# Artificial Intelligence and Machine Learning in Aviation

# Opening Remarks

Henk Mulder

Head, Digital Cargo, IATA

Track Sponsor

OpenJaw

# The Data Excellence Science and Artificial Intelligence

Dr. Walid El Abed

Founder and CEO, Global Data Excellence

Track Sponsor

OpenJaw

Global Data Excellence

Maximize the Business Value of Enterprise Data

Berlin - Thursday, 21 June 2018

# IATA Conference - Artificial Intelligence and Machine Learning in Aviation

powered by DEMS©

# DR. WALID EL ABED

## FOUNDER & CEO OF GLOBAL DATA EXCELLENCE (GDE)

- Computer scientist and linguist
- Artificial Intelligence Doctor
- Creator of the Data Excellence science and the Data Excellence Management System© (DEMS) platform

# THE DATA EXCELLENCE SCIENCE AND ARTIFICIAL INTELLIGENCE - BUSINESS EXCELLENCE AUTOMATION AND THE HUMAN-COMPUTER DIALOGUE

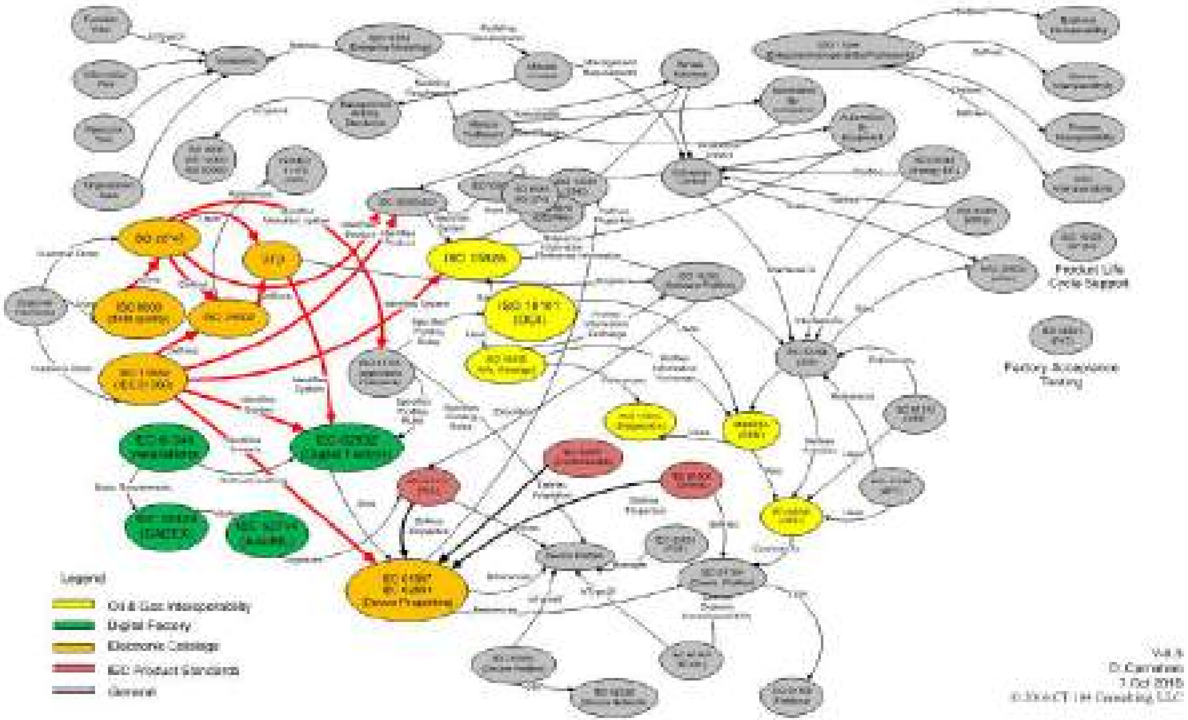
## ‘Govern by value©’

## The new paradigm shift

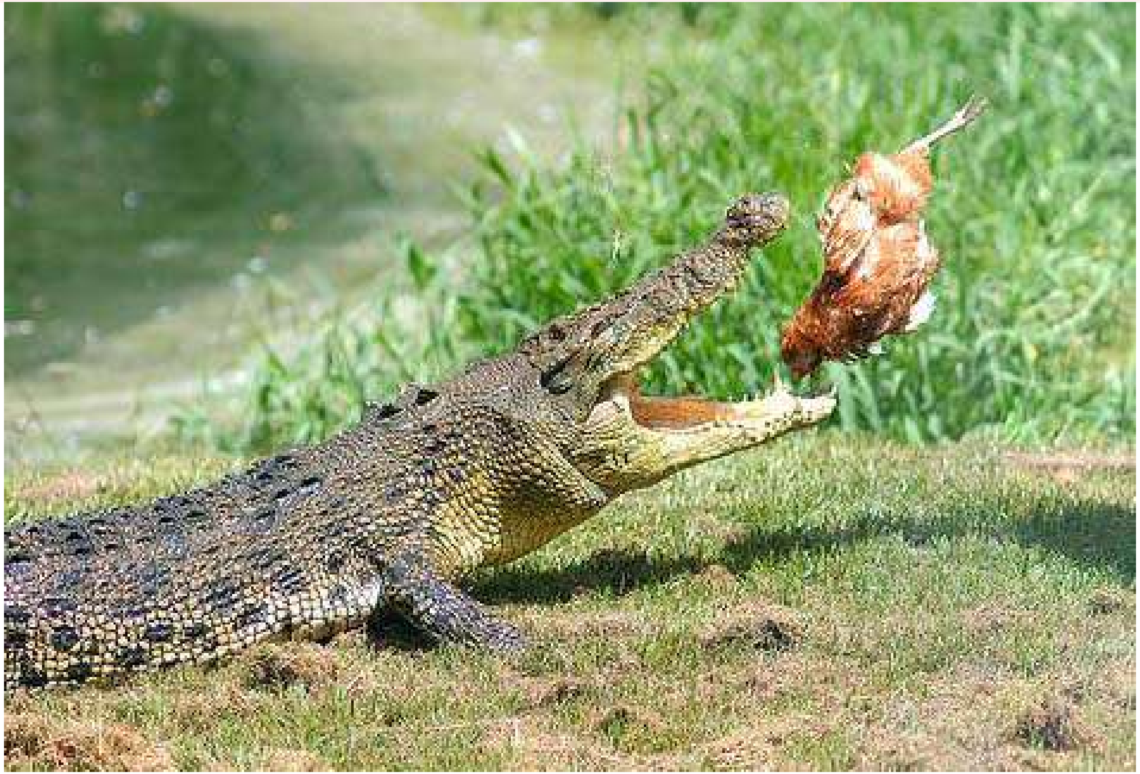
# THE STORY OF THE DATA EXCELLENCE SCIENCE

## FITS FOR ALL BUSINESS TYPES, IT LANDSCAPES AND MATURITY LEVELS

# THE CHALLENGE OF THE DIGITAL ERA

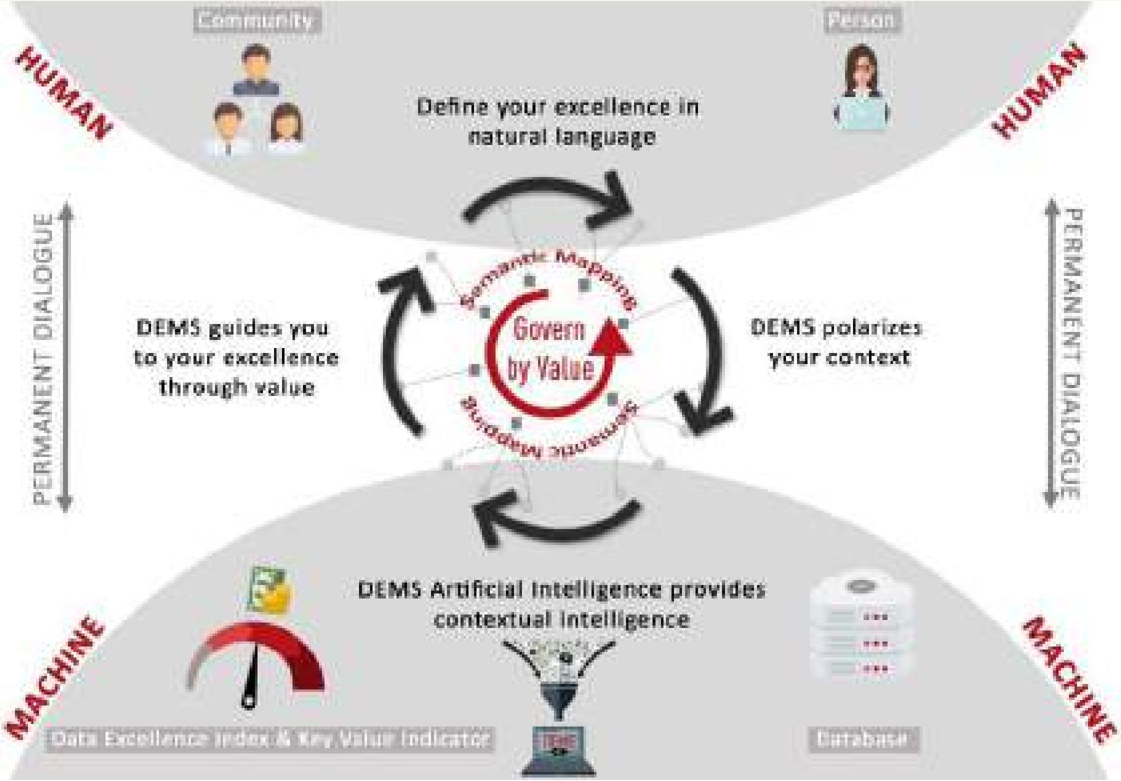


# ARE WE READY FOR IT?



# POSSIBLY IF WE AUTOMATE BUSINESS EXCELLENCE AND GOVERN BY VALUE?

# HUMAN AND MACHINE RECONCILIATION



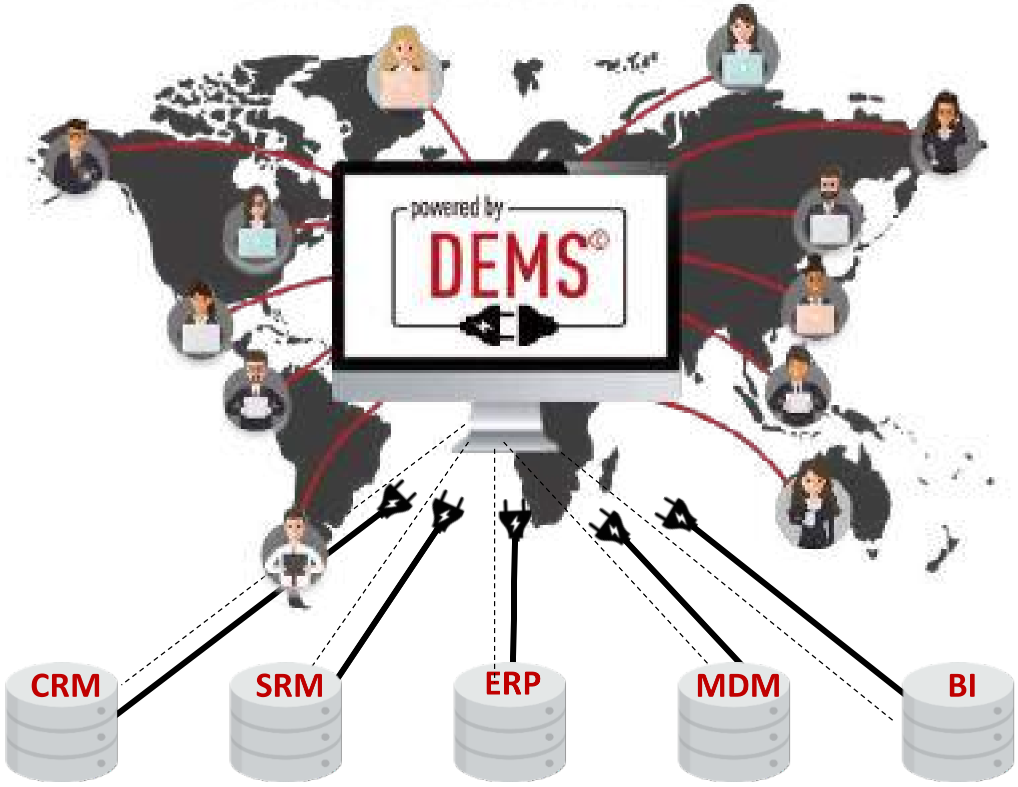
# WHAT TYPE OF INTELLIGENCE TO WIN THE DIGITAL ERA? :

ὠἐἀ

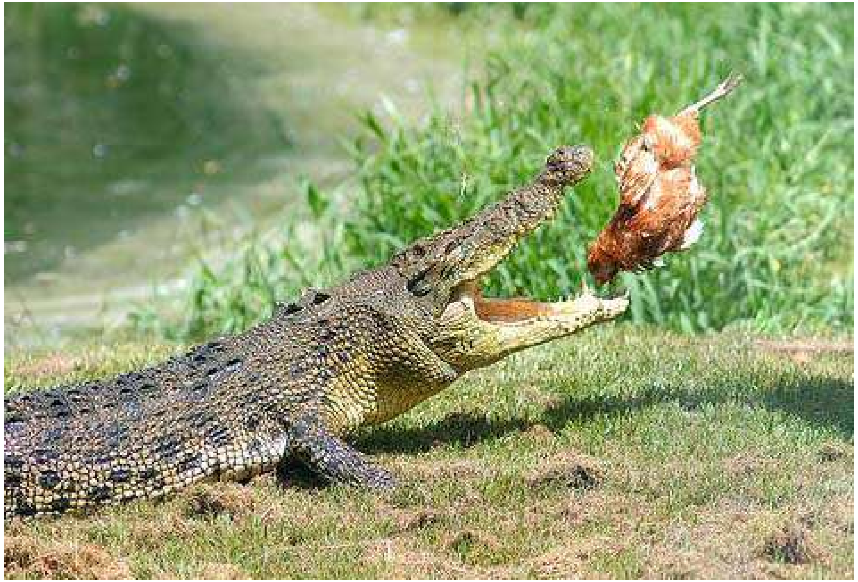
## EIGHT SMART LIMBS PLUS A BIG BRAIN ADD UP TO A WEIRD AND WONDROUS KIND OF INTELLIGENCE

# CONNECT BRAINS ACROSS THE VALUE ECOSYSTEM

## MANAGE DATA AT SOURCE



# THE PARADIGM SHIFT IN THE VALUE CREATION ECOSYSTEM



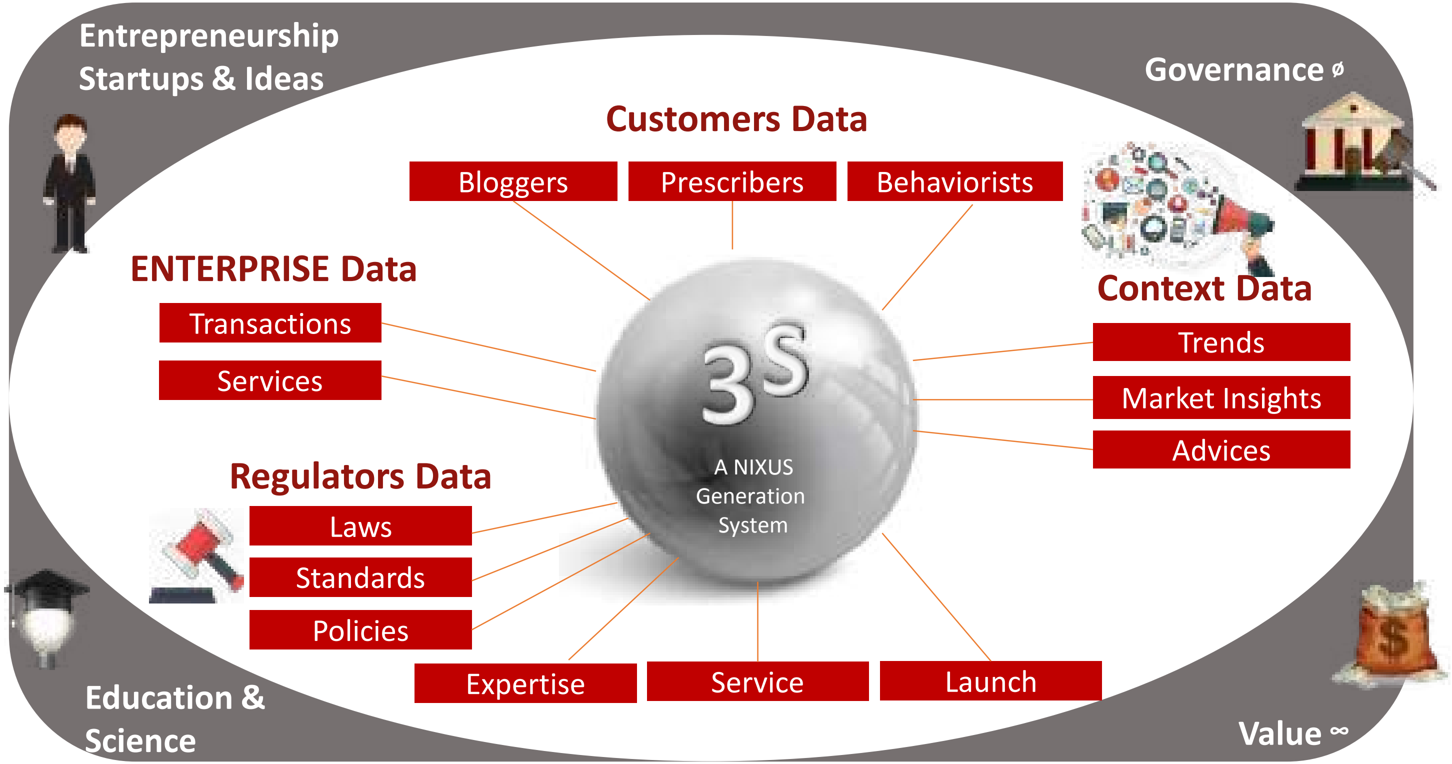
# A COLLABORATIVE FRAMEWORK AND SYSTEM TO RECONCILE HUMANS AND COMPUTERS FOR THE CREATION OF A SOCIETY OF EXCELLENCE AND TO “GOVERN BY VALUE”

## ‘Govern by value©’

## The new paradigm shift

# SMARTLAND TO EXPLORE "EXPONENTIALITY"

## SUSTAINABLE VALUE CREATION - (SIMPLIFY, STANDARDIZE AND SHARE) SHARE




***Semantic meta model***
***(Ecosystem and community)***

# Thank you

**Website: www.globaldataexcellence.com**
**Twitter: @GDE_DEMS**
**Email: info@globaldataexcellence.com**

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# An Overview of Air France–KLM Artificial Intelligence Journey Roadmap


Wail Benfatma

Program Manager, Artificial Intelligence

Air France-KLM


Track Sponsor

OpenJaw

AIR FRANCE KLM

Powered by Cognitive

# Artificial Intelligence Journey

Waïl BENFATMA

# AIR FRANCE KLM GROUP

**314** destinations in more than 116 countries

**80 595** people

**552** aircrafts

GRO

**25,8** Billions € in 2017

**2 000** Aircrafts (E&M)

**200** Airlines are customers worldwide

**98,7** millions of passengers in 2017

# AI program : an IT initiative

## Lead by CIO Office and OR/DS dept

### Ambition

Reinforce AFKL value proposition by offering cognitive services to customers and employees

Impact AFKL profitability substantially by optimizing processes and transform organizations

### Objectives

Create awareness on AI through use cases

Coordinated different organization around similar initiatives

Reinforce internal capabilities

# AI application domains

**AUGMENT**

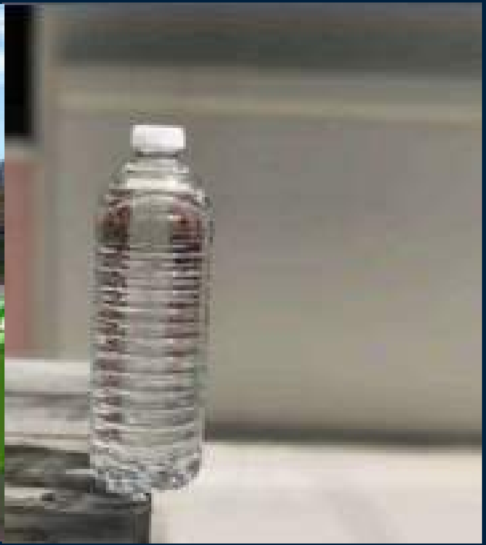

Check-in counter
Follow the line

MRO AIR
ARTIFICIAL INTELLIGENT REALITY
AIR
AIR
AIR

# AI application domains

**AUGMENT**

**PREDICT**



Prognos®

AIR FRANCE KLM

# *AI application domains*

**AUGMENT**

**PREDICT**

**UNDERSTAND**

# Conversational Initiatives

*Through the Traveler journey*

**Inspirational Bot AF :** ●
Find your next destination using your preferences

**Booking Bot KL :**
Reserve your next KL flight on the BB

**Bag Bot AF :**
Ask any question regarding bags

**Disruption Bot AF :** ●
Get supports and vouchers when a disruption occurs on your flight

**Flight Program AFKL:** ●
Get information on flights and destinations

**KL Packing bot :**
Voice assistant helping to pack your bags

**Flight Status AFKL:** ●
Get vocal status on your flight with Alexa

**Bag bot AF:**
Ask any question about your bag on Google Home


● *Project initiatives*

# *AI application domains*

**AUGMENT**

**PREDICT**

**UNDERSTAND**


**AUTOMATE**

# Type of automations

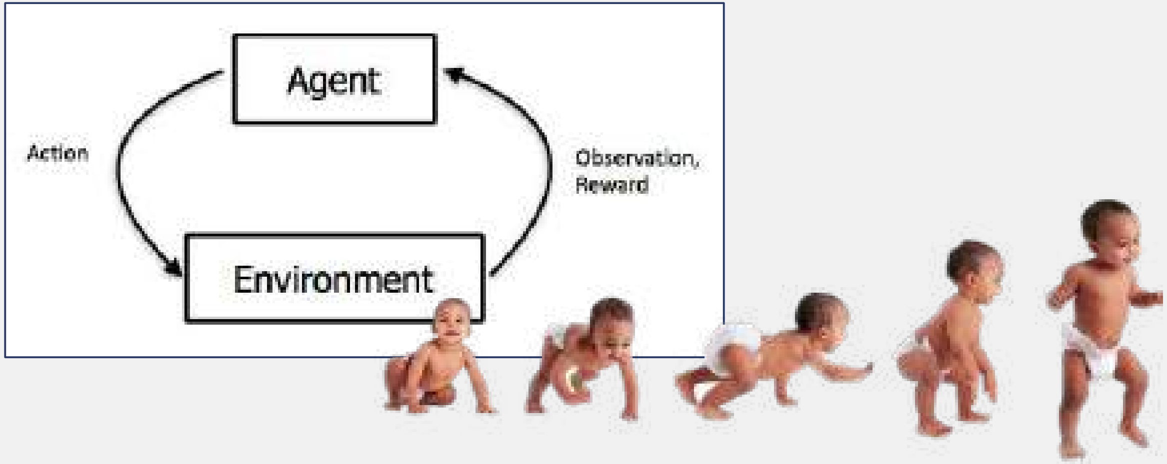
MORE PROVEN — INCREASED “INTELLIGENCE”

| Desktop Automation | Robotic Process Automation | Digital Assistance | Smart Automation |
|---|---|---|---|
| Manual operator initiates sequence of automated steps | Scheduled virtual worker mimics execution of manual user's repetitive activities without intervention | Computer-generated conversations to answer questions or queries and provide guidance. | Artificial intelligence & automation technology that can replace more human judgement-driven tasks |

TRANSACTIONAL — JUDGEMENT-DRIVEN

# Reinforcement Learning

Reinforcement Learning allows machines and software agents to automatically determine the ideal behavior within a specific context, in order to maximize its performance






AIRFRANCE KLM

# Type of automations : Cargo Repair case

# Introduction to Repair

Remaining capacity after passengers is allocated to cargo

Sometimes, shipments cannot go in their associated flight: Repaired bookings


Multiple causes:

- Late shipment
- Cancelled flight, strike, …
- Wrong overbooking
- Priority bookings or previous repairs

Repairs must then be reallocated to new flights : Time consuming task, no previously existing process

How to reallocate the repairs?

