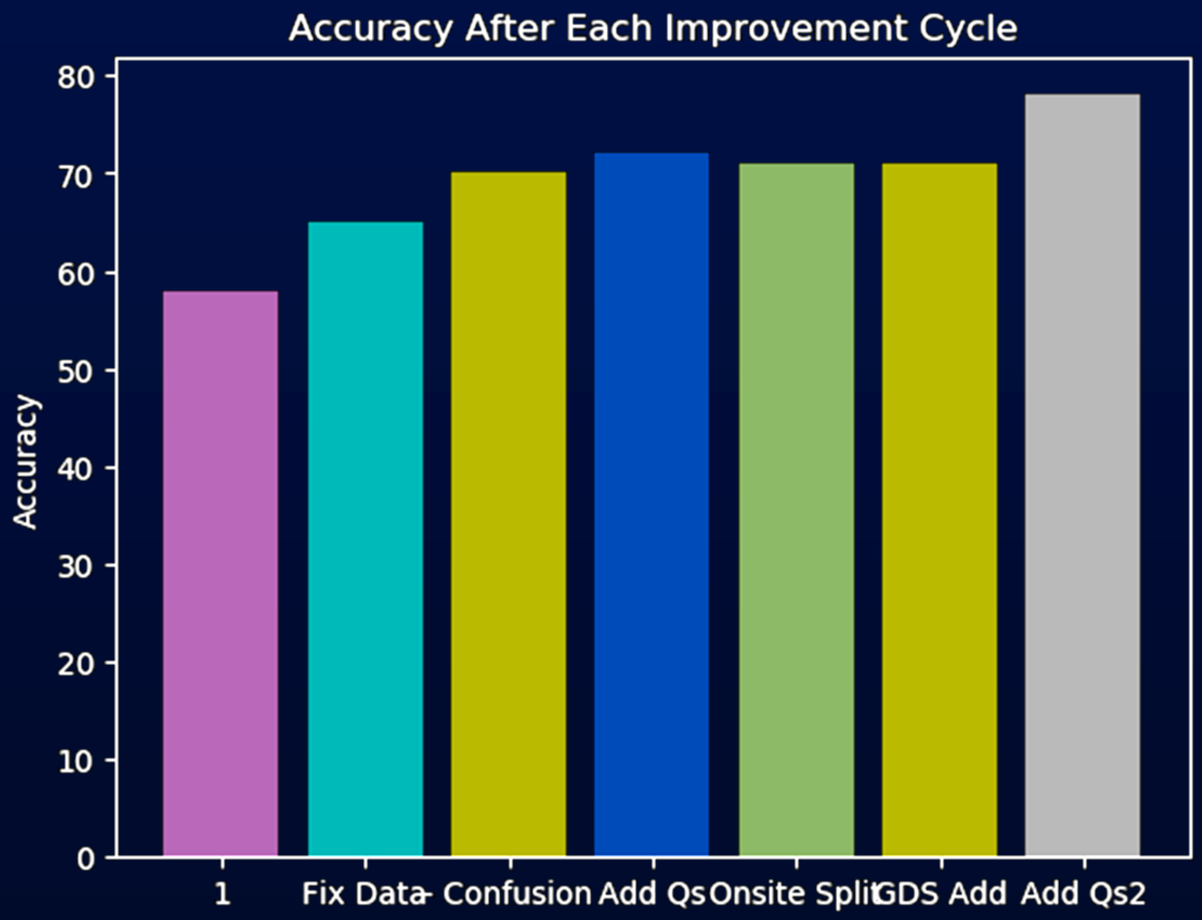
Programming

23. Rewrite the following **switch** statement as a nested **if** statement using a series of **else...if** statements:

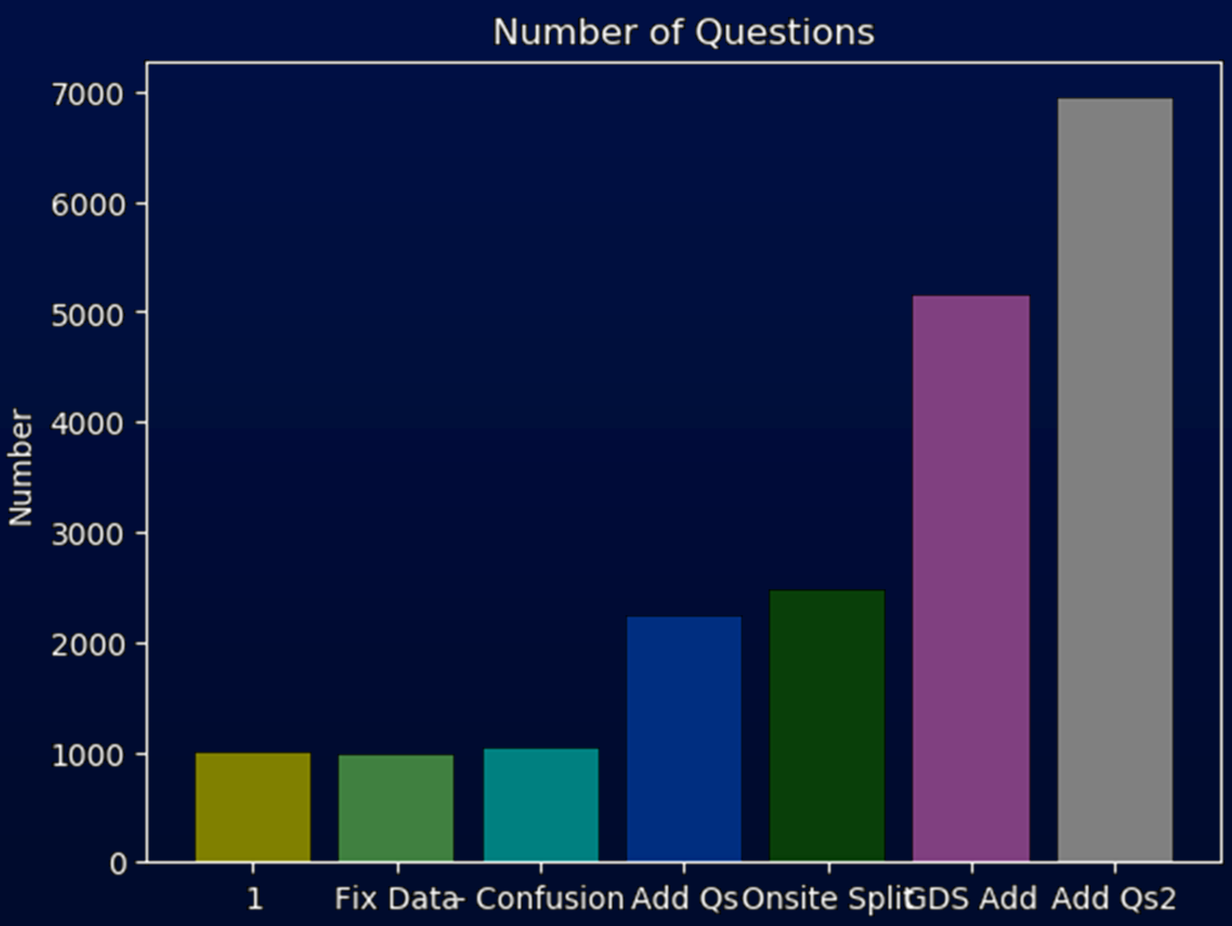
```
string birdName;
switch (birdName)
{
  case "Pelican":
          Console.WriteLine("Lives near water.");
          break;
  case "Cardinal":
          Console.WriteLine("Beautiful in the snow.");
          break;
  case "Owl":
          Console.WriteLine("Night creature.");
          break;
  case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

Measure and monitor accuracy



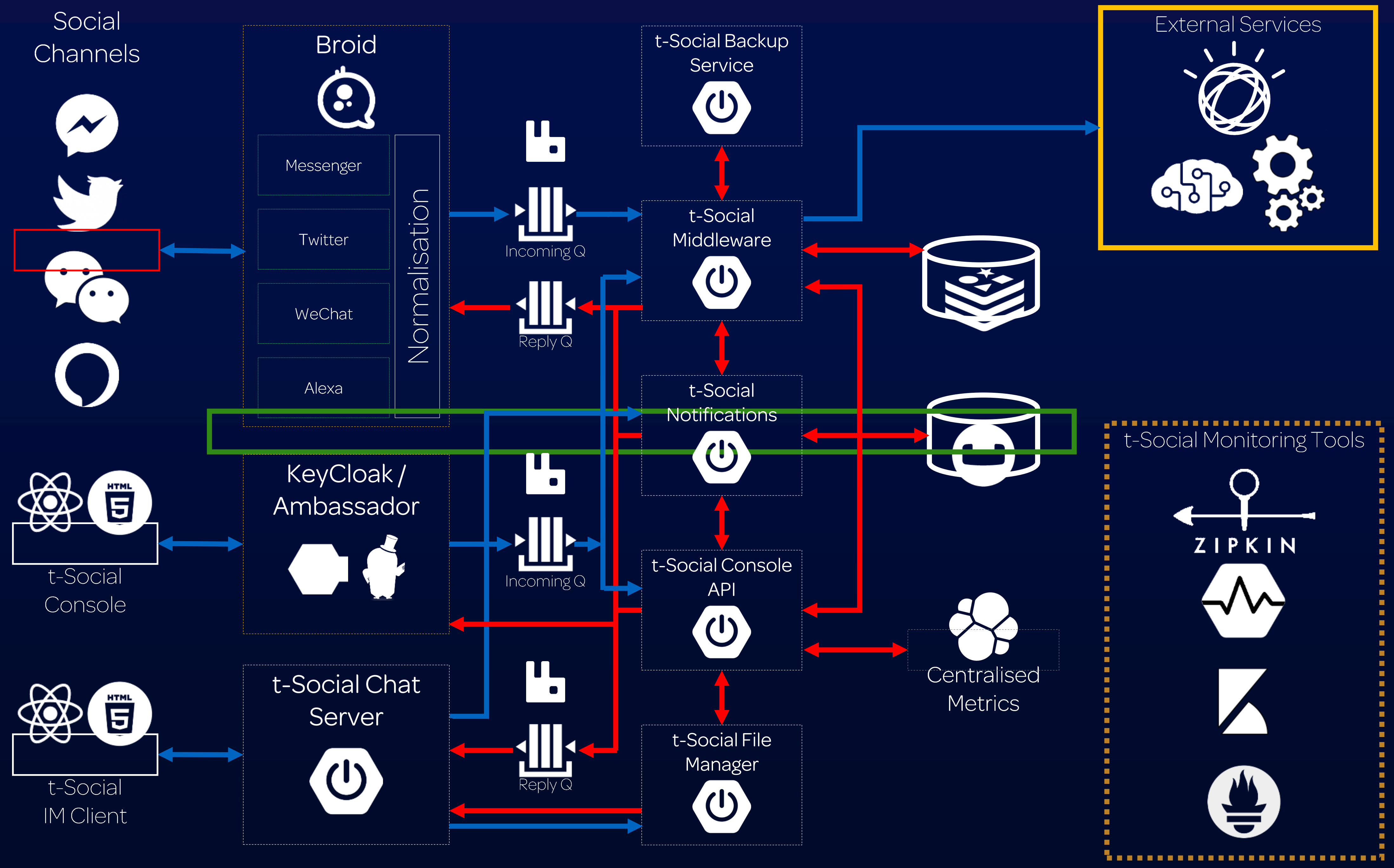


Improve the data, fix misclassifications



	size	z_score	mad_scores	to_check
cluster_id				
客票变更_改期_TRI 自动改期_问题类	228	2.208183	0.037072	True
客票变更_退票_咨询类	386	4.264052	0.067110	True
报销凭证_打印方查询	287	2.975881	0.048289	True

Architecting the eco-system



Social Channels
Broid
Messenger
Twitter
WeChat
Alexa
Normalisation
Incoming Q
Reply Q
t-Social Backup Service
t-Social Middleware
t-Social Notifications
t-Social Console API
t-Social File Manager
External Services
KeyCloak / Ambassador
Incoming Q
t-Social Console
t-Social Chat Server
Reply Q
t-Social IM Client
HTML 5
Centralised Metrics
t-Social Monitoring Tools
ZIPKIN

Middleware

Spring Boot based.