# Introduction to Repair


Today :

- Analysts are doing it manually
- Time consuming (10-15% of their time)
- Not efficient (multiple application to dig into)
- Solution not optimal

Opportunities :

- Let analysts focus on added value tasks
- Time saving
- Good quality of solution
- Better quality of service

# Cargo Smart Repair

## Historical data

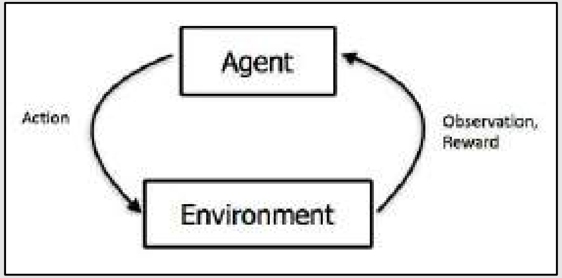
First idea was to look at historical data to apply Machine Learning algorithms; but it was not usable regarding the disparity in the process

- We needed to explore a new domain : simulations

**Automatize cargo repair process**

## Simulations

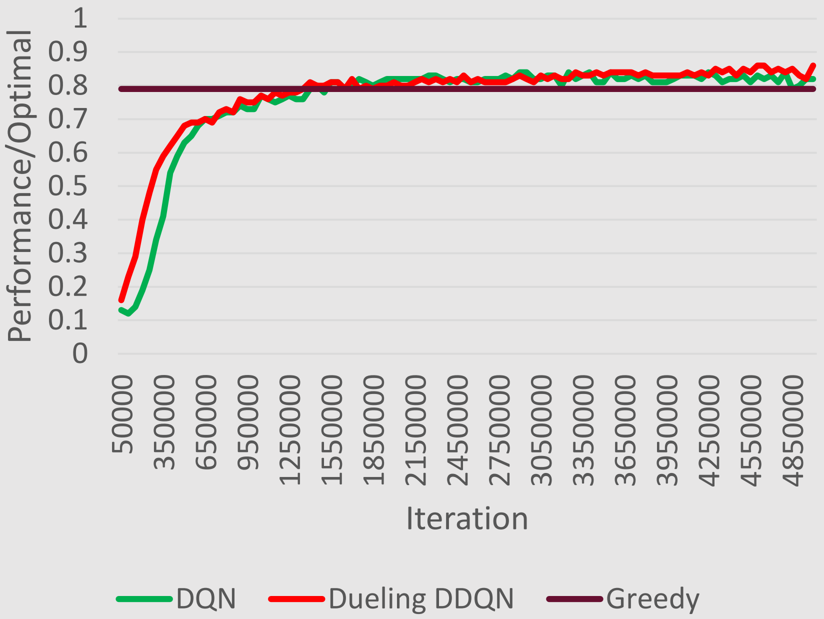
- Create fictive flights
- Create fictive bookings/events
- Environment representation :
  - **State:** Booking configurations and available capacities of flights
  - **Actions:** Remove booking of the category volume and put it in a backlog
  - **Rewards:** Penalty corresponding to the removed booking category



# Timeline & Results

## Timeline

- First discussions in oct 2017 to define the use case
- Historical data exploration in nov-dec 2017
- Modelisation and simulations 3 months jan to march 2018
- Proposal in april 2018




## Nexts steps

- More training, tuning of the model, modelisation
- Run a pilot this summer on selected flights
- Implement the solution to give an advise to analyst before the end of the year : real time data + integration

# Artificial Intelligence in Airlines Customer Service

Brian Lewis

CTO, OpenJaw

Track Sponsor

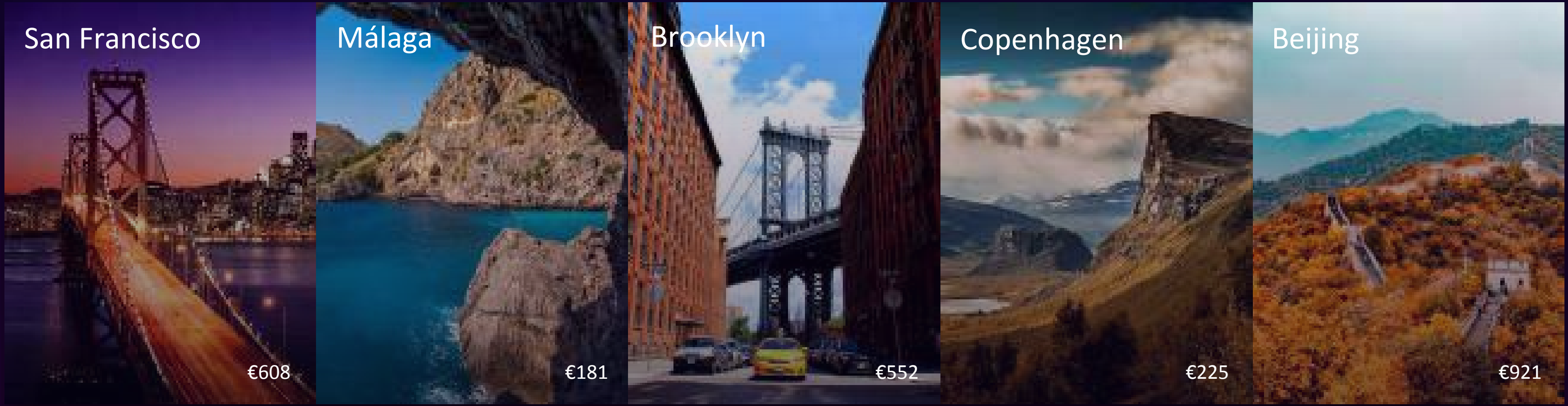
Brian Lewis, Chief Technology Officer

# Artificial Intelligence in Airlines Customer Service

OpenJaw

A TravelSky Company

# Inspiring your customers




Airlines often focus on finding the perfect flight for their customers

# Moving beyond air fare


Applying retailing techniques
across the full customer journey

# From the time of thinking about the trip to the journey home

# The full customer journey

First Wallet

Second Wallet

Inspiration

Research

Shopping

Booking

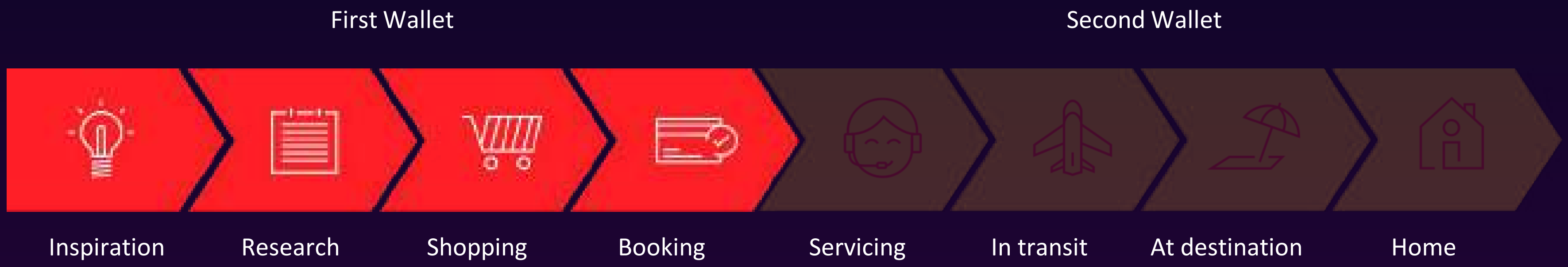
Servicing

In transit

At destination

Home

# The full customer journey

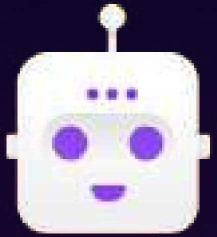


# The full customer journey

First Wallet

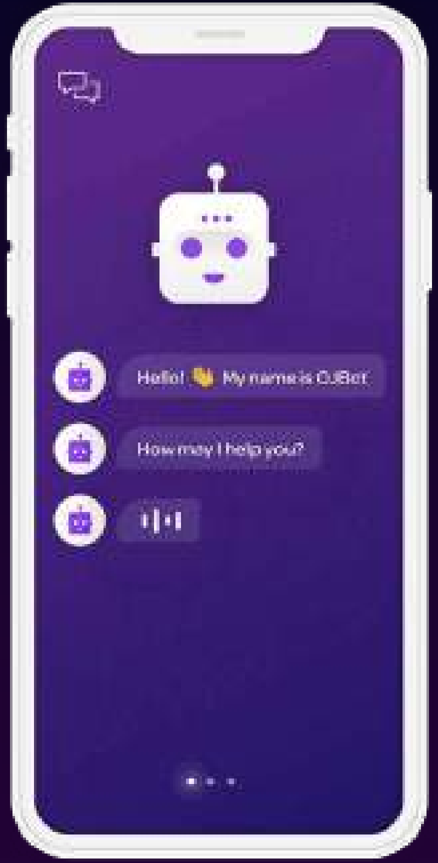
Second Wallet

Inspiration | Research | Shopping | Booking | Servicing | In transit | At destination | Home



# Let’s talk about Artificial Intelligence & Chatbots

Artificial Intelligence allows airlines to better engage with customers through automated servicing and ancillary product offerings



We deliver these services through messaging applications

# The reach of these messaging applications

WhatsApp & FB Messenger
100+ billion messages p/d

WeChat
230+ billion messages p/d

Meet customers where they are

# Customer Centricity

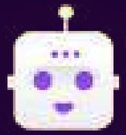
# Enhance Cost Efficiency

- A small set of queries occupy the majority of call centre time

- Chatbots can handle basic queries about common error scenarios

"Not only do chatbots help make reservations, they are also used to respond to common questions and requests.

This way, companies can free up their customer care staff and involve these people only when a chatbot can't handle a request."



Source: altexsoft, July 2017

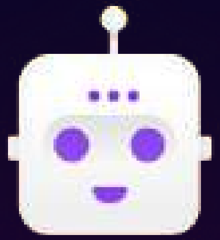
# Efficiency & experiential gains


Average handling time

Agent response time

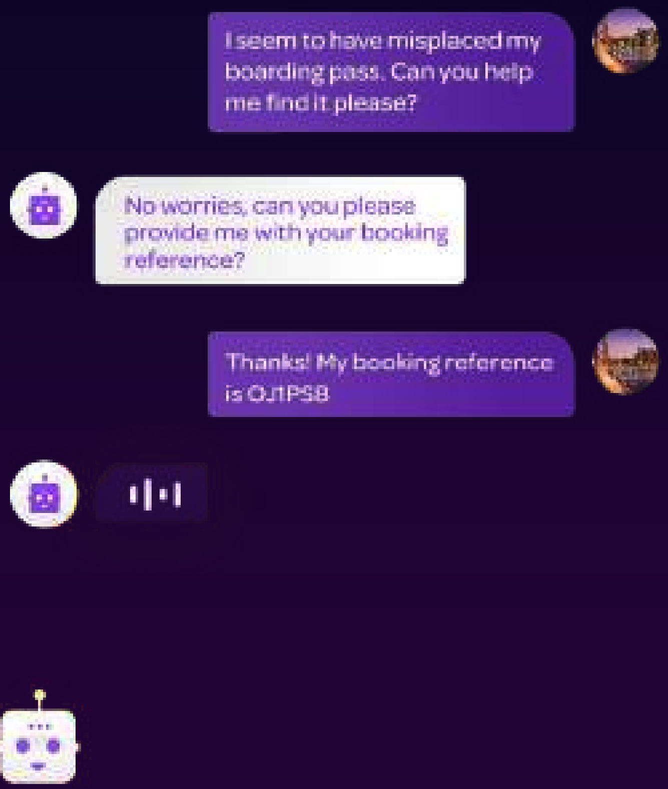
First response time

Cost efficiency per interaction via Chatbot

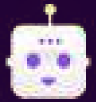


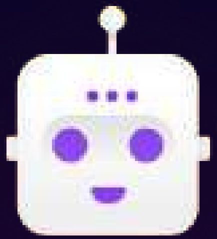
# How does this work?

Offering a helping hand…




Helping you choose the right seat…

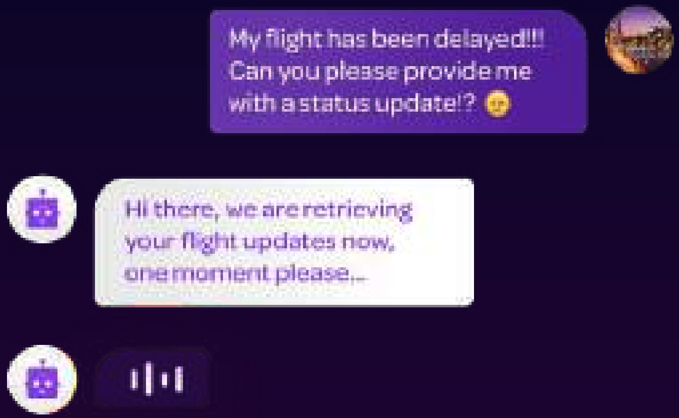



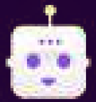


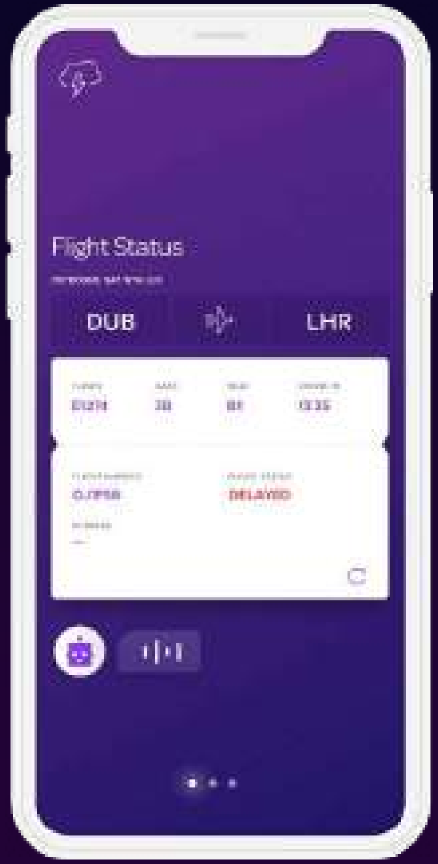
This goes beyond everyday servicing
to solve unexpected circumstances


22
22

Keeping you aware of disruptions…





t-Social
OpenJaw

Airlines use our t-Social Platform powered by IBM Watson to automate customer engagement

# t-Social Chatbot powered by IBM Watson

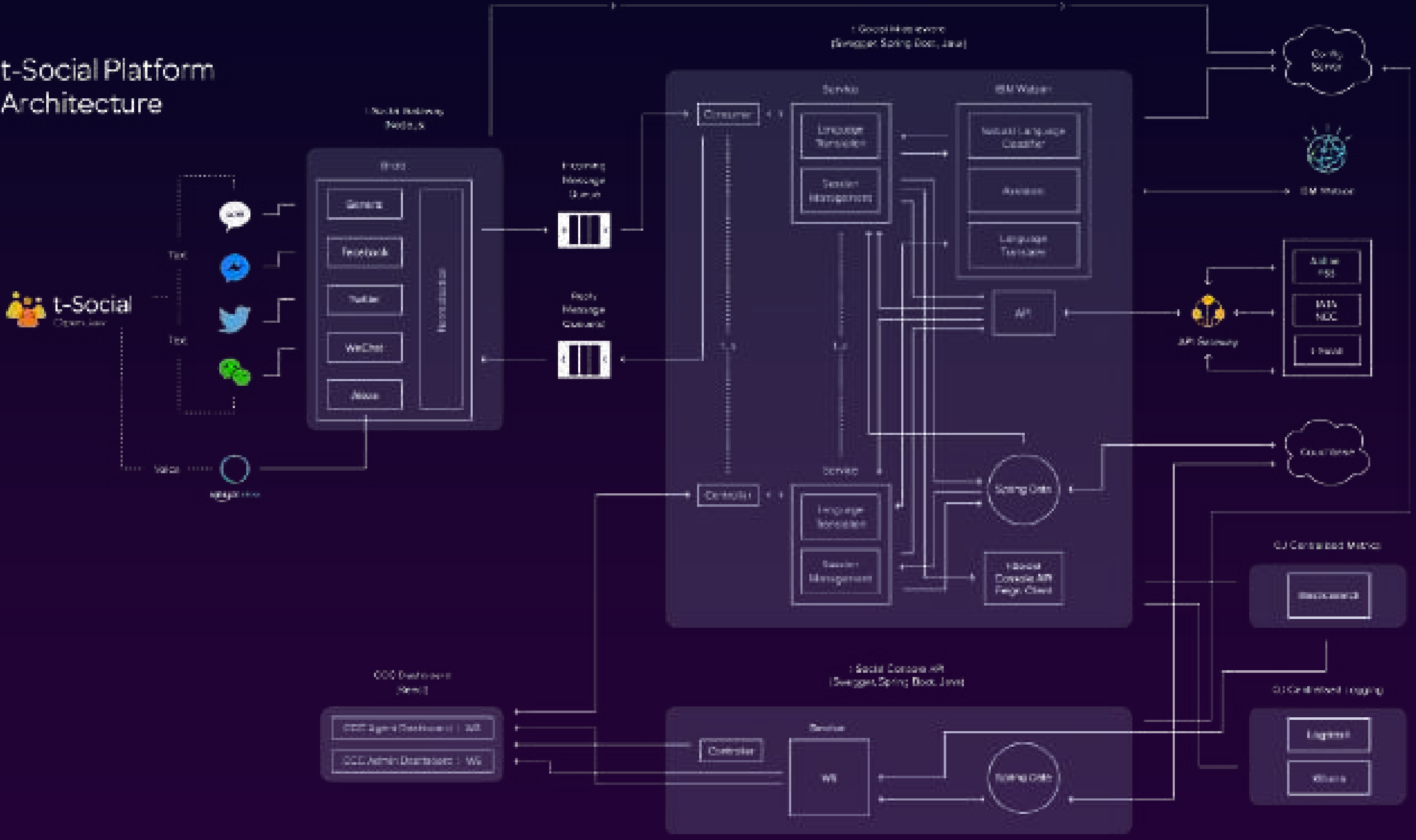
Most accurate system of Intents and Entity recognition (over 80%)

Integrated Answer Store and Conversation Flows

Framework designed for rapid roll out

Support for multi-language implementation

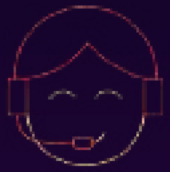
# t-Social Platform Architecture



IBM Watson typically handles 80% of users conversations

# What about the other 20%?

# t-Social Management Console

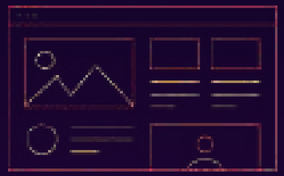


## Agent Escalation

Intent based workflow management

## Conversation Search

Interrogate, assign, review and resolve

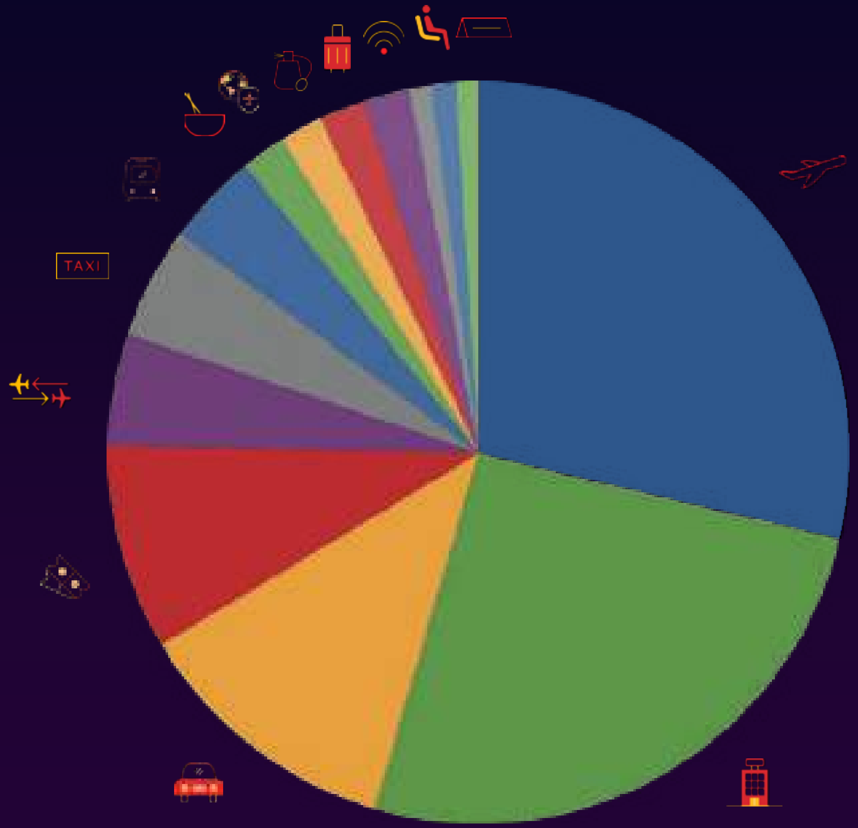


## Social Dashboard

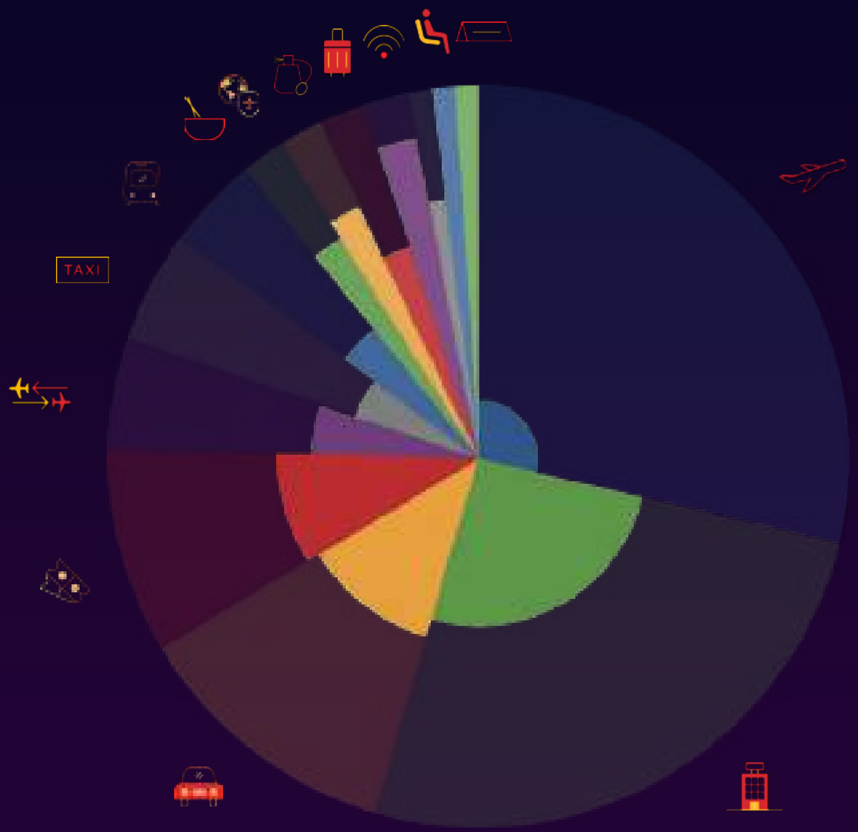
Instrumentation and visualisation

How do we capture additional revenue for airlines across the customer journey?