'Core' of the system
Integration and orchestration layers
Configuration
Queuing, Databases, Caches

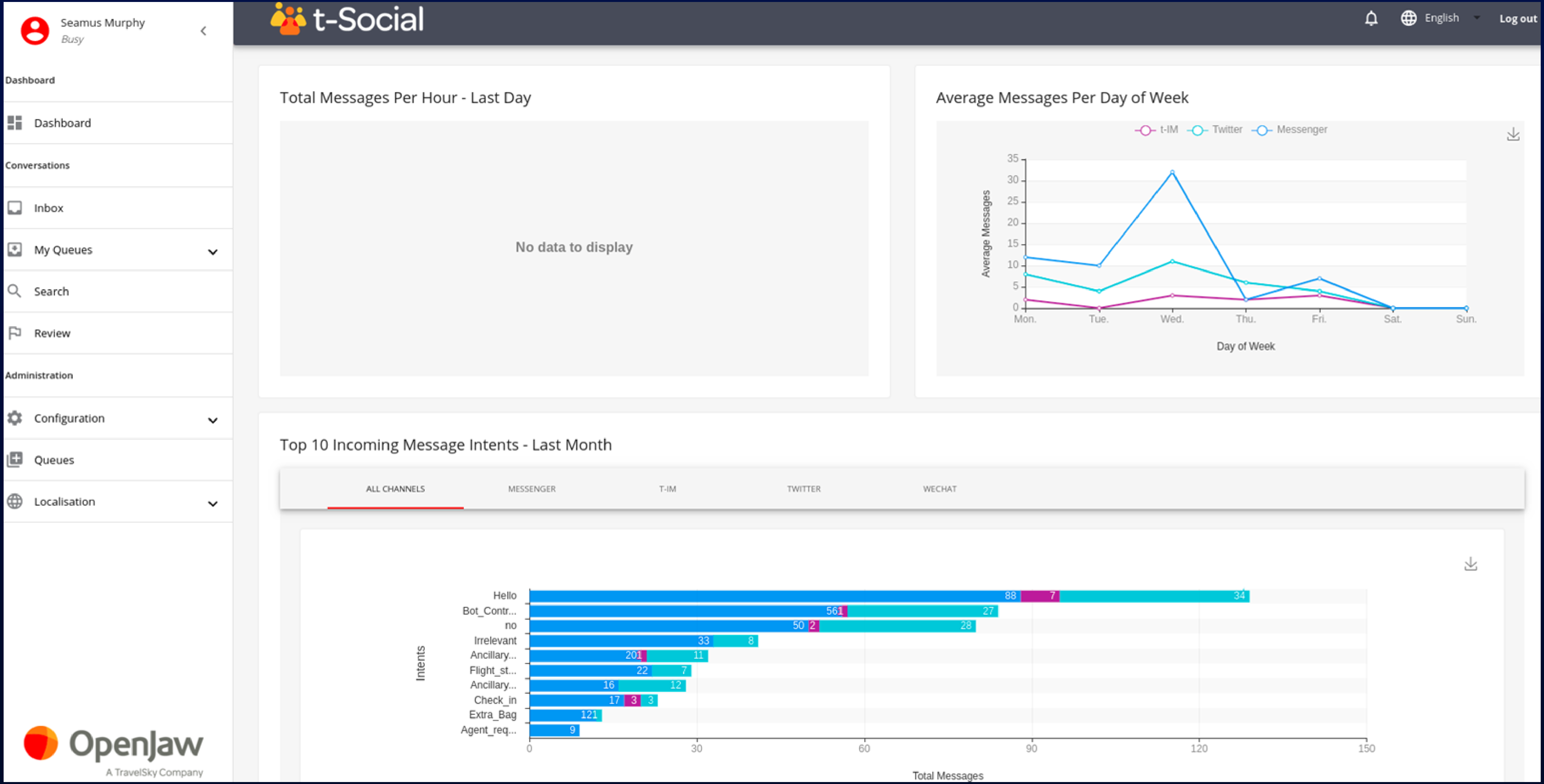
Console UI

Built using React & Redux

ECharts visualisation framework

Material UI

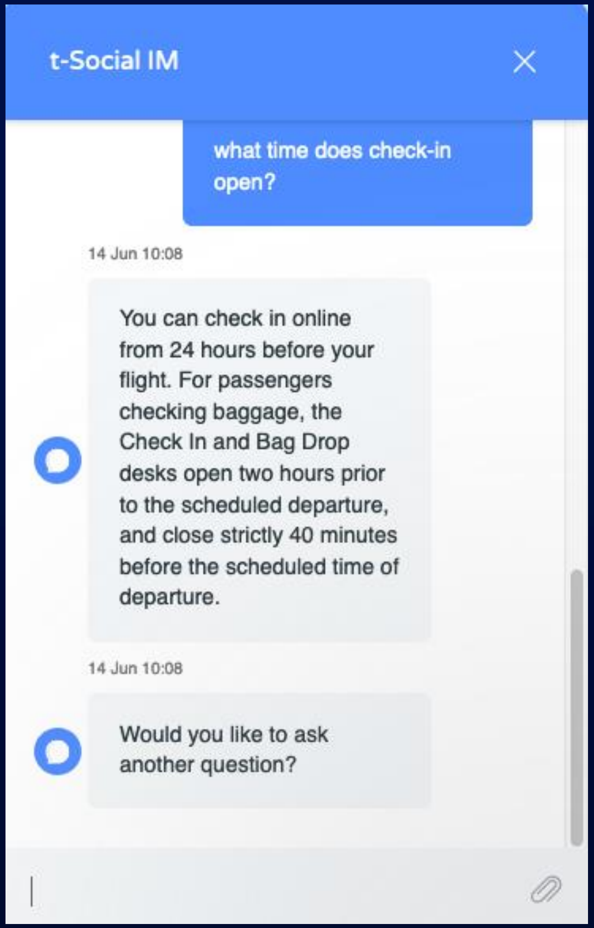
Console UI



Seamus Murphy
Busy
Dashboard
Dashboard
Conversations
Inbox
My Queues
Search
Review
Administration
Configuration
Queues
Localisation
OpenJaw
A TravelSky Company
t-Social
English
Log out
Total Messages Per Hour - Last Day
No data to display
Average Messages Per Day of Week
t-IM
Twitter
Messenger
Average Messages
35
30
25
20
15
10
5
0
Mon.
Tue.
Wed.
Thu.
Fri.
Sat.
Sun.
Day of Week
Top 10 Incoming Message Intents - Last Month
ALL CHANNELS
MESSENGER
T-IM
TWITTER
WECHAT
Intents
Hello
Bot_Contr...
no
Irrelevant
Ancillary...
Flight_st...
Ancillary...
Check_in
Extra_Bag
Agent_req...
88
7
34
561
27
50
2
28
33
8
201
11
22
7
16
12
17
3
3
121
9
0
30
60
90
120
150
Total Messages

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

Brian Lewis, Chief Technology Officer

Thanks for listening!