# Revenue mix of flights and ancillary products



# Margin mix of flights and ancillary products



Create a Customer Centric Chatbot

That is informed by Big Data analytics

Allowing the presentation of context-aware offers and conversations

With integration to downstream APIs

And a seamless escalation path

Brian Lewis, Chief Technology Officer

# Thanks for listening!

Brian.Lewis@OpenJawTech.com

@BrianLewisCTO

BrianLewis68

www.linkedin.com/in/brian-lewis

OpenJaw

A TravelSky Company

# A Journey from Data to Insights

Daniel Perez
AI and Data Engineer, Amadeus

Track Sponsor

OpenJaw

# Networking Break in Foyer

amadeus

# A journey from data to insights

## The ML practitioner perspective

Daniel Perez
AI and Data Engineer
June 2018
Berlin



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# Data

... why?

# Operational efficiency

## Operational efficiency

## Customer centricity


The Silos

# The data silos



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# The data silos




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# The data silos




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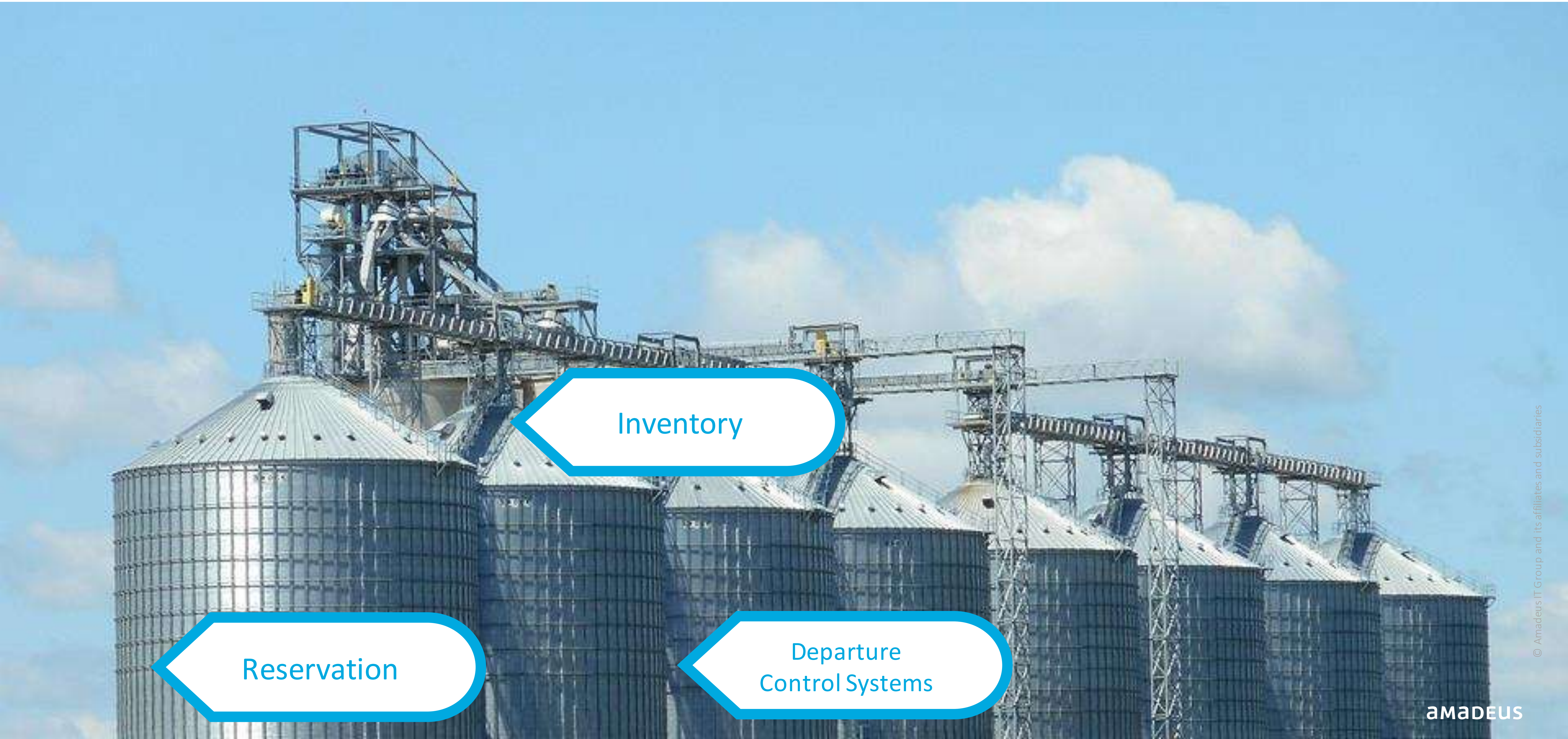
# The data silos



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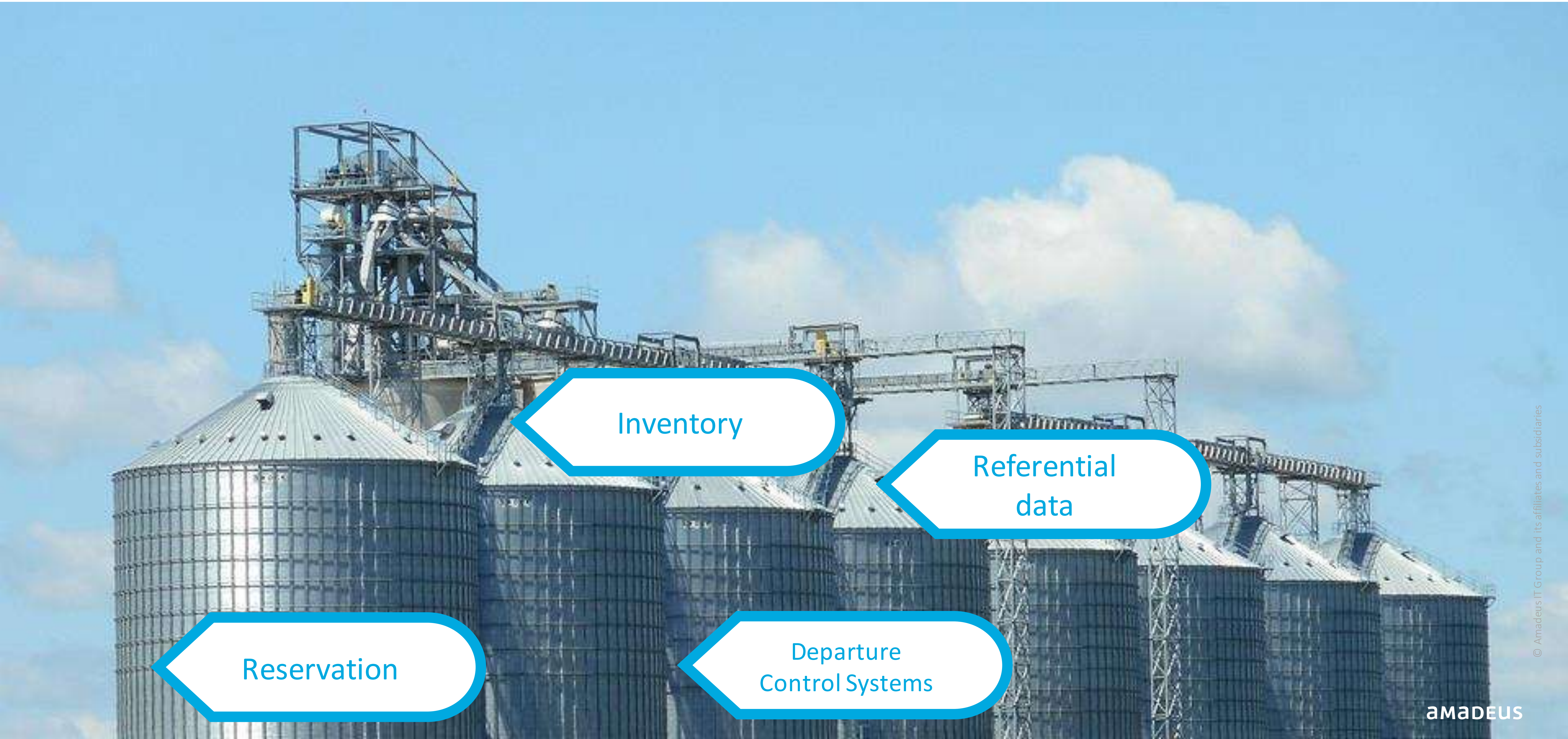
# The data silos



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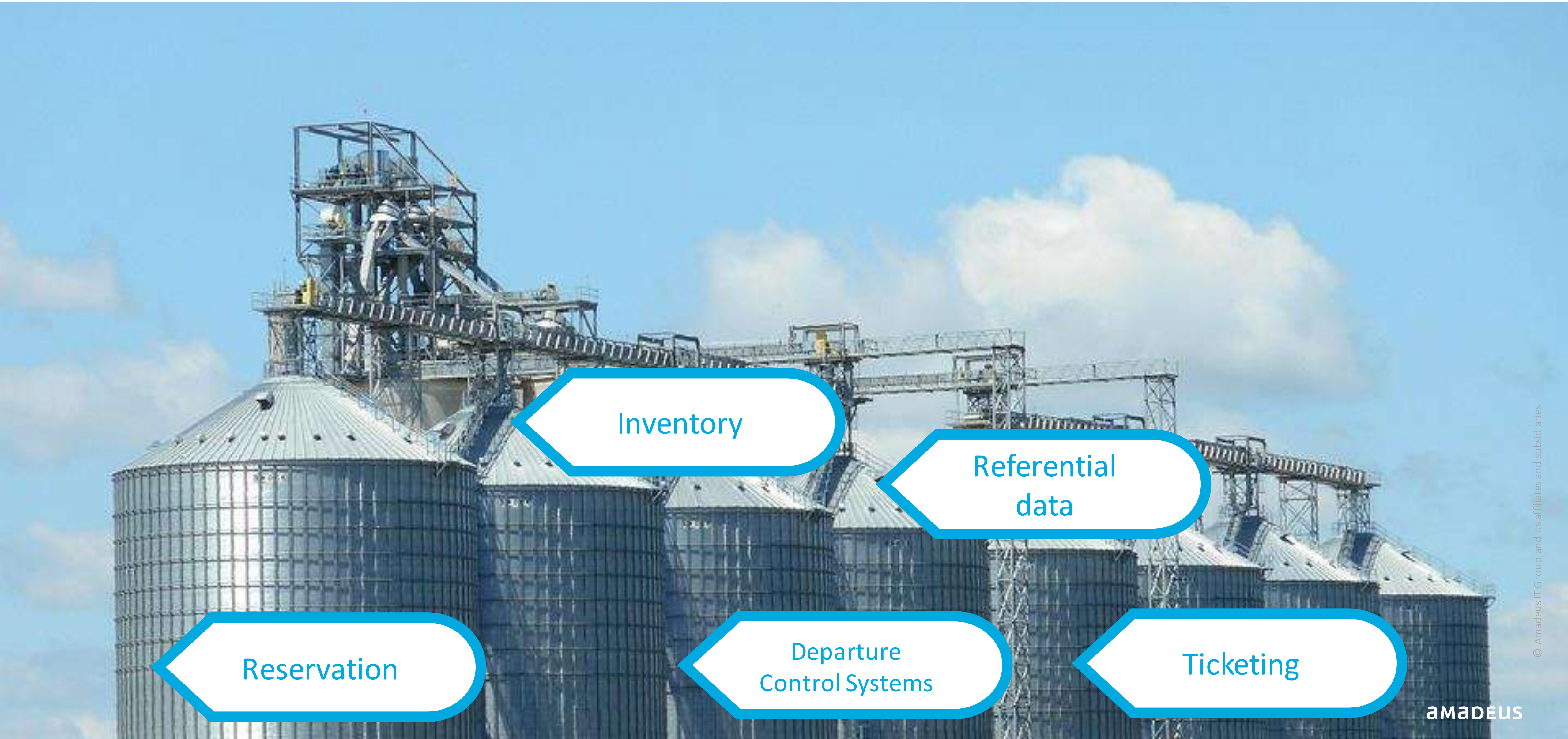

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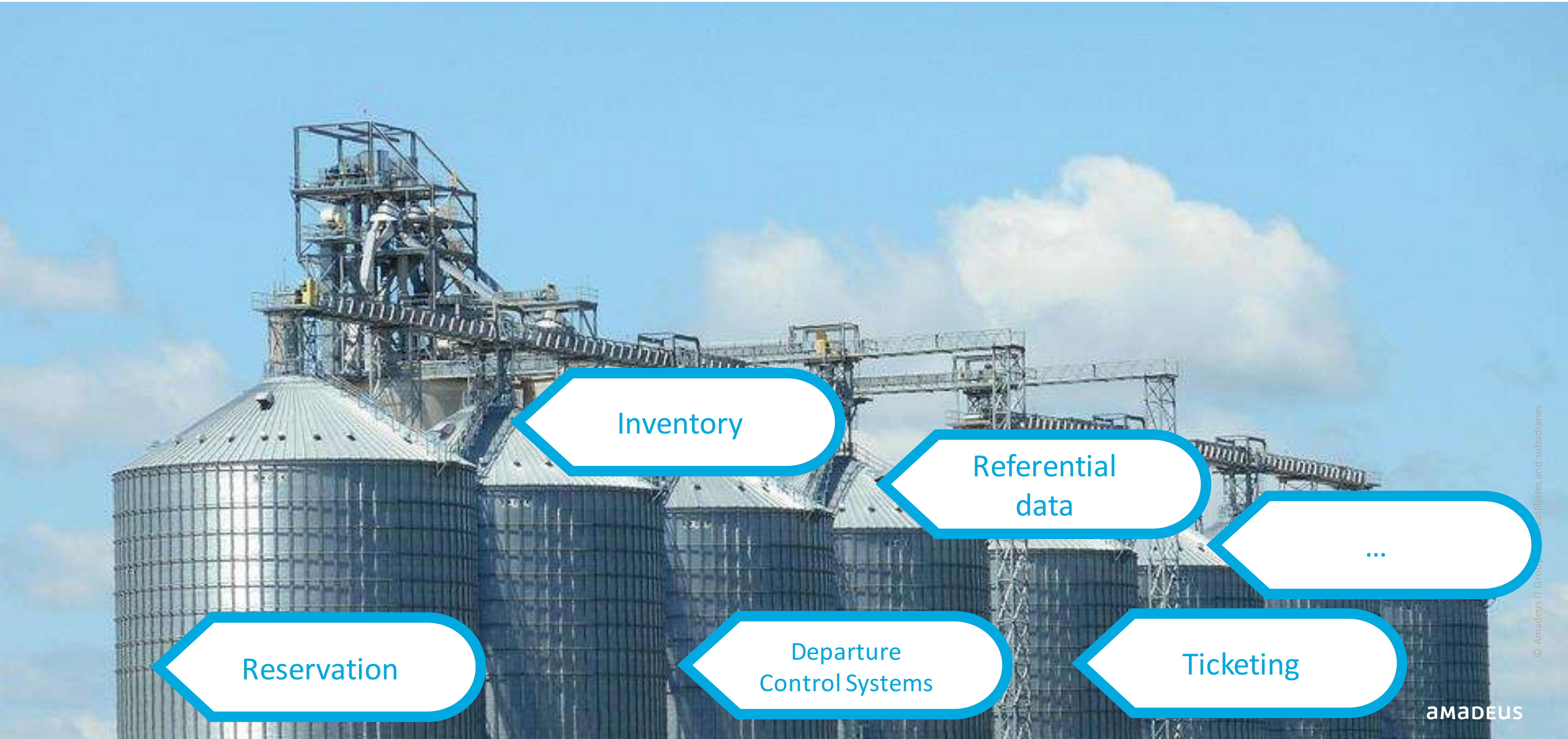

# The corporate silos

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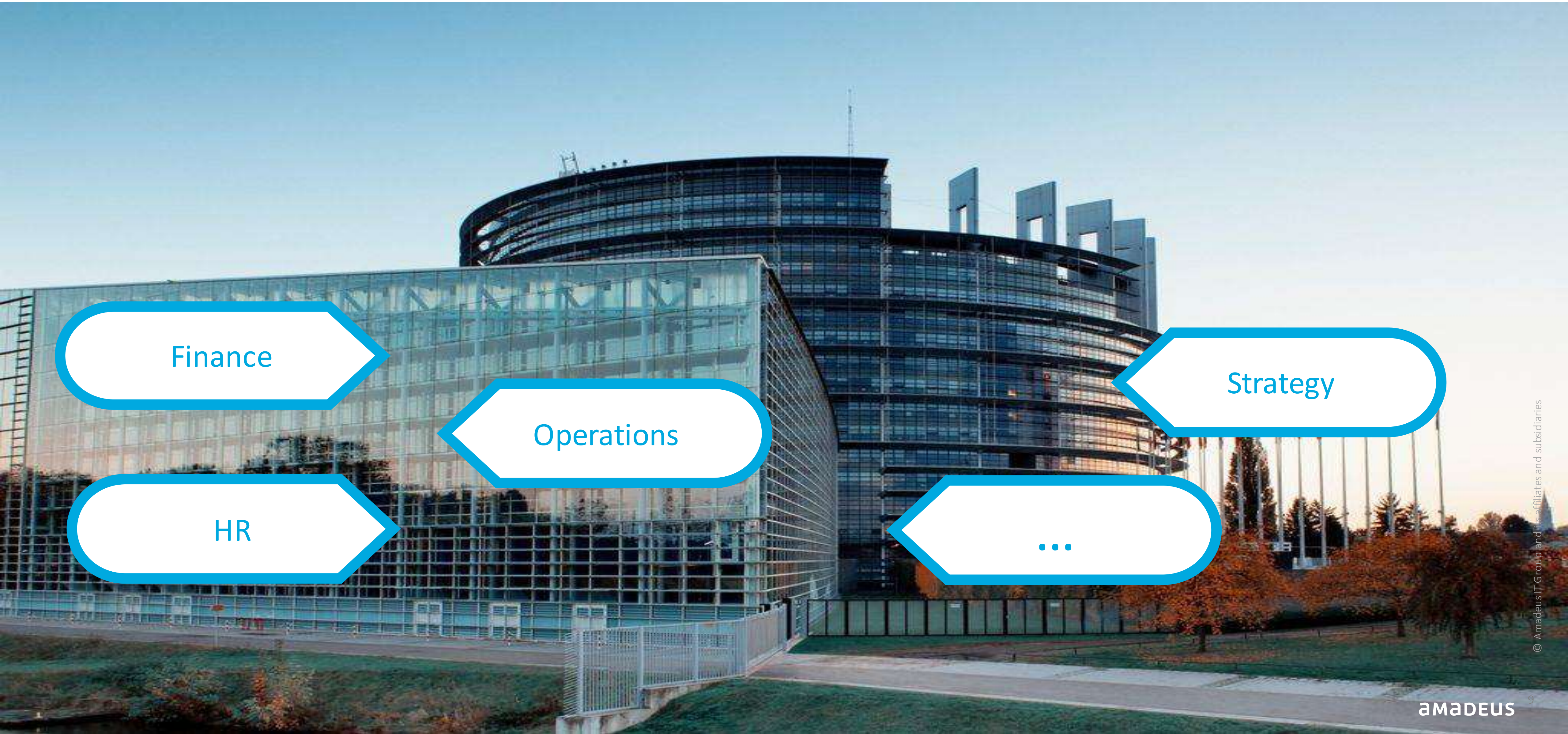