brian.lewis@openjawtech.com

BrianLewis68

@BrianLewisCTO

www.linkedin.com/in/brian-lewis

OpenJaw

A TravelSky Company

Project DeepSky: A playful approach towards Reinforcement Learning in Aviation

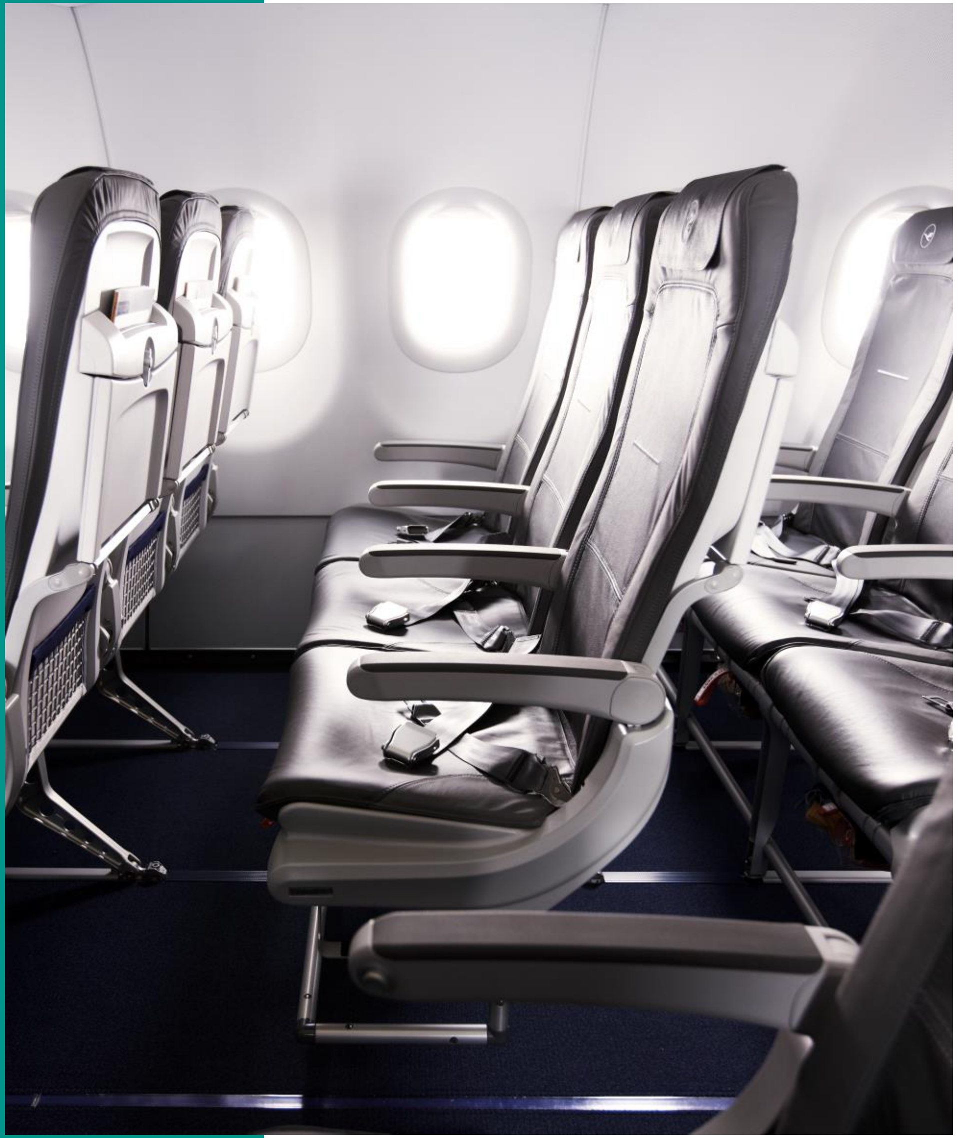
Dr. Dr. Mussie Beian, Senior Data Scientist, zeroG

Project DeepSky: A playful approach towards Reinforcement Learning

IATA Aviation Data Symposium 2019

Greece, Athens

Dr. Dr. Mussie Thomas Beian – Senior Data Scientist



ZERO G

Combining the best out of two worlds: zeroG & Lufthansa Systems

2015

Founded by Lufthansa Systems
Dynamic start-up to keep up with technical developments

>50

People work at zeroG
With a very diverse and international background

>20

Assignments within the aviation world
Working in both commercial and operation areas

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

ZERO G

What is Artificial Intelligence?

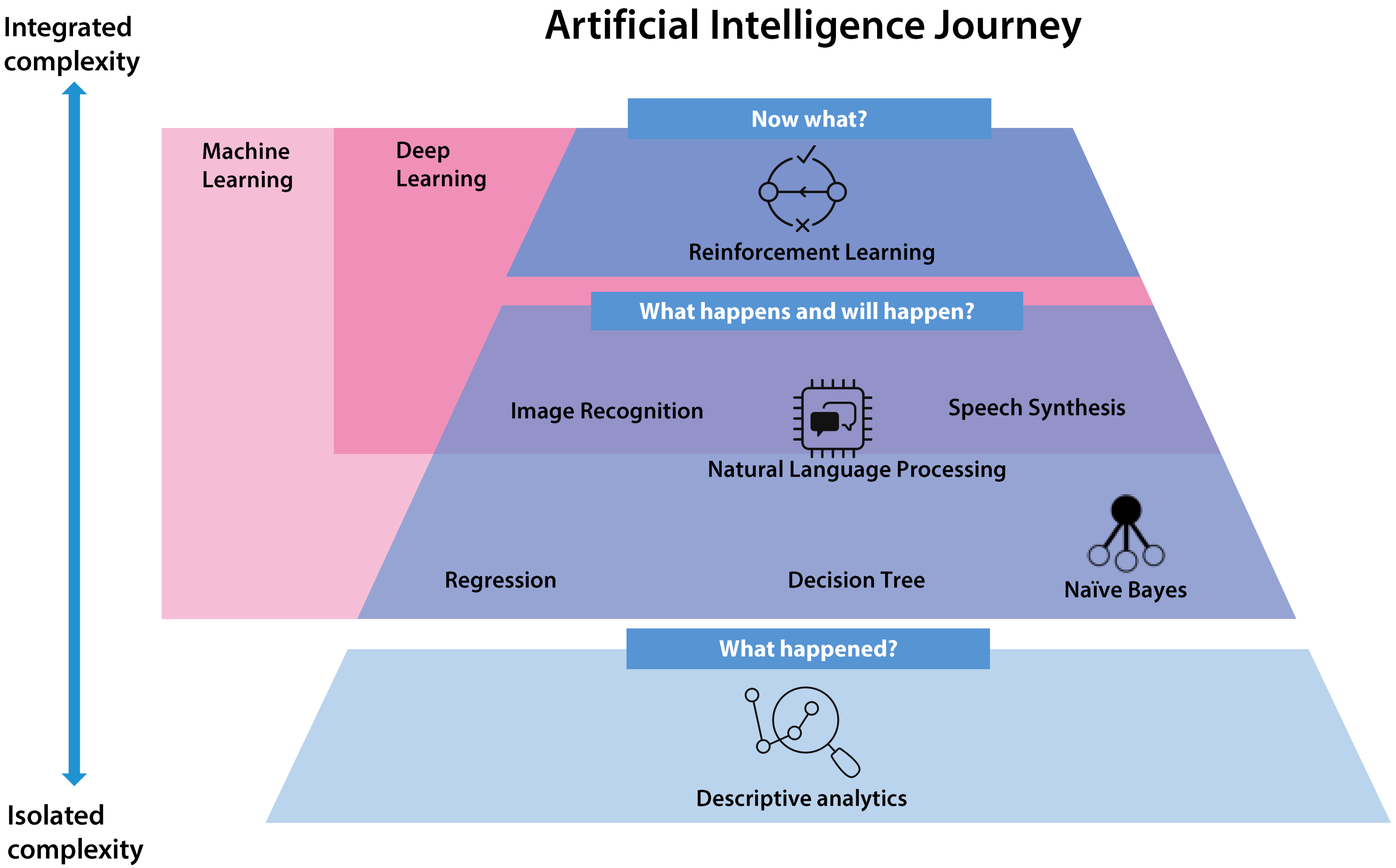
What is Artificial Intelligence?

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



ZERO G

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

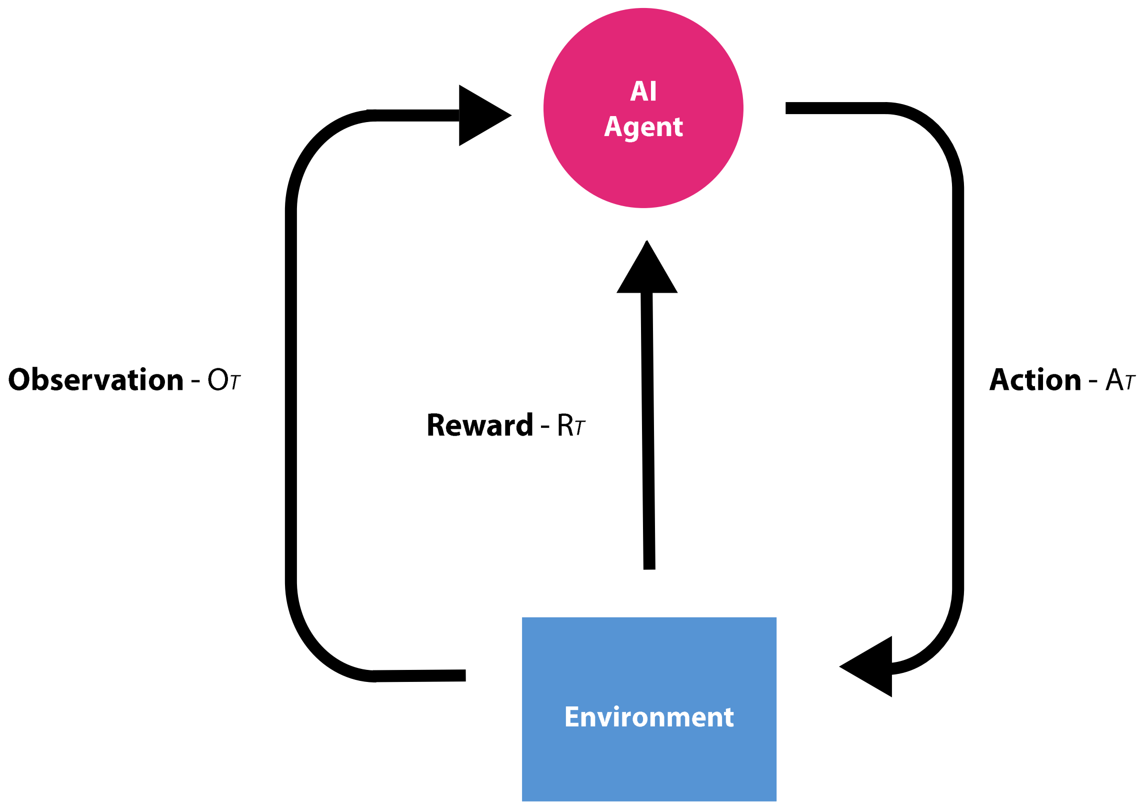
AI Agent
Autonomous system that will teach itself through trial and error.

Environment
World in which the agent acts, learns and aims to influence.

Observation Input
Representation of environment that serves as the basis for the agent's decisions.

KPI Driven Reward System
Essential KPI's/goals that teaches Agent how well he is performing through reward and punishment.

Situational Sketch



IMPACT: agent independently develops strategy to optimize actions towards highest possible result

Example 1: Alphabet´s (Google´s) AlpaGo

Key Elements	Situational Sketch

AI Agent
Alpha Go

Environment
Chinese game Go – the most complex game in the world!

Observation Input
Game environment, position of stones on the board, previous moves

KPI Driven Reward System
Beat opponent!

AlphaGo now beats the best human Go-Player in record time

ZERO G

Example 2: zeroG's DeepSky

Key Elements

AI Agent
DeepSky

Environment
Air Bucks – an airline management computer game.

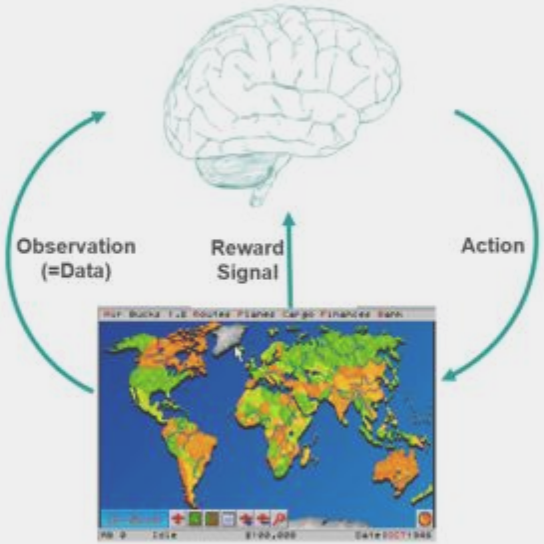
Observation Input
Bank balance, fleet size, landing rights, date, available airport, company worth, etc.

KPI Driven Reward System
Build an airline that will generate biggest company worth within four (game) years.

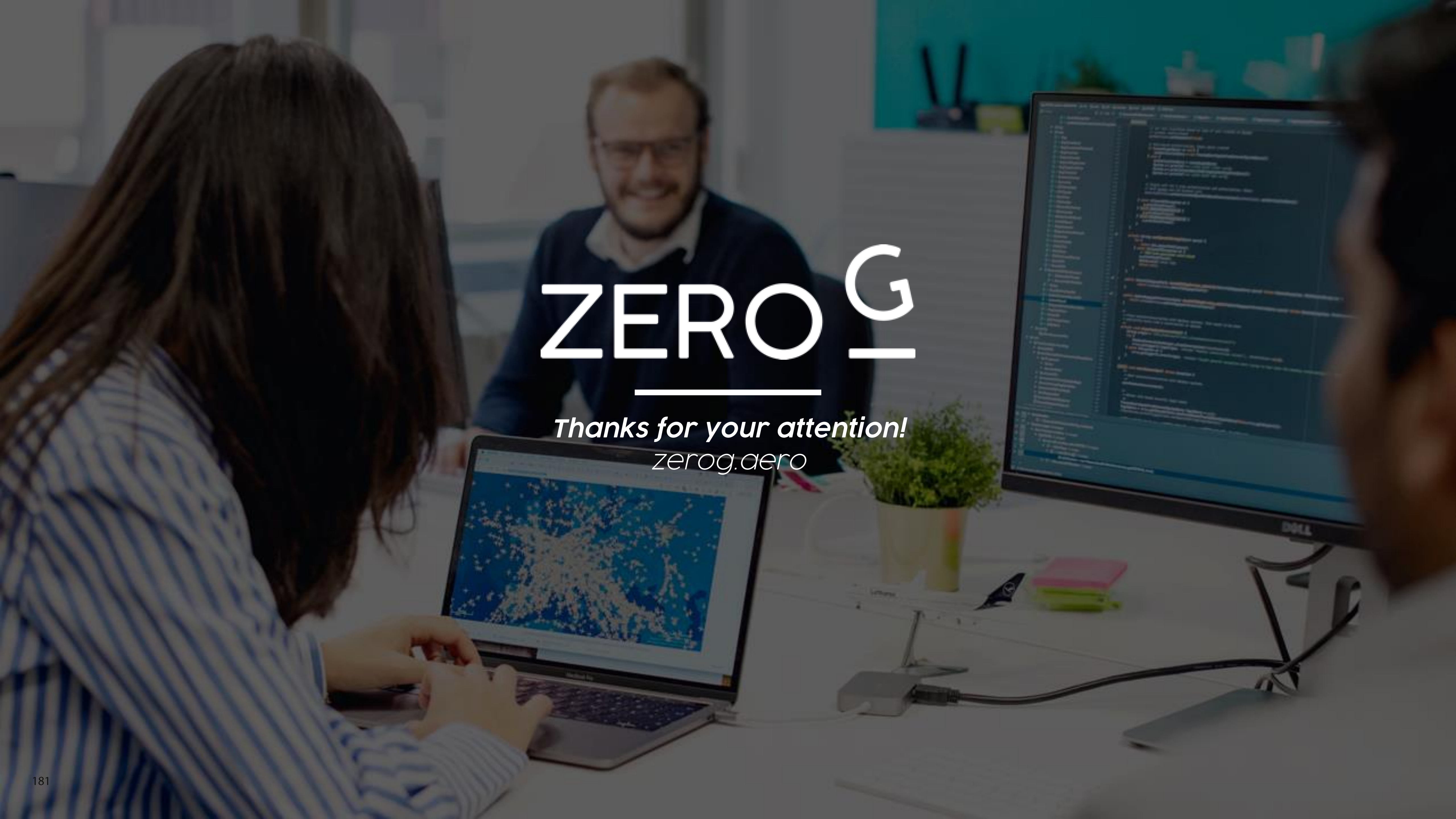
Situational Sketch

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

Step 1: play	Step 2: translating game towards reality	Step 3: Transfer learnings to reality
		

ZERO G



ZERO G

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?