# The functional silos

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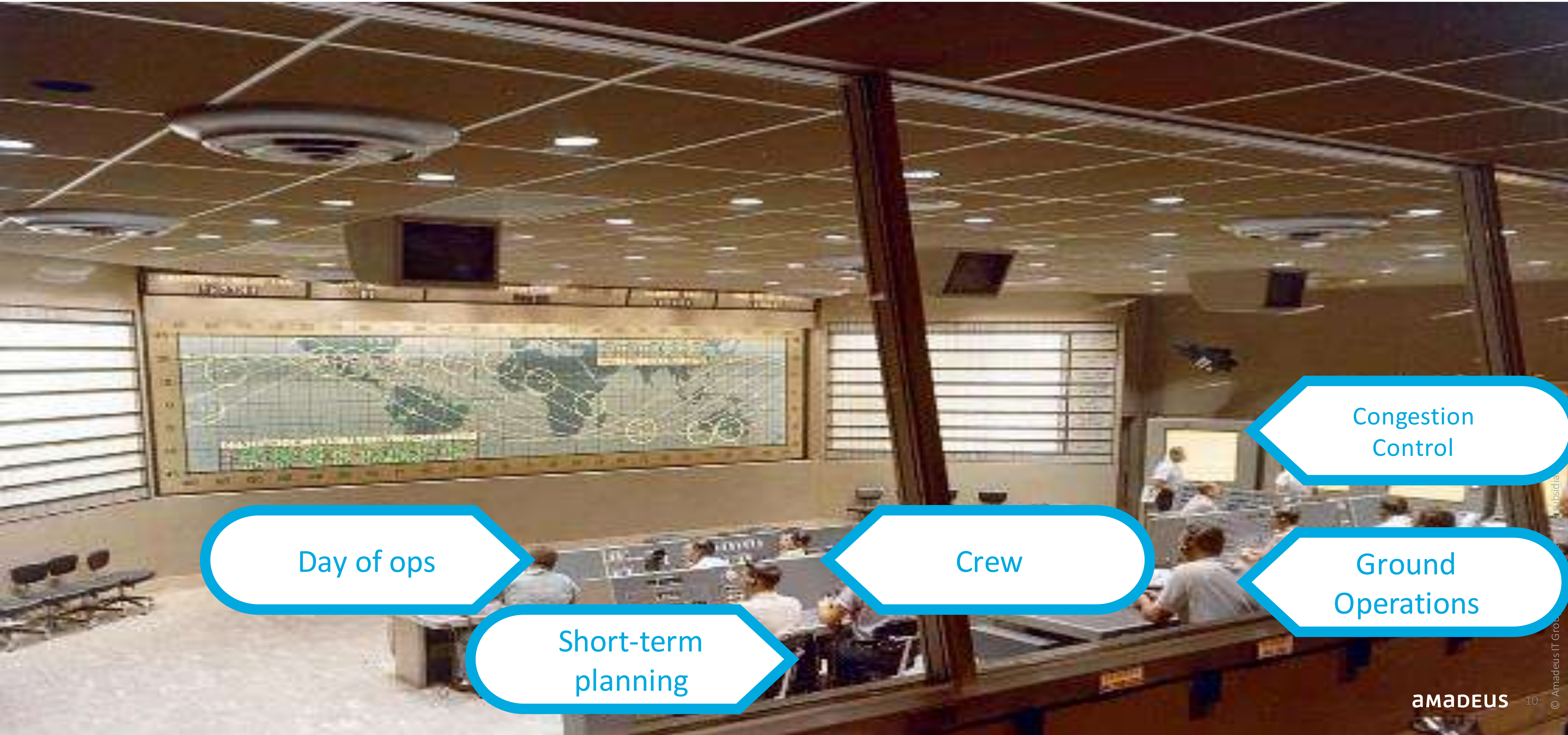

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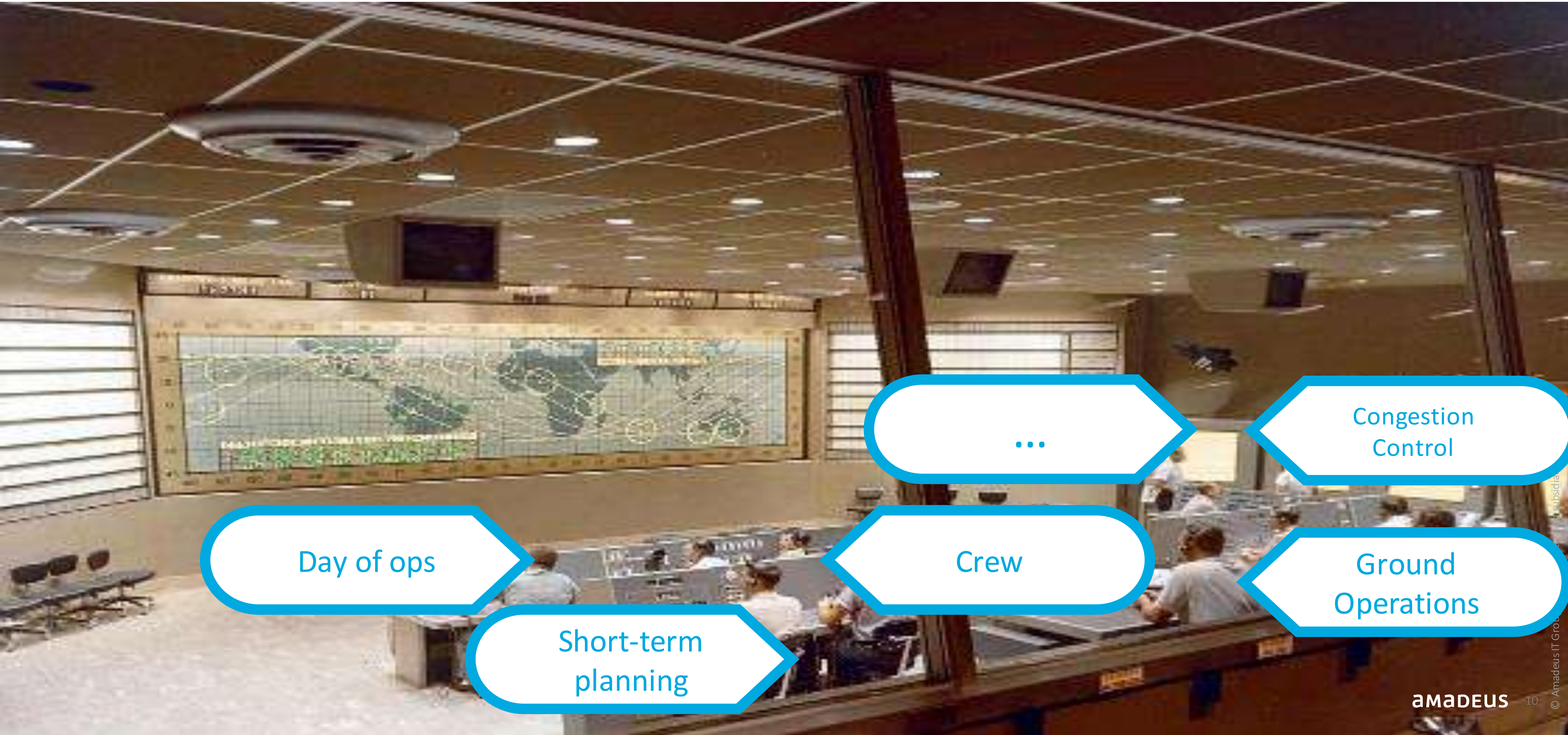


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# Other data challenges faced by airlines

**UNSTRUCTURED**
data governance

**COMPLEX**
organizational structure

**LACK**
of data expertise

**RISK**
of security and data protection

**INACCURATE**
data collection

**VOLUME**
Is unmanageable

**FRAGMENTED**
from different sources

**DISCONNECTED**
between data and opportunity

# Our approach


amadeus

# Amadeus Data & Analytics Suite

# Amadeus Data & Analytics Suite

Refdata

Search

Reservation

Inventory

Ticketing

Departure control

# Amadeus Data & Analytics Suite

Refdata

Search

Reservation

Inventory

Ticketing

Departure control

# Amadeus Data & Analytics Suite

- Refdata
- Search
- Reservation
- Inventory
- Ticketing
- Departure control

## Market Insight

- Booking Analytics
- Global Booking Processing
- Traffic Analytics
- Schedule Analytics
- Search Analytics
- Price Benchmark

## Performance Insight

- Business Analytics Centre
- Advanced Sales and Rev
- Advanced Ground Ops /IROPs
- Advanced RM & Pricing

# Amadeus Data & Analytics Suite

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- Marketing
- Finance
- Strategy
- …

# Amadeus Data & Analytics Suite

- Refdata
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**Market Insight**

- Booking Analytics
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**Performance Insight**

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# Amadeus Data & Analytics Suite

- Refdata
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- Departure control

**Market Insight**

- Booking Analytics
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- Price Benchmark

**Performance Insight**

- Business Analytics Centre
- Advanced Sales and Rev
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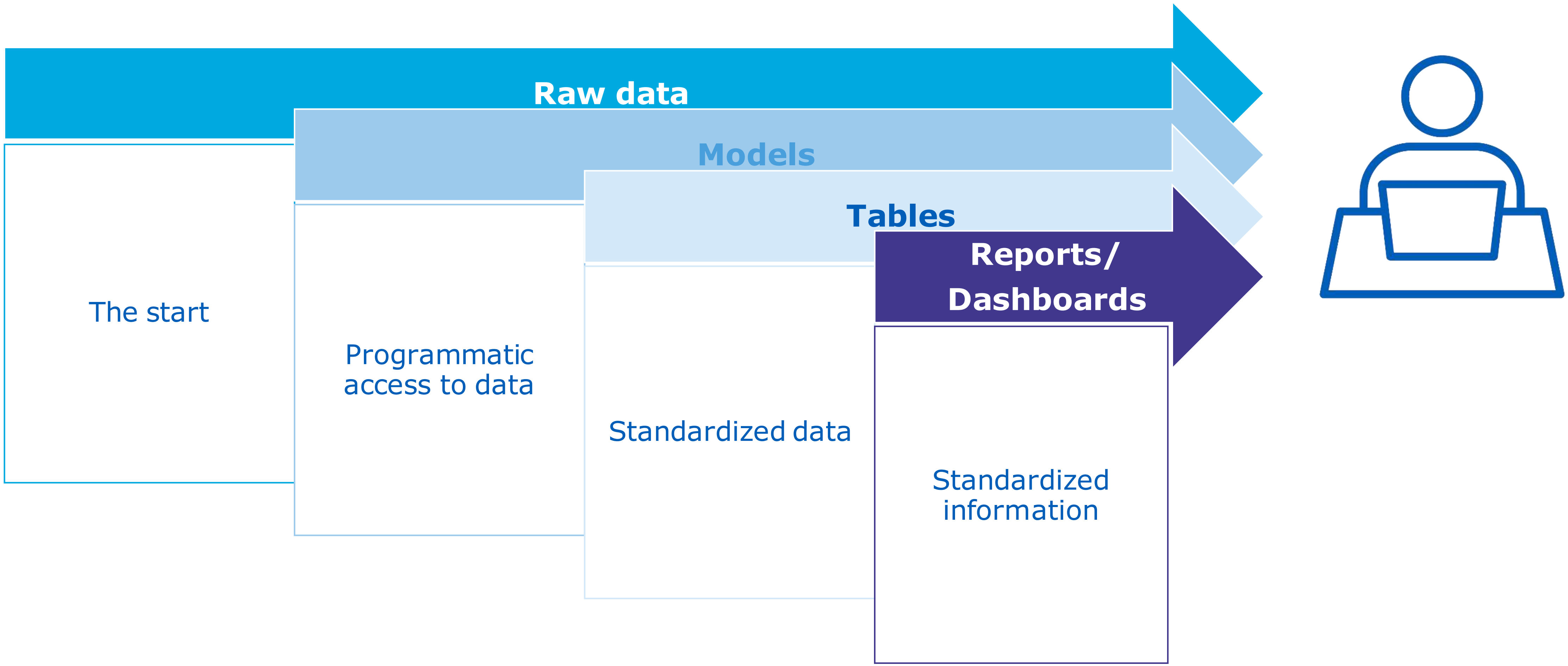
- ...

# Amadeus Data & Analytics Suite: architecture



# From data to insights

## Raw data › **Models** › Tables › Reports/Dashboards

# From data to insights

## Raw data › **Models** › Tables › Reports/Dashboards

Ticketing

# From data to insights

## Raw data › **Models** › Tables › Reports/Dashboards

Ticketing

- HOT
- LIFT
- EMD
- APRA
- TOF
- RET
- Other

# From data to insights

## Raw data › <u>**Models**</u> › Tables › Reports/Dashboards

Ticketing

- HOT
  - v1.00
  - v1.02
  - v1.02
  - v2.00
  - v2.20
  - v2.40
  - v2.50
  - v2.60
  - Other
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- Other

# From data to insights

## Raw data › **Models** › Tables › Reports/Dashboards

Ticketing

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  - v1.00
    - XML
    - Edifact
    - Other
  - v1.02
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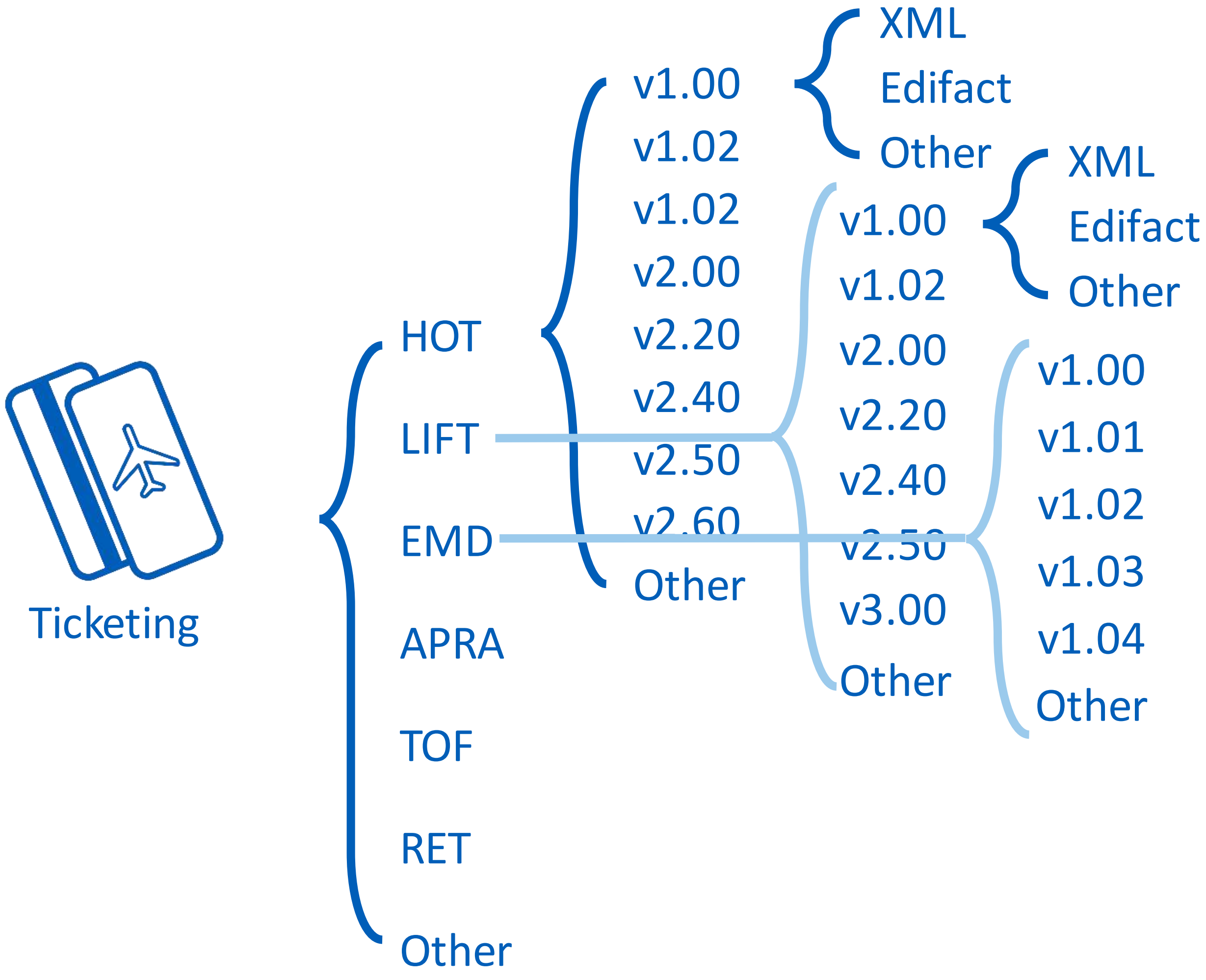
- TOF
- RET
- Other

# From data to insights

## Raw data › **Models** › Tables › Reports/Dashboards



# From data to insights

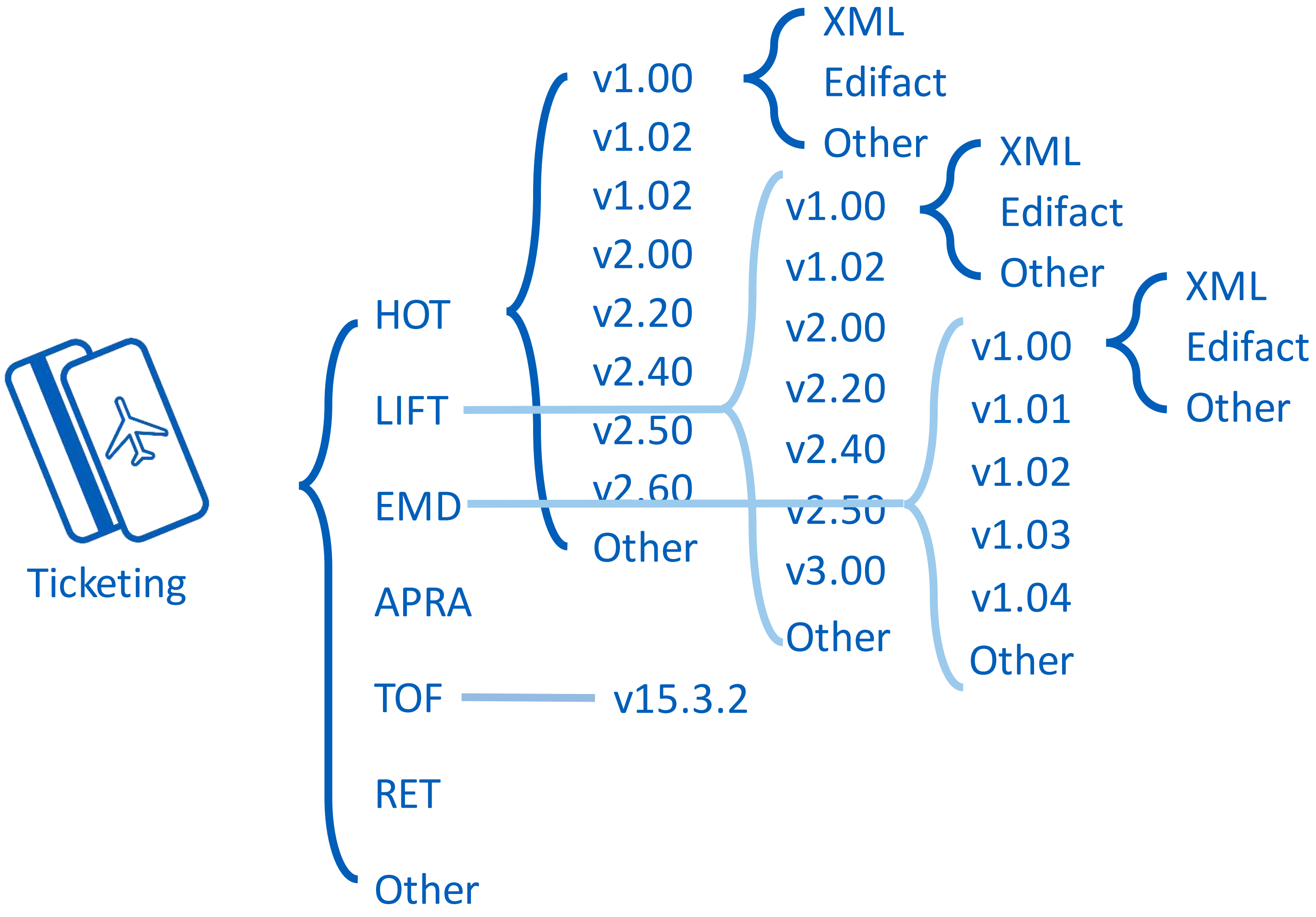
## Raw data › **Models** › Tables › Reports/Dashboards

Ticketing

- HOT
  - v1.00
    - XML
    - Edifact
    - Other
  - v1.02
  - v1.02
  - v2.00
  - v2.20
  - v2.40
  - v2.50
  - v2.60
  - Other
- LIFT
  - v1.00
    - XML
    - Edifact
    - Other
  - v1.02
  - v2.00
  - v2.20
  - v2.40
  - v2.50
  - v3.00
  - Other
- EMD
  - v1.00
    - XML
    - Edifact
    - Other
  - v1.01
  - v1.02
  - v1.03
  - v1.04
  - Other
- APRA
- TOF
- RET
- Other

# From data to insights

## Raw data › **Models** › Tables › Reports/Dashboards



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  - v1.02
  - v1.03
  - v1.04
  - Other
- APRA
- TOF
  - v15.3.2
- RET
  - v2.20
- Other

# From data to insights

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  - v2.00
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- EMD
  - v1.00
    - XML
    - Edifact
    - Other
  - v1.01
  - v1.02
  - v1.03
  - v1.04
  - Other
- APRA
- TOF
  - v15.3.2
- RET
  - v2.20
- Other

**Parsers**

# From data to insights

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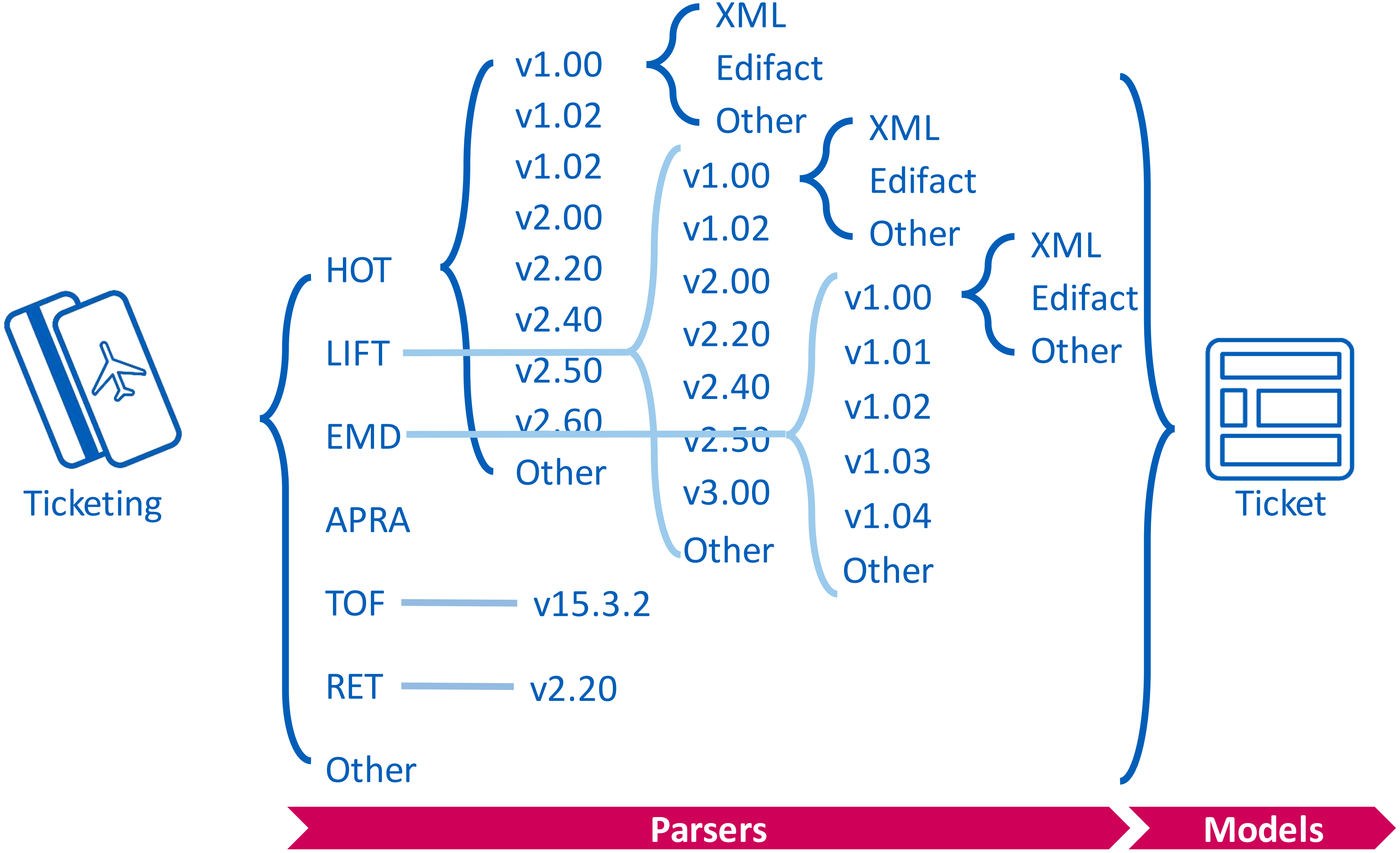

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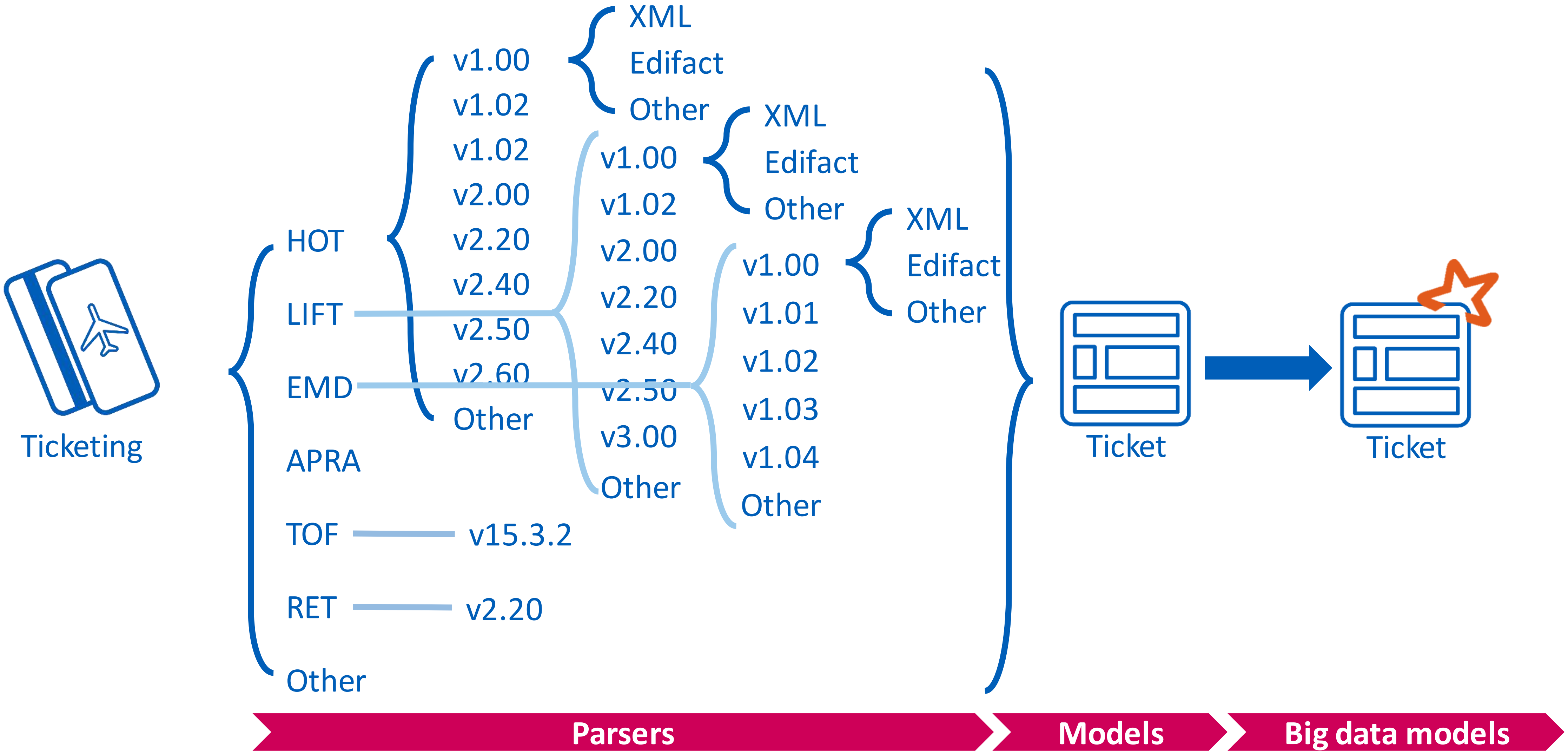

# From data to insights

## Raw data › **Models** › Tables › Reports/Dashboards

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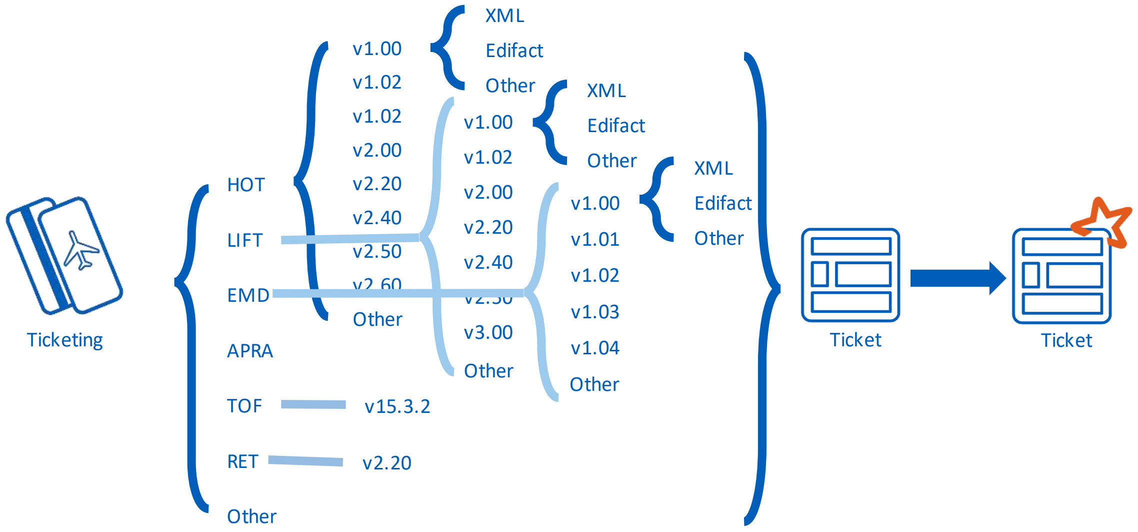

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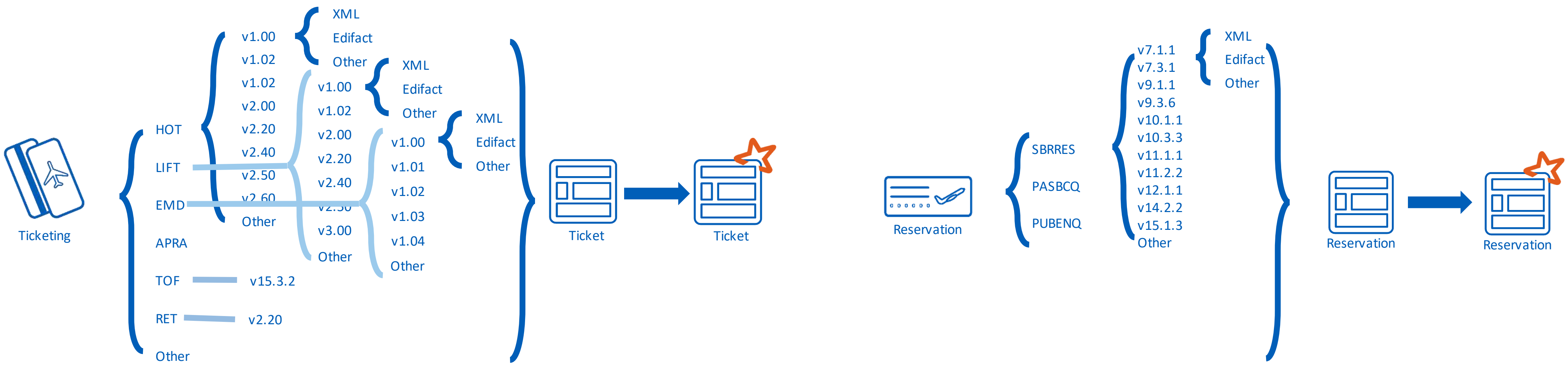

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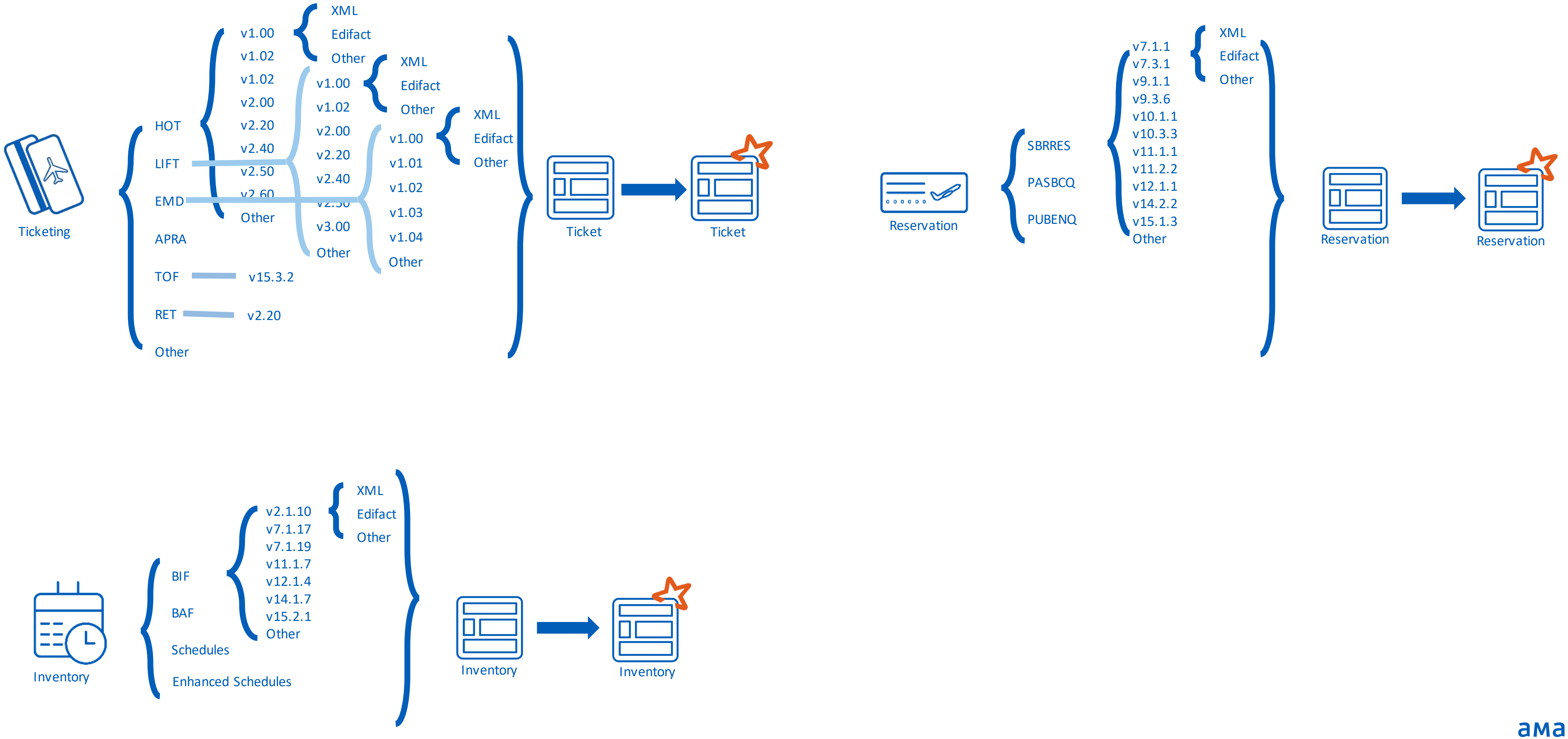

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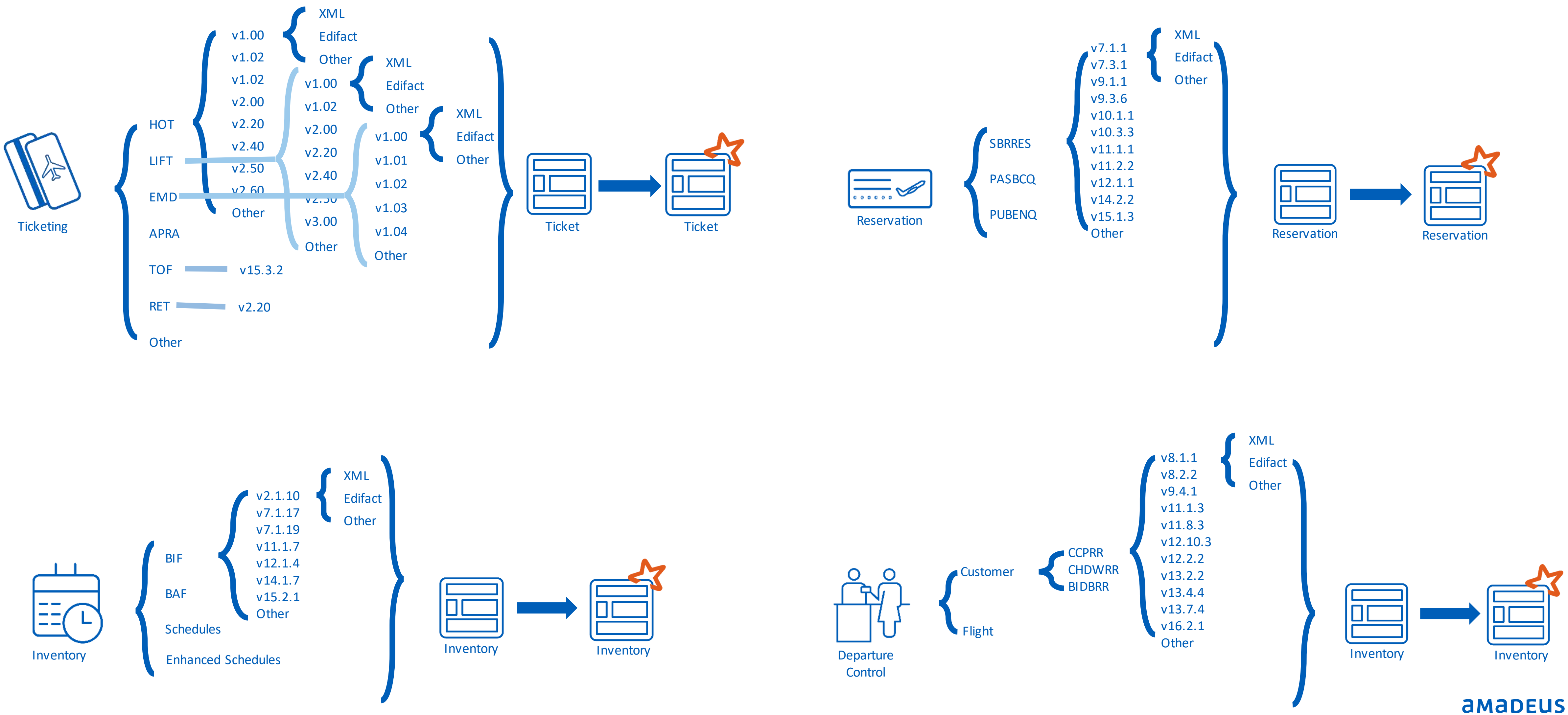

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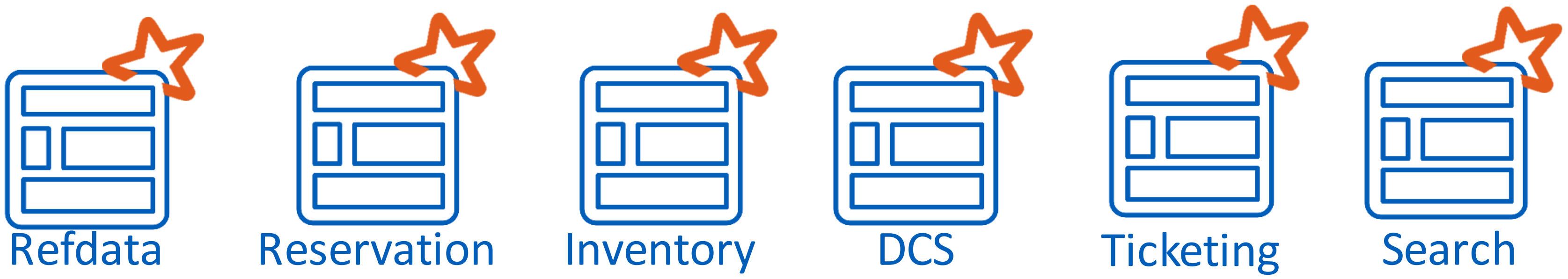

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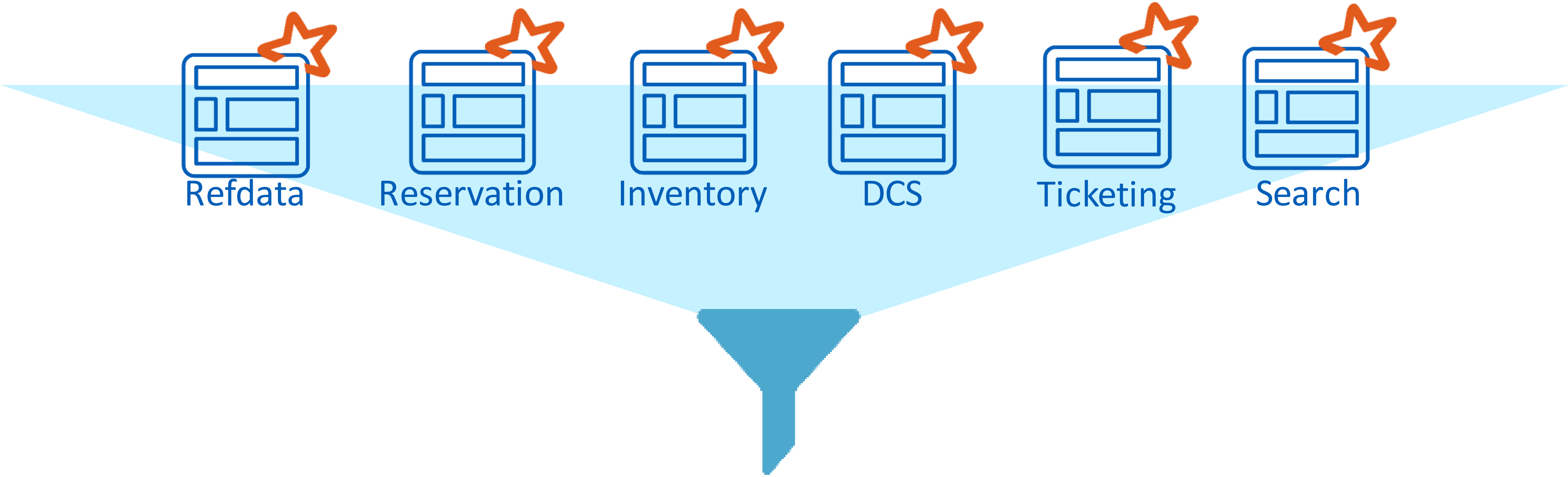

# From data to insights

Raw data › Models › **Tables** › Reports/Dashboards


**“Tables”**

Ready-to-use data

# From data to insights

Raw data › Models › <u>Tables</u> › Reports/Dashboards


**“Tables”**

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# From data to insights

## Raw data › Models › <u>Tables</u> › Reports/Dashboards

**“Tables”**

Ready-to-use data

# From data to insights

## Raw data › Models › Tables › Reports/Dashboards

**“Tables”**

Ready-to-use data

- Coupon conciliation

# From data to insights

## Raw data › Models › Tables › Reports/Dashboards

**“Tables”**

Ready-to-use data

- Coupon conciliation
- OD reconstruction

# From data to insights

## Raw data › Models › <u>Tables</u> › Reports/Dashboards

**“Tables”**

Ready-to-use data

- Coupon conciliation
- OD reconstruction
- Leg/Segment matching

# From data to insights

## Raw data › Models › <u>Tables</u> › Reports/Dashboards

**“Tables”**

Ready-to-use data

- Coupon conciliation
- OD reconstruction
- Leg/Segment matching
- Missing data

# From data to insights

## Raw data › Models › Tables › Reports/Dashboards

**“Tables”**

Ready-to-use data

- Coupon conciliation
- OD reconstruction
- Leg/Segment matching
- Missing data
- Source conciliation

# From data to insights

## Raw data › Models › Tables › Reports/Dashboards

**"Tables"**

Ready-to-use data

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- OD reconstruction
- Leg/Segment matching
- Missing data
- Source conciliation
- Ancillary conciliation

# From data to insights

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**“Tables”**

Ready-to-use data

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- OD reconstruction
- Leg/Segment matching
- Missing data
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- Remove duplicates
- Consolidation of current status

# From data to insights

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- ...