105 AIRCRAFT
+15 MM PAX CARRIED
$2.7 BILLION REVENUE
80 DESTINATIONS
32 COUNTRIES
LAS VEGAS
CHICAGO
SAN FRANCISCO
LOS ANGELES
BOSTON
NEW YORK
MEXICO DF
MIAMI
HAVANA
QUITO
BRASIL
LIMA
SANTIAGO
ARGENTINA
CopaAirlines

ARTIFICIAL INTELLIGENCE

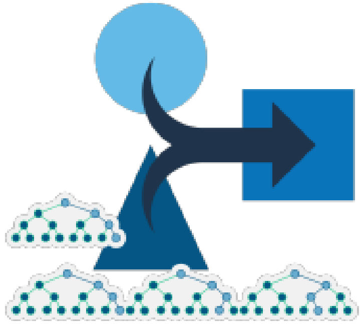
What is Artificial Intelligence?

" 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

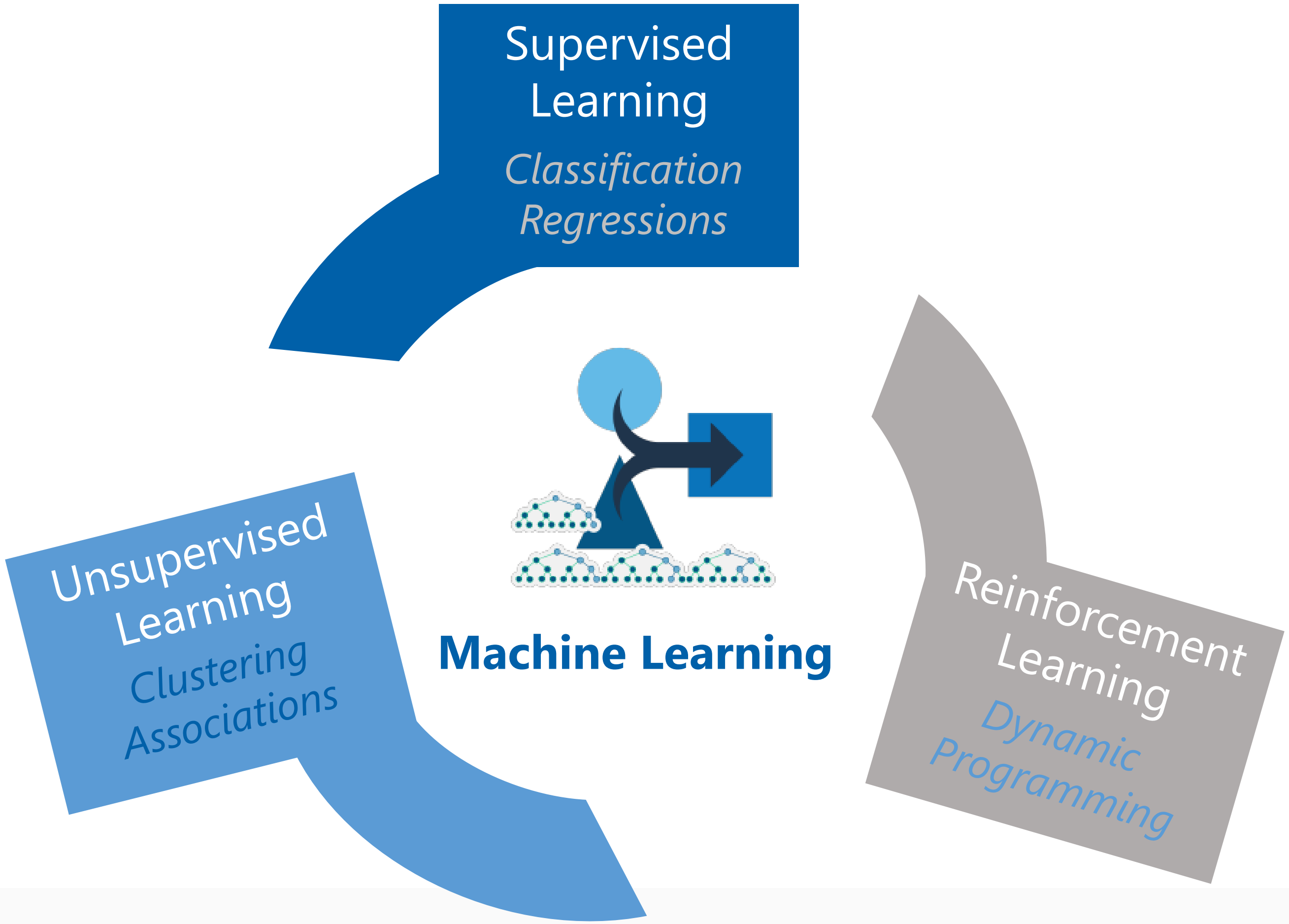
Present Day

Deep Learning

Deep Learning breakthroughs drive AI boom

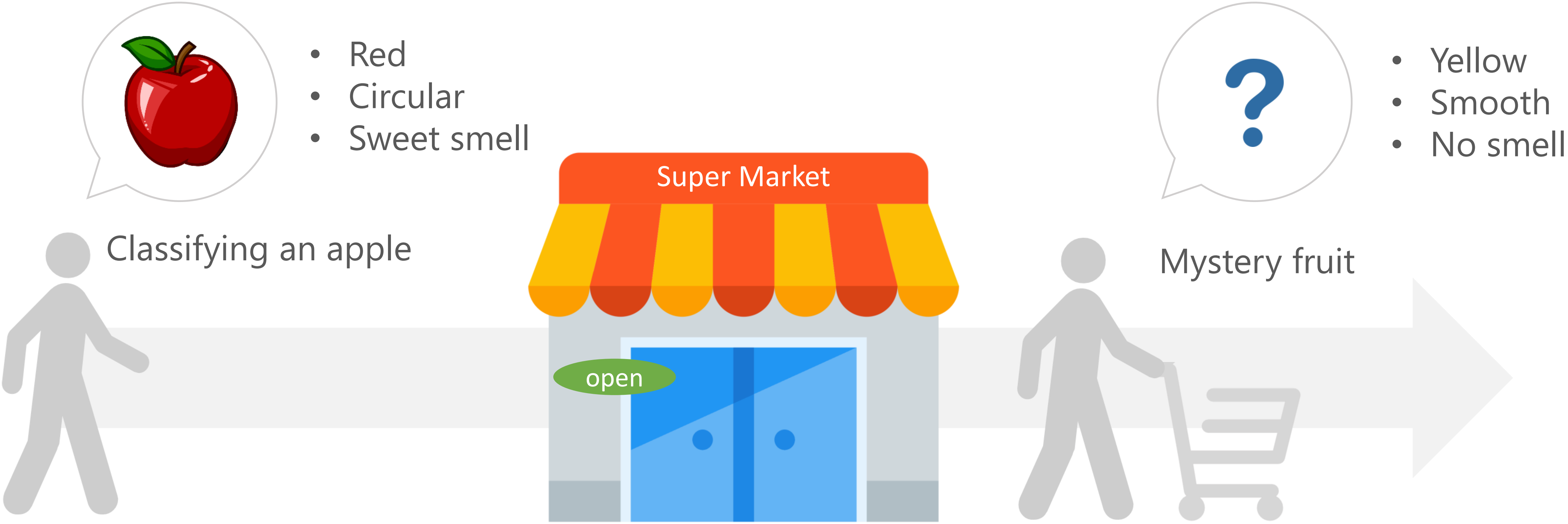
COPA AIRLINES + MACHINE LEARNING

Machine learning is one of the most common types of artificial intelligence in development for business purposes today



CLASSIFICATION ALGORITHMS

Let´s understand how classification algorithms work



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

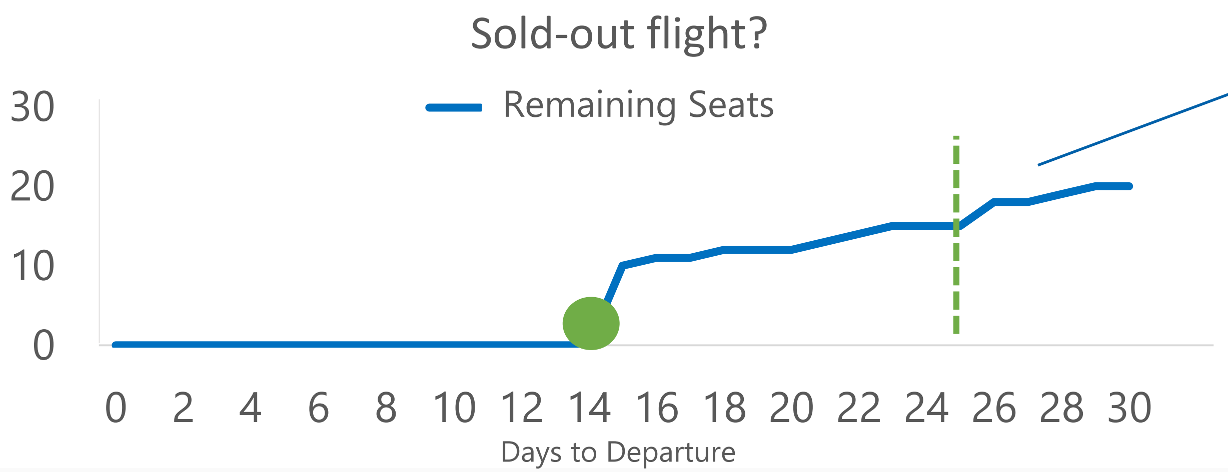
PREDICTING SOLD-OUT TOO SOON FLIGHTS

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?

Flight No	Origin	Destination	Departure	Remaining Seats	Sold-out flight?
1200	PTY	SFO	08/01/2019	0	1

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

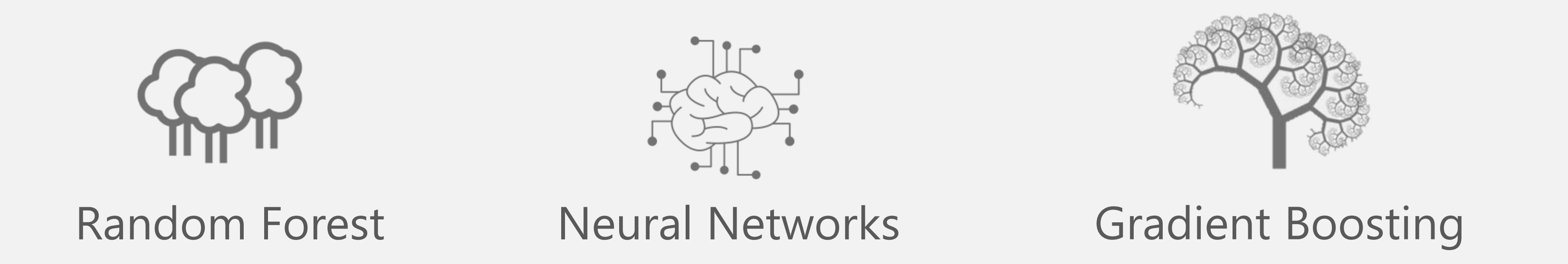


14 days before departure the flight was full

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

Once the variables are selected, test several classifications algorithms:



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

Copa Airlines

CO-BRAND CREDIT CARD ACQUISITION

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

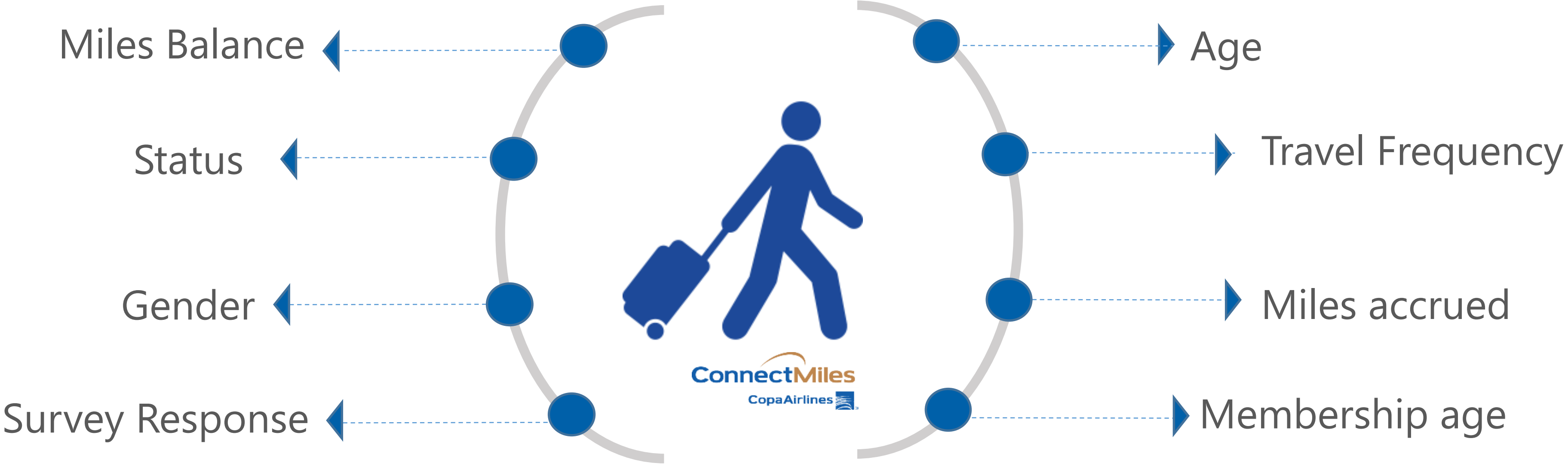
Use miles on flights operated by Copa Airlines and on selected flights operated by Star Alliance member airlines

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



CO-BRAND CREDIT CARD ACQUISITION

The second step consists of developing a model that identifies potential customers