An ML use case

# Customer Segmentation

# Customer Segmentation

## The old way

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_E.g. Revenue Management, merchandising, ...

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_E.g. Revenue Management, merchandising, …

_Marketing-driven effort

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_Able to cope with few variables

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- Time of purchase

# Customer Segmentation

## The old way

_E.g. Revenue Management, merchandising, ...

_Marketing-driven effort

_Able to cope with few variables

- Time of purchase
- Business/Economy/...

# Customer Segmentation

## The data-driven way

# Customer Segmentation

## The data-driven way

Refdata

Reservation

Ticketing

Departure control

# Customer Segmentation

## The data-driven way

Refdata

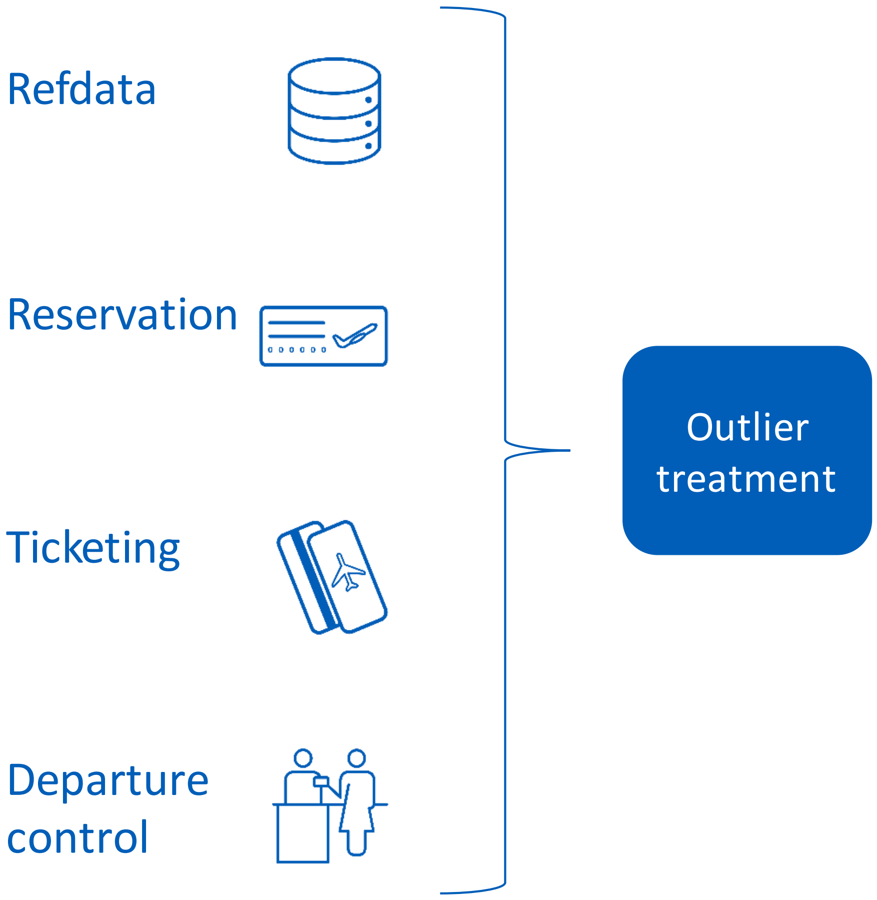
Reservation

Ticketing

Departure control

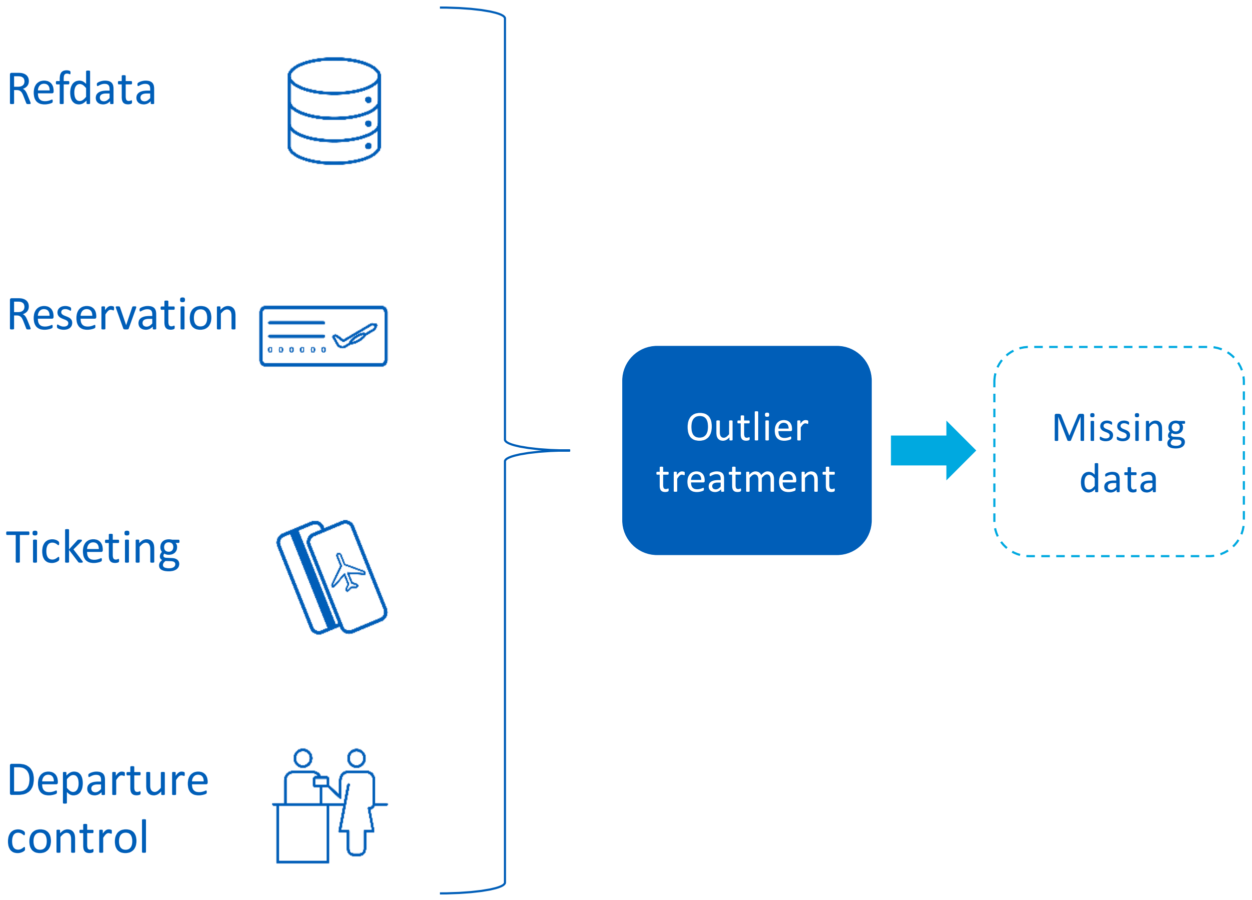
# Customer Segmentation

## The data-driven way



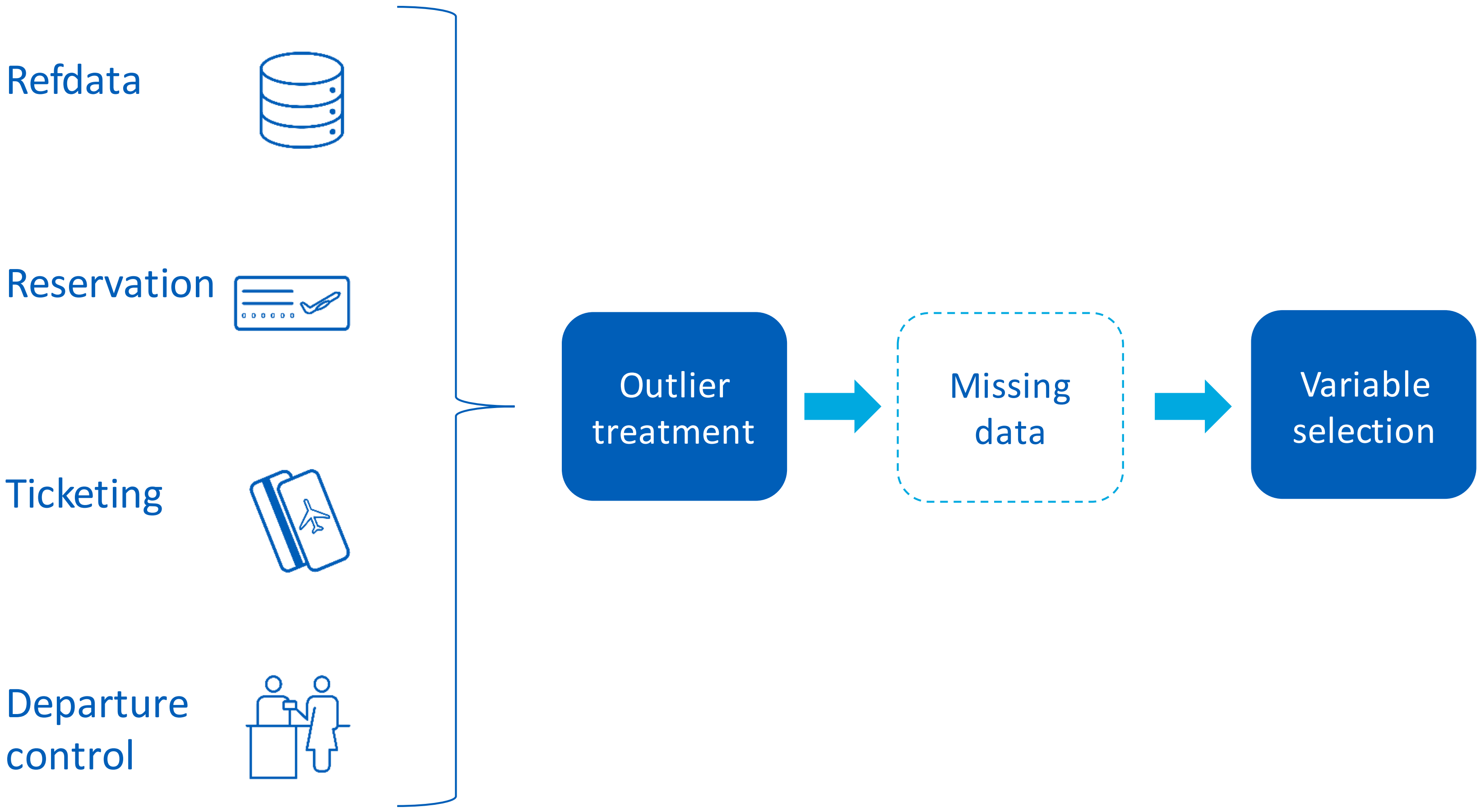
# Customer Segmentation

## The data-driven way



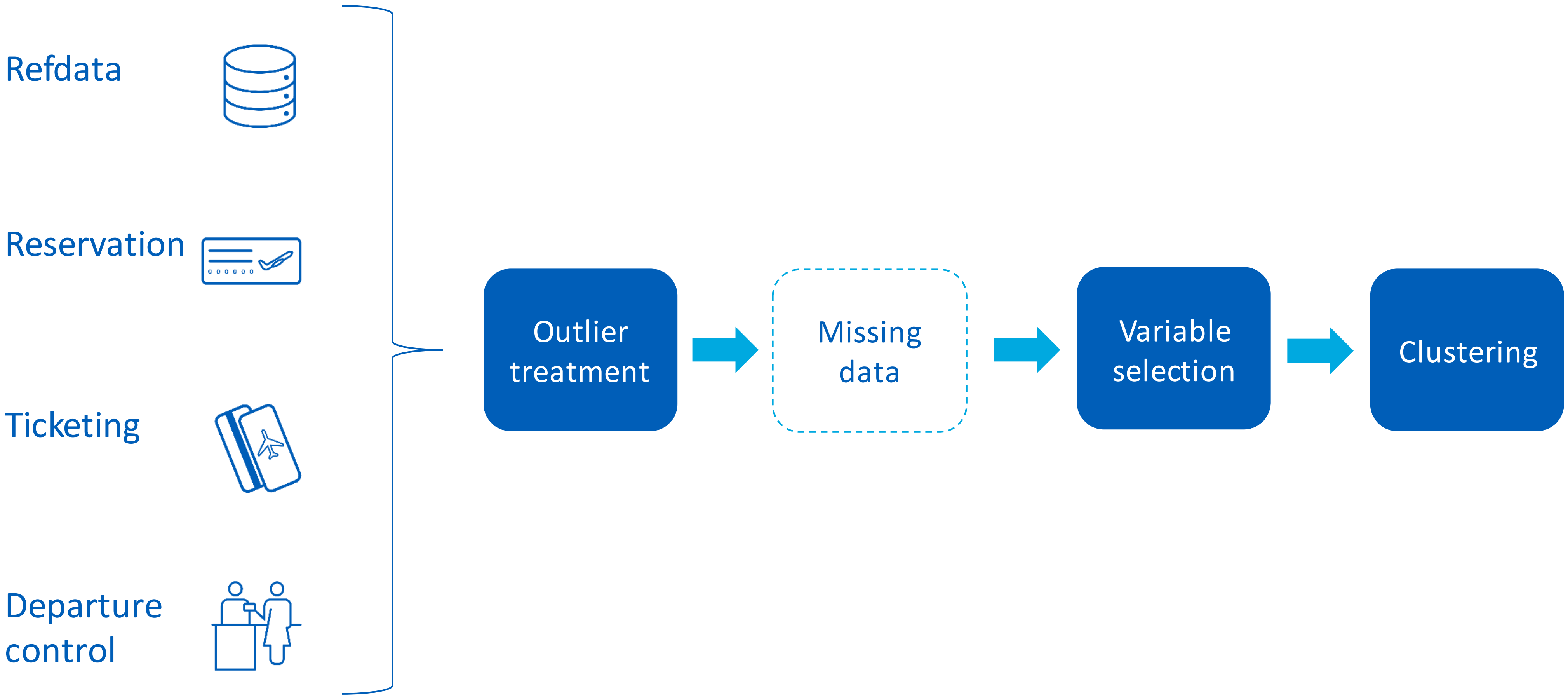
# Customer Segmentation

## The data-driven way



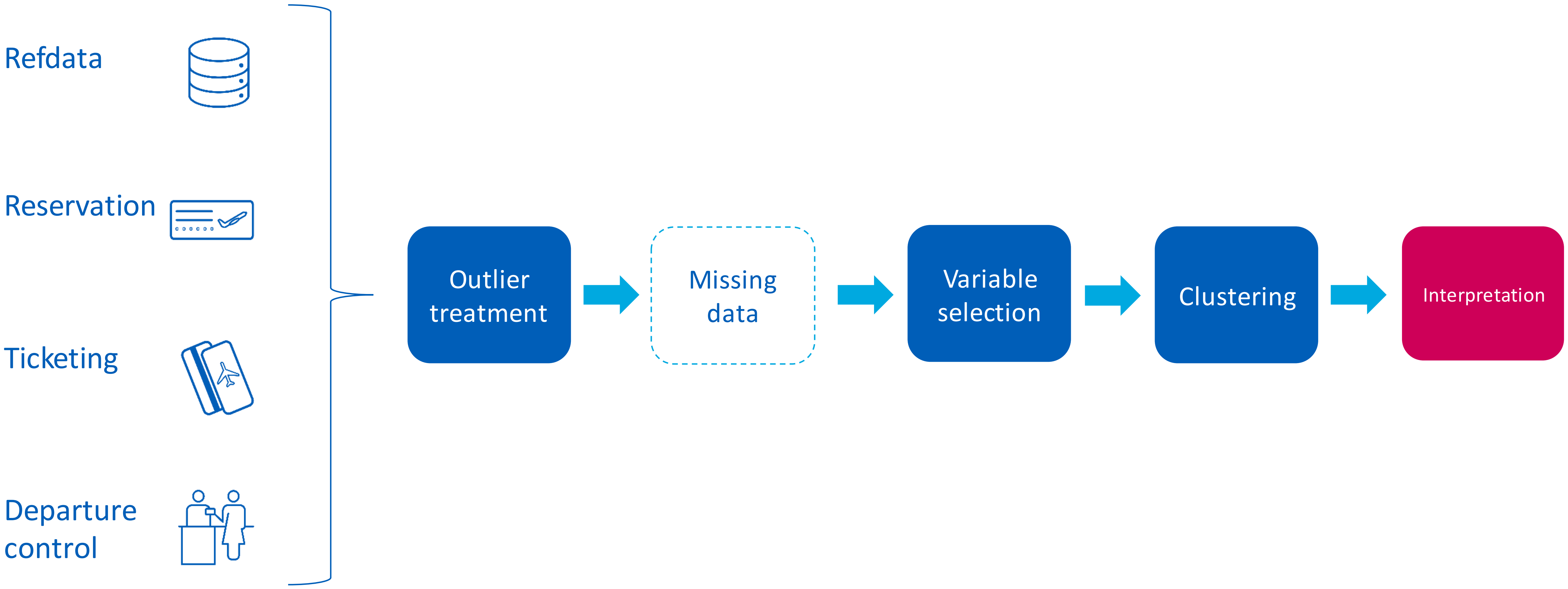
# Customer Segmentation

## The data-driven way



# Customer Segmentation

## The data-driven way



# Takeaways

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1. Free your data from the silos

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2. Having an efficient data pipeline from raw data to actionable data pays off

# Takeaways

1. Free your data from the silos
2. Having an efficient data pipeline from raw data to actionable data pays off
3. If you want to improve your operations or better understand your customer, we are happy to help with that ☺

# Thank you!

Questions?
daniel.perez@amadeus.com


Download

# How Data and Machine Learning can Improve Your Customer Experience

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

Track Sponsor

OpenJaw

# AI/ML for better customer experience

Massimo Morin

*Head Worldwide Business Development, Travel*

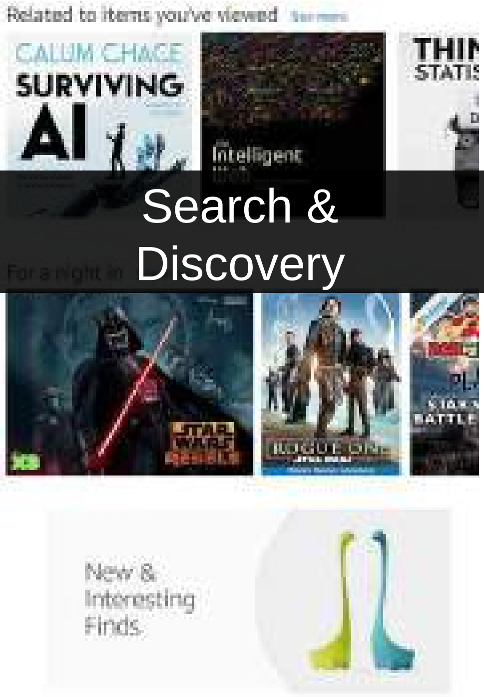
*Berlin, 21st June 2018*

*AI Technologies Will Be in Almost Every New Software Product by 2020* – **Gartner**

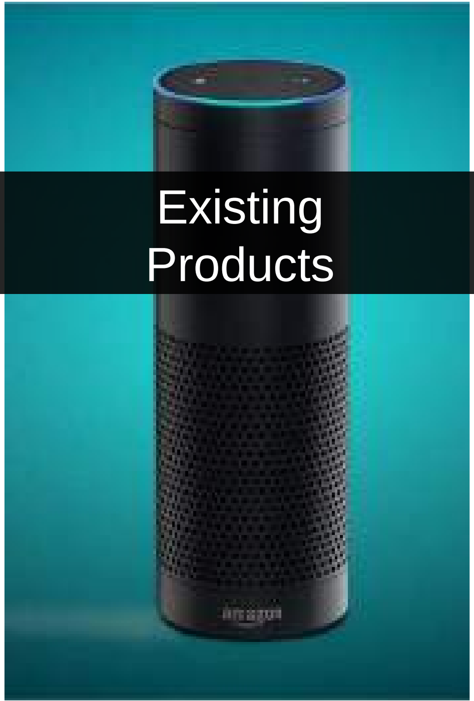
*By 2020, AI will be a top five investment priority for more than 30 percent of CIOs* – **Gartner**

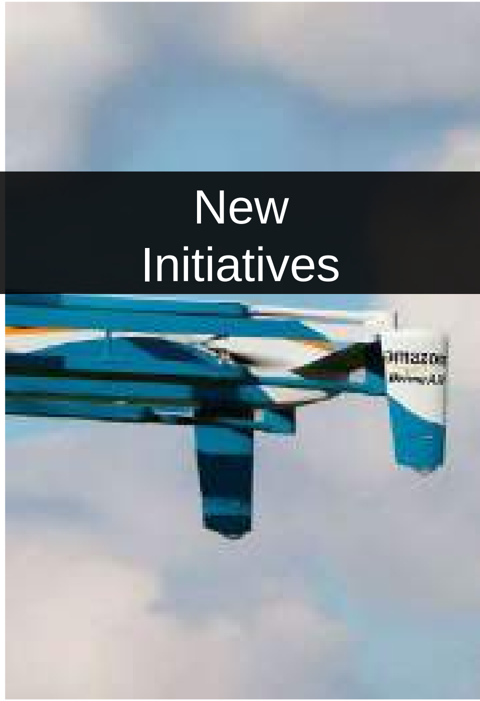
*The market for cognitive/AI solutions will experience a compound annual growth rate (CAGR) of 55.1 percent…to more than $47 billion in 2020* – **IDC**

# At Amazon, we’ve been making investments in ML for the last 20 years…







# AWS AI/ML: Solutions for Every Skill Level

**Services**

- Designed for Application Developers
- Solution-oriented Prebuilt Models Available via APIs
- Image Analysis, Text-to-Speech, Conversational UX

**Platforms**

- Designed for Data Scientists to Address Common Needs
- Fully Managed Platform for Model Building
- Reduces the Heavy Lifting in Model Building & Deployment

**Frameworks**

- Designed for Data Scientists to Address Advanced / Emerging Needs
- Provides Maximum Flexibility to develop on the leading AI Frameworks
- Enables Expert AI Systems to be Developed & Deployed

**Infrastructure**

- Regions / Availability Zones as AWS core

# The Amazon ML Stack

## Services

- **Vision:** Rekognition Image, Rekognition Video
- **Speech:** Polly, Transcribe
- **Language:** Lex, Translate, Comprehend

## Platforms

- Amazon SageMaker
- AWS DeepLens
- Amazon Machine Learning
- Spark & EMR
- Mechanical Turk

## Frameworks

- AWS Deep Learning AMIs
- Caffe2
- CNTK
- Apache MXNet
- PyTorch
- Tensor Flow
- Keras
- Gluon

## Infrastructure

- GPU (P3)
- CPU
- IoT & Edge
- Mobile

# Use case: Bag Tracking - IATA R753


Objectives:

- Reduce mishandling
- Reduce baggage fraud
- Reduce flight delays
- Earn and keep passenger trust

But also:

- Keep passenger informed
- Identify bottlenecks
- Train handling personnel
- Staff up resources

Source: IATA Resolution 753 Implementation Guide, November 2017

# The problem: tracking bags can we do better?

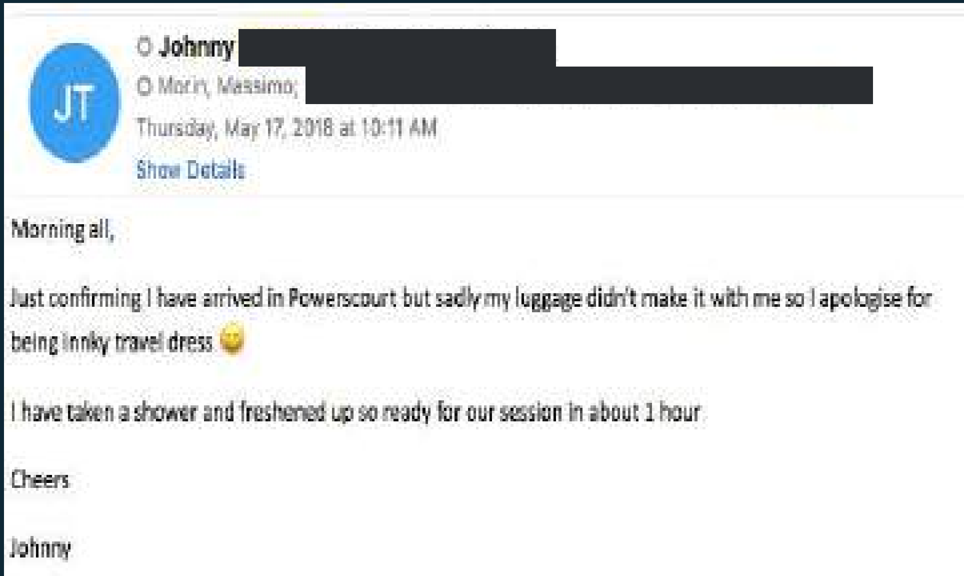
## Johnny’s example:

- Trip from San Francisco to Dublin via Toronto
- 9 hours connection in Toronto
- Checked in, full size bag
- 5 days Trip
- Important business meetings on first 2 days

- Johnny makes it to Dublin, but the bag does no

# Typical actions / reactions

- Arrived in Dublin @ 8am, but bag does not
- Called call center ➔ Airline can't find bag
- Called again @ noon ➔ Still nobody knows where the bag is
- Email / Text message received ➔ Bag is in Toronto will arrive soon
- Replied to message (frustrated), and got back "***you cannot reply to this message, call the airline for more info" …***
- **…** and there was of course no number included to call back
- Received a call in the evening: *"the bag had been located and will arrive in Dublin airport tomorrow morning"*
- Bag delivered mid-morning



JT

Johnny [redacted]

Morin, Massimo; [redacted]

Thursday, May 17, 2018 at 10:11 AM

Show Details

Morning all,

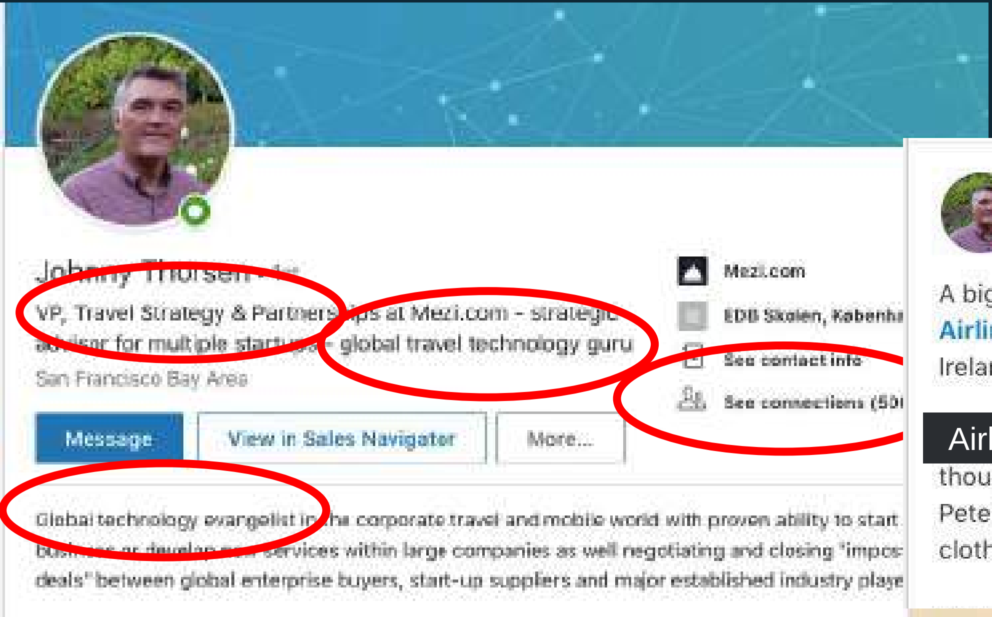
Just confirming I have arrived in Powerscourt but sadly my luggage didn't make it with me so I apologise for being inky travel dress

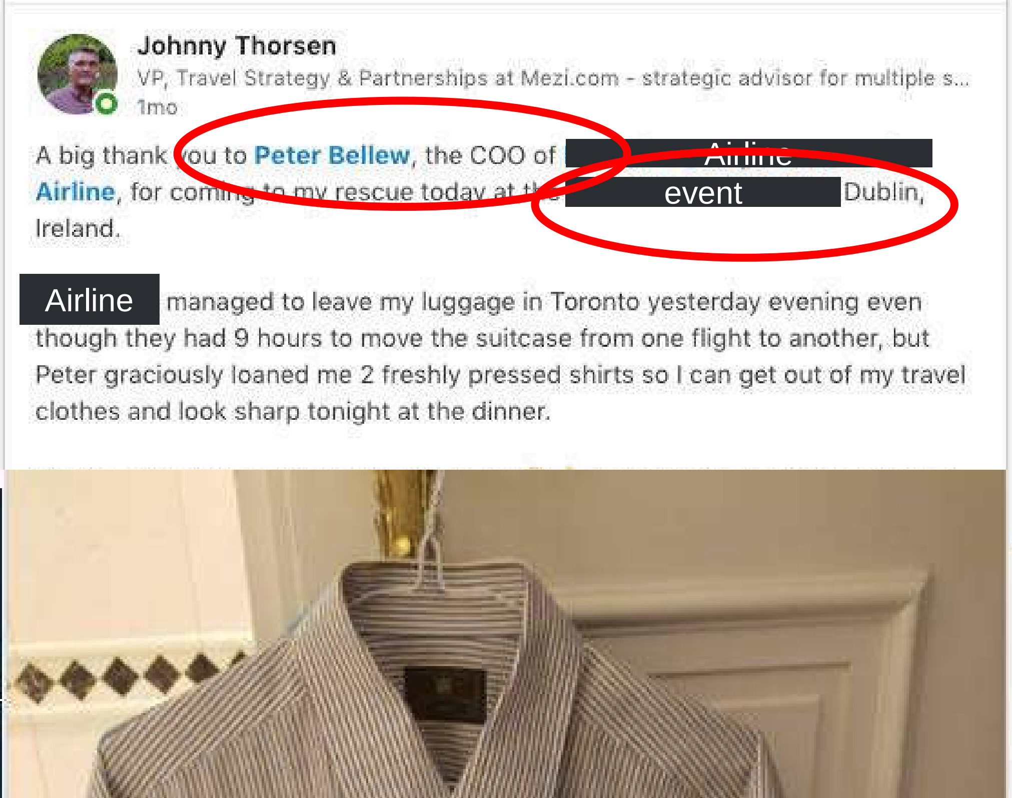
I have taken a shower and freshened up so ready for our session in about 1 hour

Cheers

Johnny

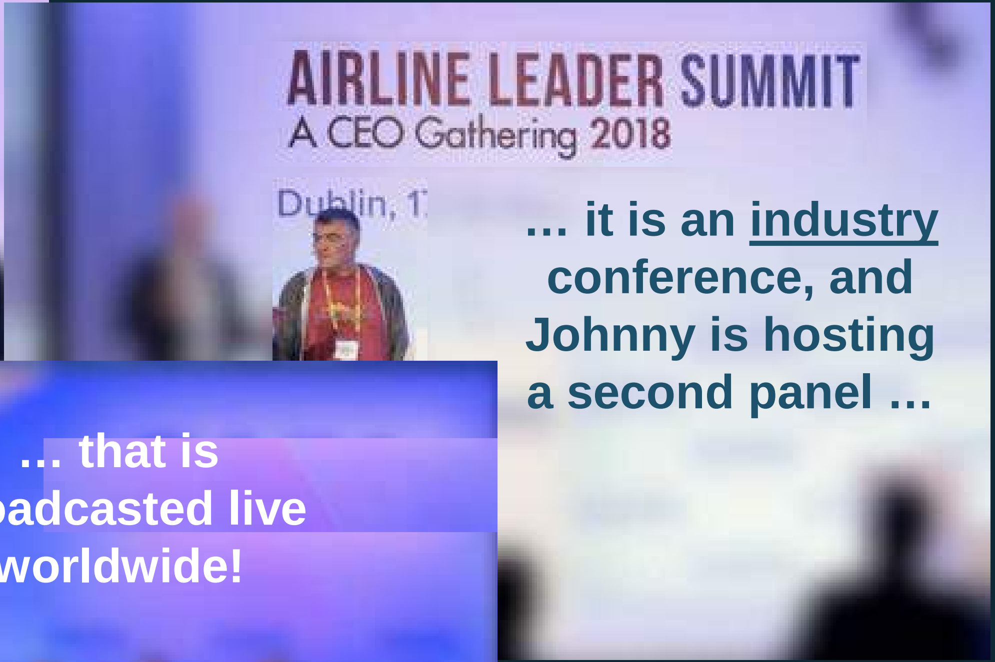
# What the airline did not know



# What the airline did not know

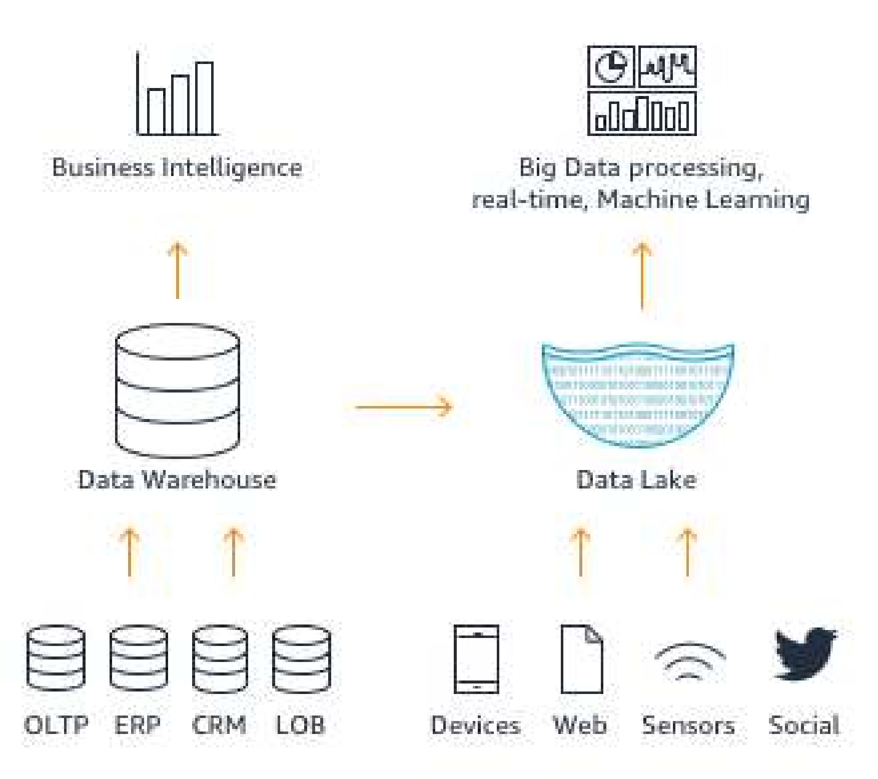
*Johnny is on a Panel at conference…*




… it is an <u>industry</u> conference, and Johnny is hosting a second panel …

… that is broadcasted live worldwide!

# What if you could collect all this data points?




- operational, loyalty, and social data
- Real time interactions from all sources
- Relational and non-relational data
- TBs–EBs scale
- Diverse analytical engines
- Low-cost storage & analytics

# Data Lakes as a Single Source of Truth driving Actionable Insights

## Machine Learning

Amazon SageMaker
AWS Deep Learning AMIs
Amazon Rekognition
Amazon Lex
AWS DeepLens
Amazon Comprehend
Amazon Translate
Amazon Transcribe
Amazon Polly

## Analytics

Amazon Athena
Amazon EMR
Amazon Redshift
Amazon Elasticsearch service
Amazon Kinesis
Amazon QuickSight

## Data Lake on AWS

Storage | Archival Storage | Data Catalog

## On-premises Data Movement

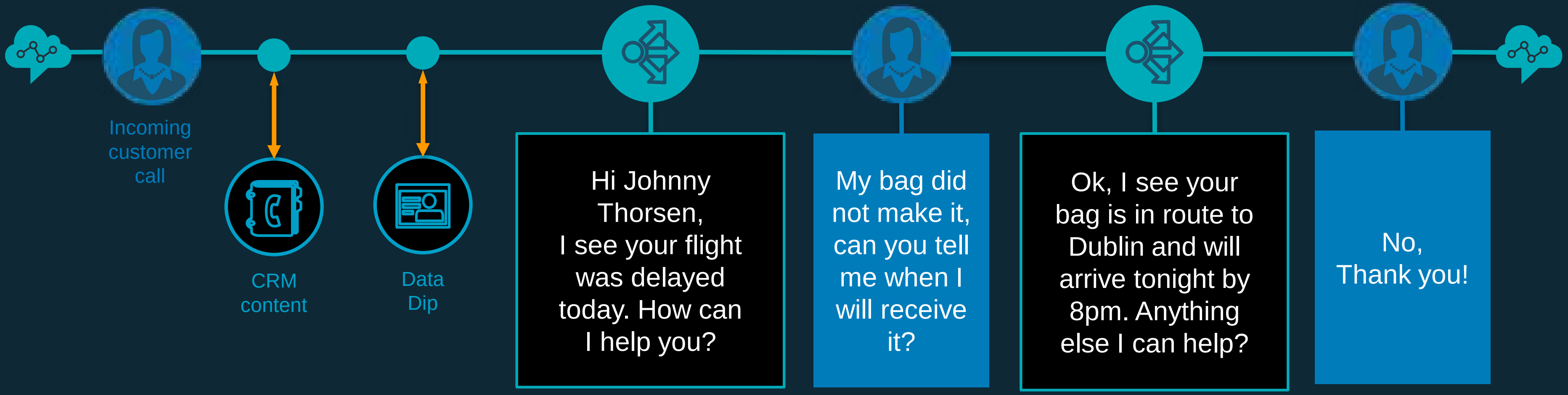
AWS Direct Connect
AWS Snowball
AWS Snowmobile
AWS Database Migration Service

## Real-time Data Movement

AWS IoT Core
Amazon Kinesis Data Firehose
Amazon Kinesis Data Streams
Amazon Kinesis Video Streams

# AWS Connect

## Ease to use, cloud base contact center supporting business of any size



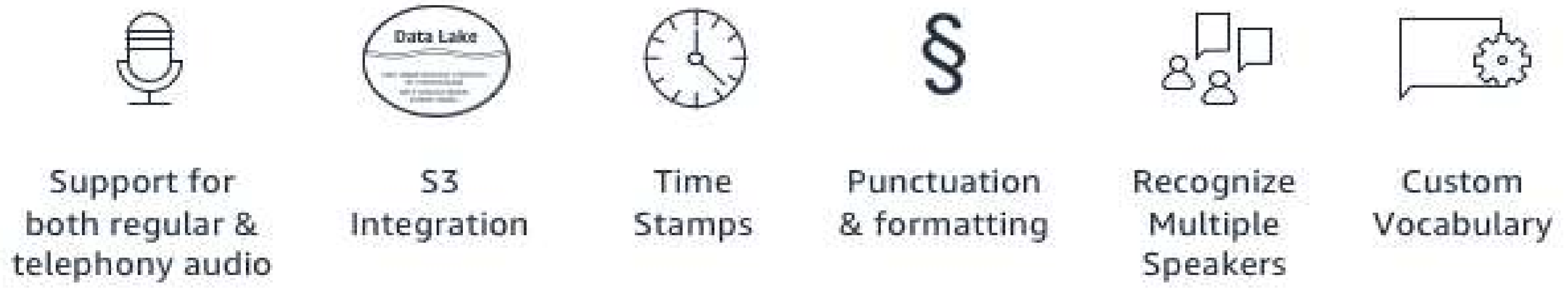

DYNAMIC
Answer customer questions before they are even asked

PERSONAL
Contact flows adapt on a per customer basis

NATURAL
Amazon Lex Chatbots use the same technology that powers Alexa

# Amazon Transcribe

## Automatic Speech Recognition → Create formatted documents

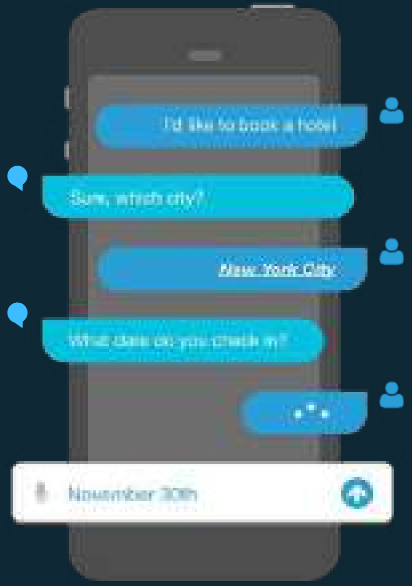



Amazon Transcribe can be used for lots of common applications, including the transcription of **customer service calls** and generating subtitles on audio and video content. The service can transcribe audio files stored in common formats, like WAV and MP3, with time stamps for every word so that you can easily locate the audio in the original source by searching for the text.

# Amazon Lex

## Turn text into lifelike speech using deep learning

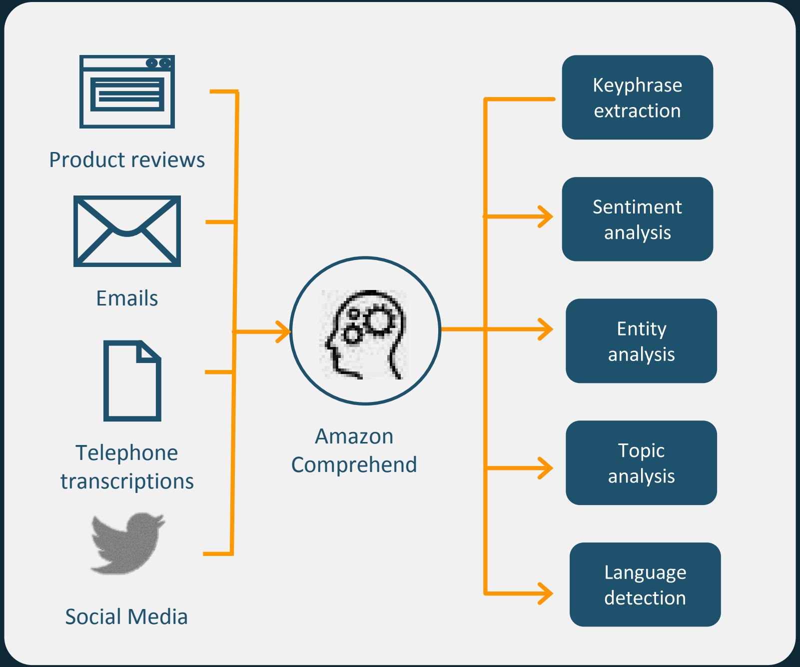
**Customer Support**




- Text and speech language understanding: powered by the same technology as Alexa
- Build once and deploy to multiple platforms
- Efficient and intuitive tools to build conversations; scales automatically
- Enterprise Ready: connect to enterprise systems via SaaS connectors
- Continuous Learning: monitor and improve your bot

# Amazon Comprehend

## Natural Language Processing to discover insights from text




- Classify language, extract key phrases, understand sentiment, identify/organize documents by topic
- Continuously trained and constantly improving
- Integrated with Amazon S3 and AWS Glue

# Text Analysis Example

Hello, this is Johnny Thorsen, I was on flight 123, on May 16$^{th}$, and my bag did not arrive. I need it at the Hotel Powerscourt urgently as I am speaking at a conference tomorrow. Please help.

**Named Entities**

- Johnny Thorsen: Customer
- Flight 123: Flight
- May 16$^{th}$ : Date
- Hotel Powerscourt : Location
- Tomorrow: Date

**Keyphrases**

- My bag
- Did not arrive
- Urgently
- Conference

**Sentiment**

- *Negative*

**Language**

- English

# Amazon SageMaker (GA)

## The quickest and easiest way to get ML models from idea to production

Because Machine Learning Process is Hard, and Time Consuming...

End-to-End Machine Learning Platform

Zero setup

mxnet
GLUON
TensorFlow

Flexible Model Training

Pay by the second

# If I have this data, and this models what can I do?

What does the customer need?

What is the status?

How important is this?