Low probability of acquiring a credit card

High probability of acquiring a credit card

Email marketing

Accelerate growth with new partners

CO-BRAND CREDIT CARD ACQUISITION

A look into the implementation and results

2018

ALGORITHM IMPLEMENTED

~500K

ANNUAL INCREMENTAL REVENUE

EMAILS ARE SENT TO CUSTOMERS

IMPROVE PARTNERSHIPS

EXPANSION OPPORTUNITY IN NEW MARKETS

INCREASE PRESENCE IN COUNTRIES WITH NO PRESENCE

ENCOURAGE & DRIVE CUSTOMER ENGAGEMENT

ALIGNING BUSINESS STRATEGIES AND GOALS

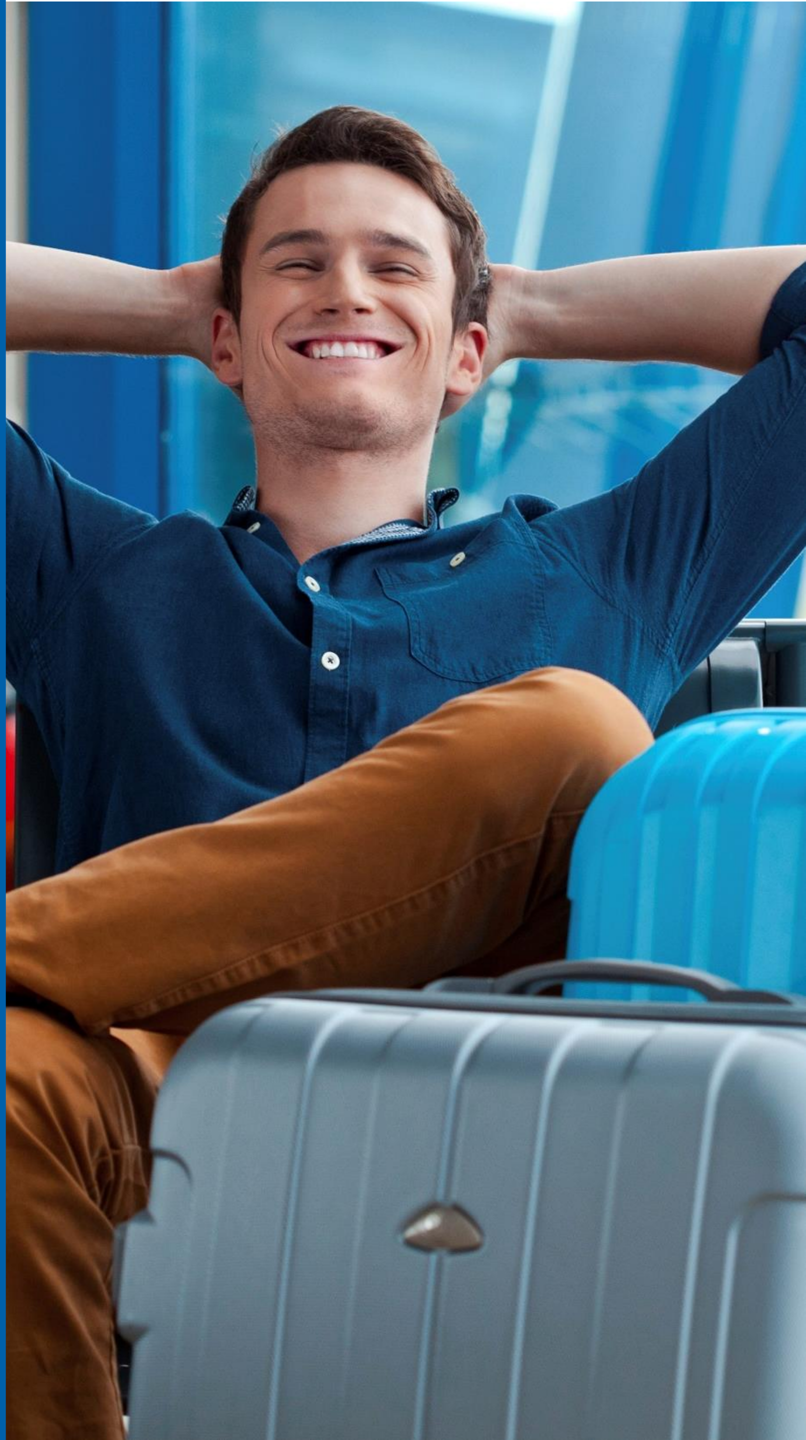
AI DRIVING REVENUE STREAMS

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!

CopaAirlines

Maria Agustina Toso
mtoso@copaair.com

Key Takeaways and Closing Remarks

Houman Goudarzi, Head of BI & Industry Engagement, IATA

IATA AVIATION DATA SYMPOSIUM

ATHENS, GREECE 25 – 27 JUNE 2019

AI Lab

Sponsored by:

OpenJaw

IATA