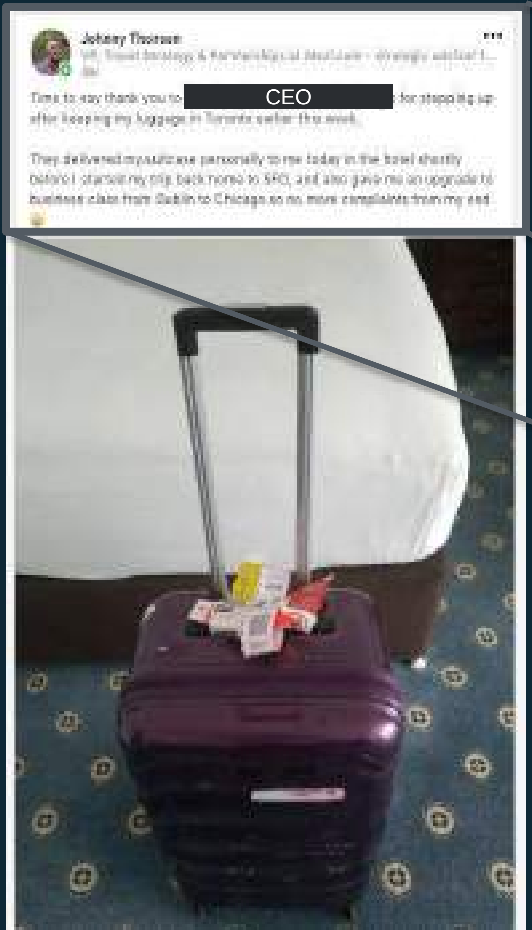
How can I compensate him?

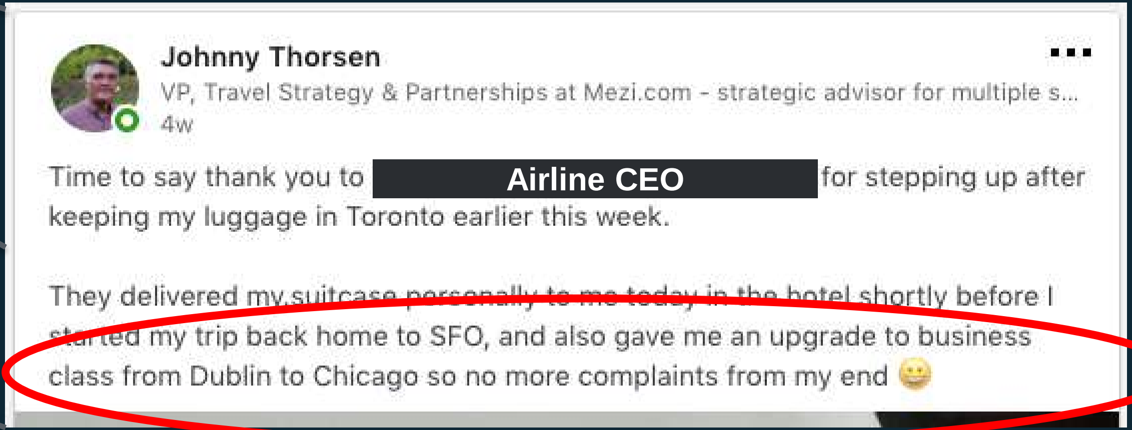
Can I convert this into an opportunity?

aws

# Many company are doing it today already

# What about Johnny?




*"[Massimo] you are absolutely right about how the whole process of lost luggage can be improved in many ways and I have a few ideas myself which I am saving for later :-)"*

**Johnny Thorsen,**
*Travel Visionary*

# Conclusion

- Create your own story
- Be customer obsessed
- Technology can help
- AWS has the capabilities you need
- Transform your weaknesses into strengths…
- … before somebody else does it!

# Thank You!


aws
Massimo G. Morin
Head, Worldwide Business Development, Travel
AWS Enterprise and Industry Verticals Business Development
101 Main Street Cambridge, MA 02142 USA
Cell (617) 401 1356 • morinmm@amazon.com
http://aws.amazon.com/
100% Recycled Paper

IATA

# How to Leverage Big Data & Machine Learning to Personalize User Experience

Bayram Annakov
Founder and CEO, Appintheair

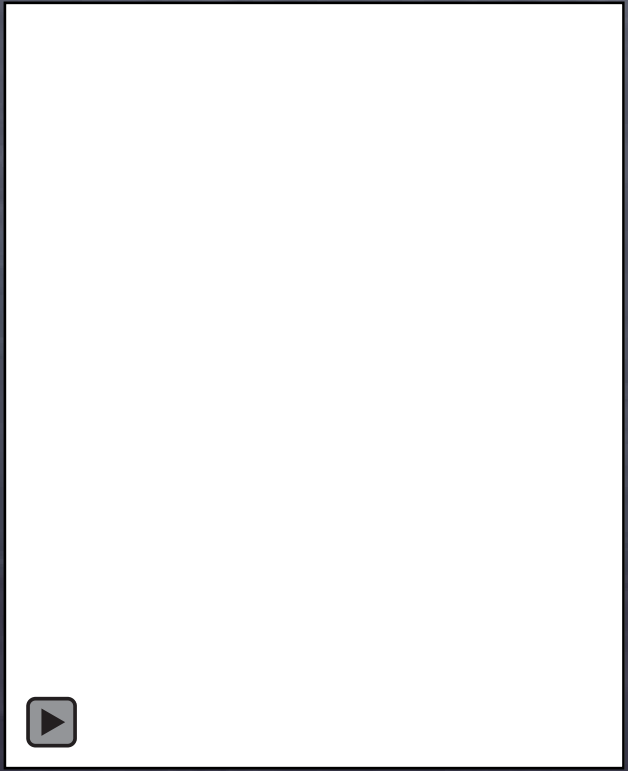
Track Sponsor

OpenJaw

# PERSONALIZATION

Bayram Annakov, App in the Air

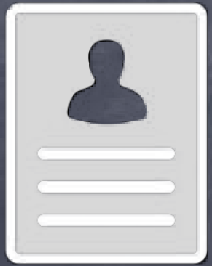
# What is AI?



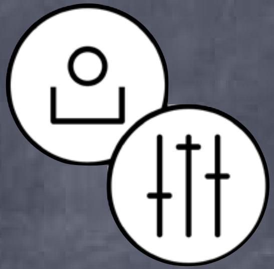
pattern recognition

to solve practical problems

# 2 problems



Best Offer

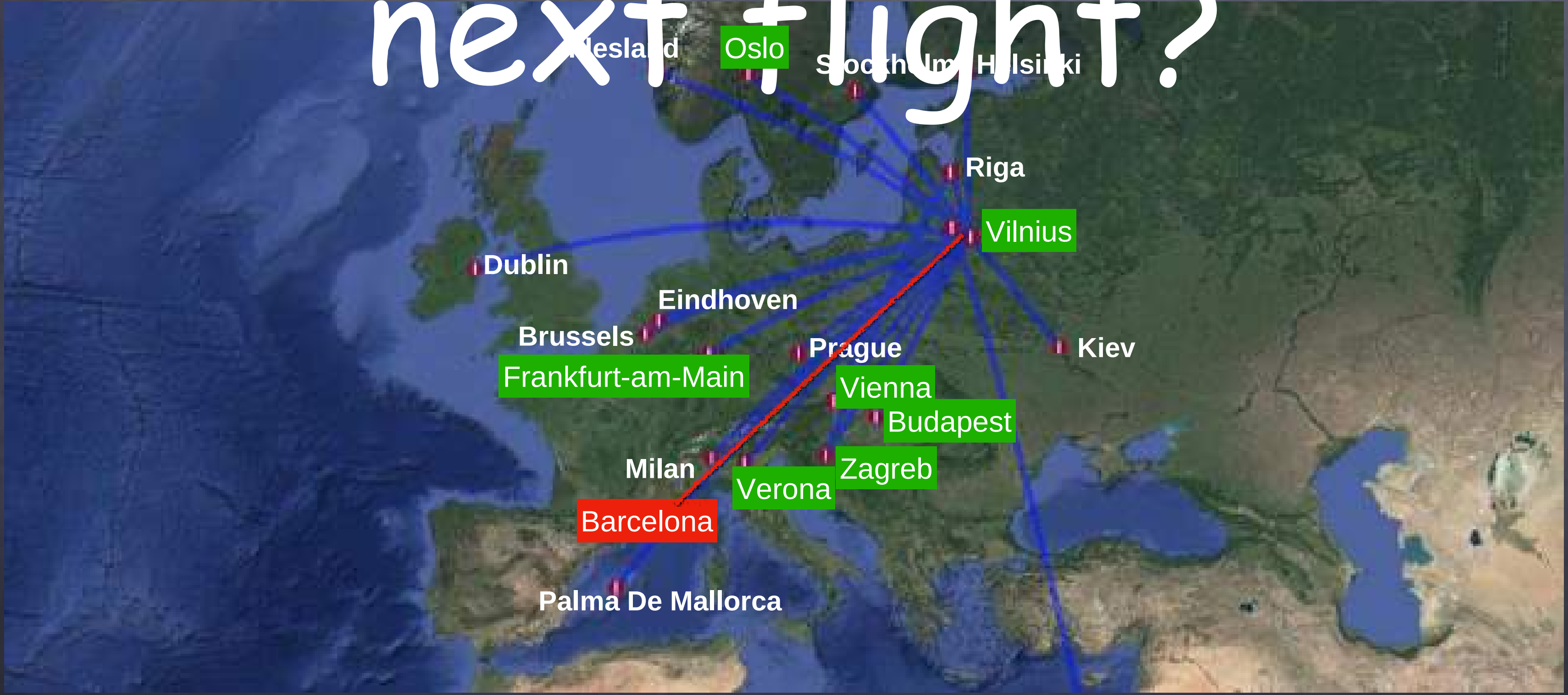


Best Results

# Best Offer

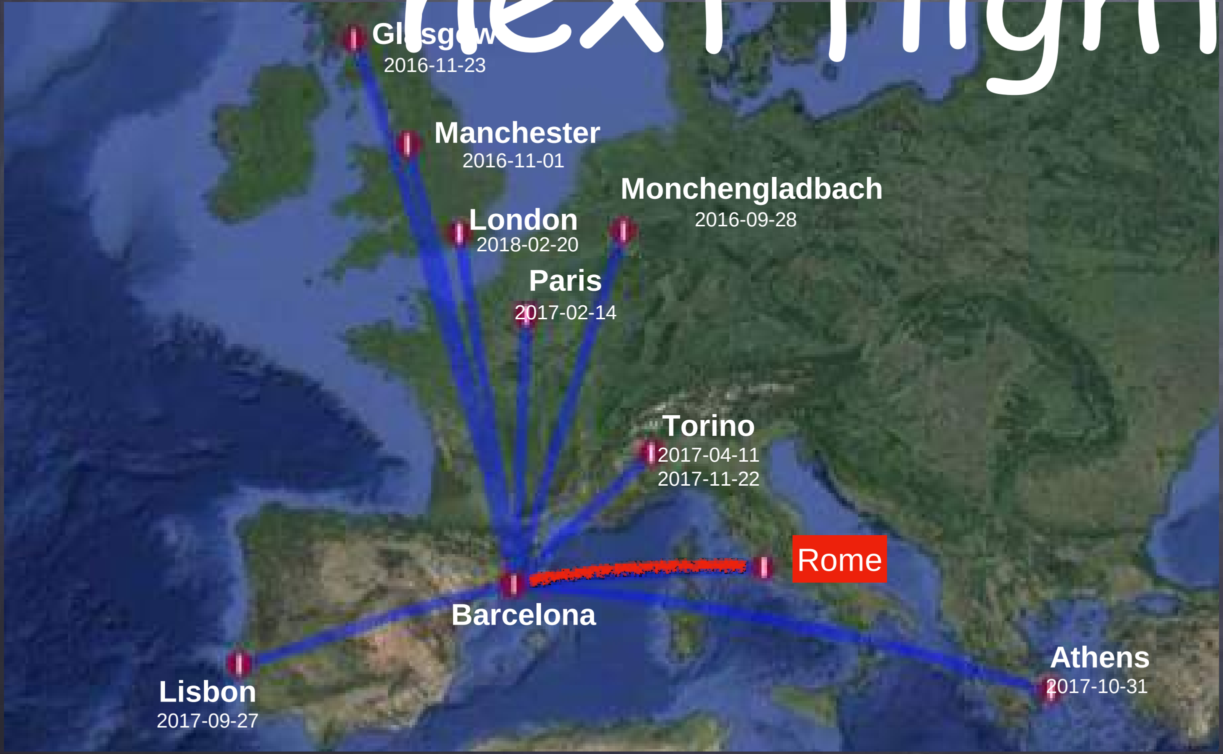
Tailored marketing emails

# Can you predict the next flight?



# Can you predict the next flight?

# Can you predict the next flight?



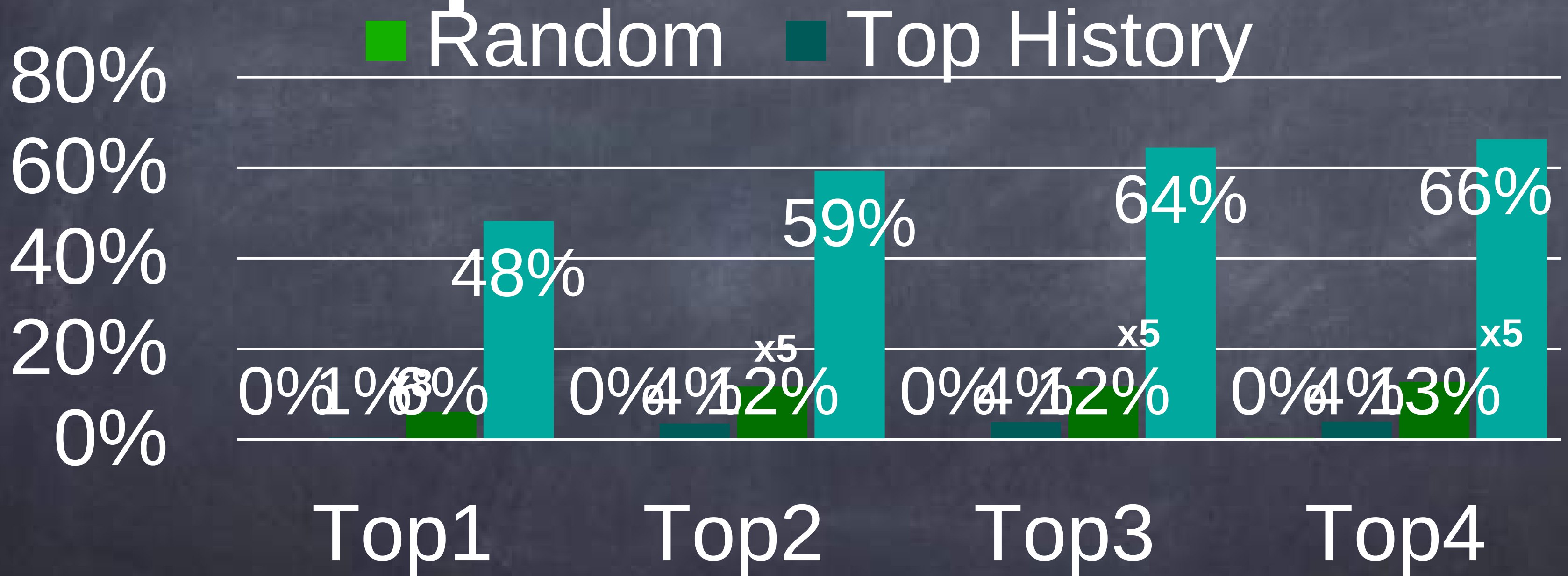

**Barcelona Matches in UEFA Champions League**

| Date | Opponent | Place |
|---|---|---|
| 2016-2017 | | |
| 2016-09-13 | Celtic | Barcelona |
| 2016-09-28 | Borussia M | Monchengladbach |
| 2016-10-19 | Manchester City | Barcelona |
| 2016-11-01 | Manchester City | Manchester |
| 2016-11-23 | Celtic | Glasgow |
| 2016-12-06 | Borussia M | Barcelona |
| 2017-02-14 | PSG | Paris |
| 2017-03-08 | PSG | Barcelona |
| 2017-04-11 | Juventus | Torino |
| 2017-04-19 | Juventus | Barcelona |
| 2017-2018 | | |
| 2017-09-12 | Juventus | Barcelona |

# About model

Top destinations from user's country
Paris
Rome
+
Barcelona
Top from user's history
Chicago
+
Dubai
Top from model
ML Model 1
London
Get pool of destination candidates
Paris
Rome
Barcelona
Chicago
Dubai
London
Rate them
ML Model 2
Get topN candidates
London
Rome
Barcelona
Dubai

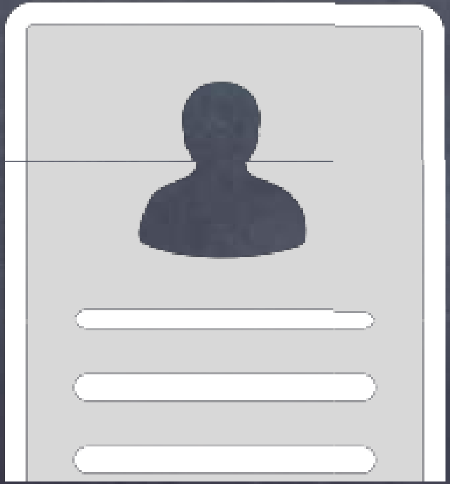
# ML can make a prediction



# Best Results

Tailoring flight search results

# Travel Data



Search patterns

Itineraries

Loyalty programs

Travel expenses

Travel preferences

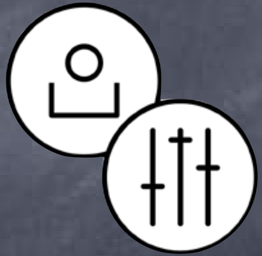
Flight reviews

Payment data

# Infer
# Passenger Preferences

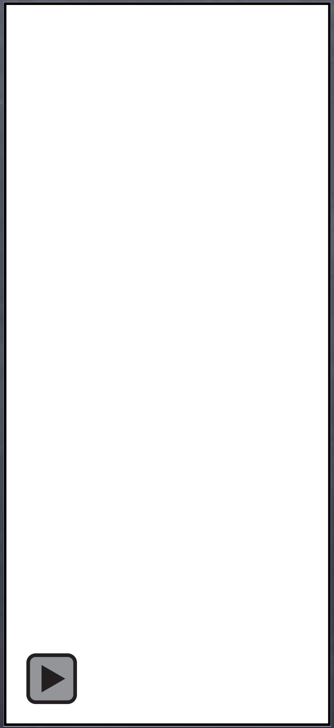
Bookings

Machine learning →

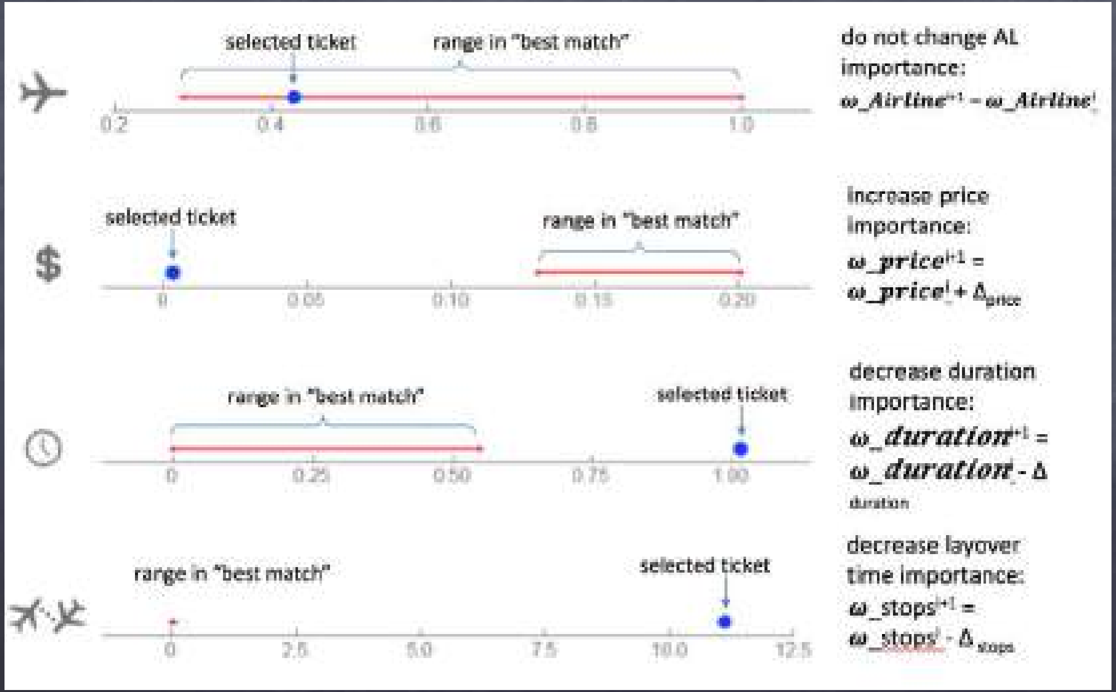


Individual
Preferences

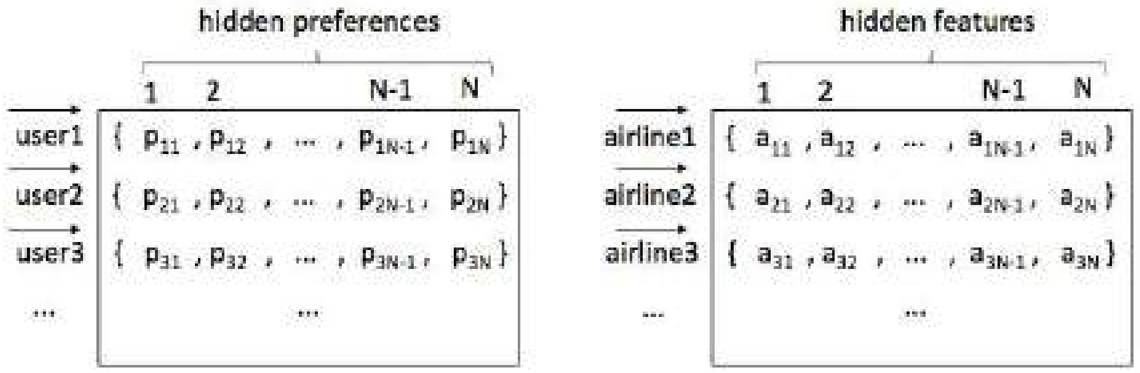
# Search & Book



# Self-Learning Algorithm



# Customer




Maximize the likelihood of AITA travel history:

$$\begin{matrix}\{p_1 \;\ldots, p_N\}_i \\ \{a_1 \;\ldots, a_N\}_i\end{matrix} = argmax\left[Log\left(\prod_{\substack{all\\users\,k}}\;\prod_{\substack{all\,trips\\of\,user\,k}} P(A_i|\{A_1,\ldots,A_n\})\right) - \lambda\sum_{i=1}^{N}(pref_i^{\,2}+AL_i^2)\right]$$

84% match

Wanna learn more?

ai@appintheair.mobi

# AI in Revenue Management.
# Is it Really New?

Laurent Lebard
CEO, YieldIn

Track Sponsor

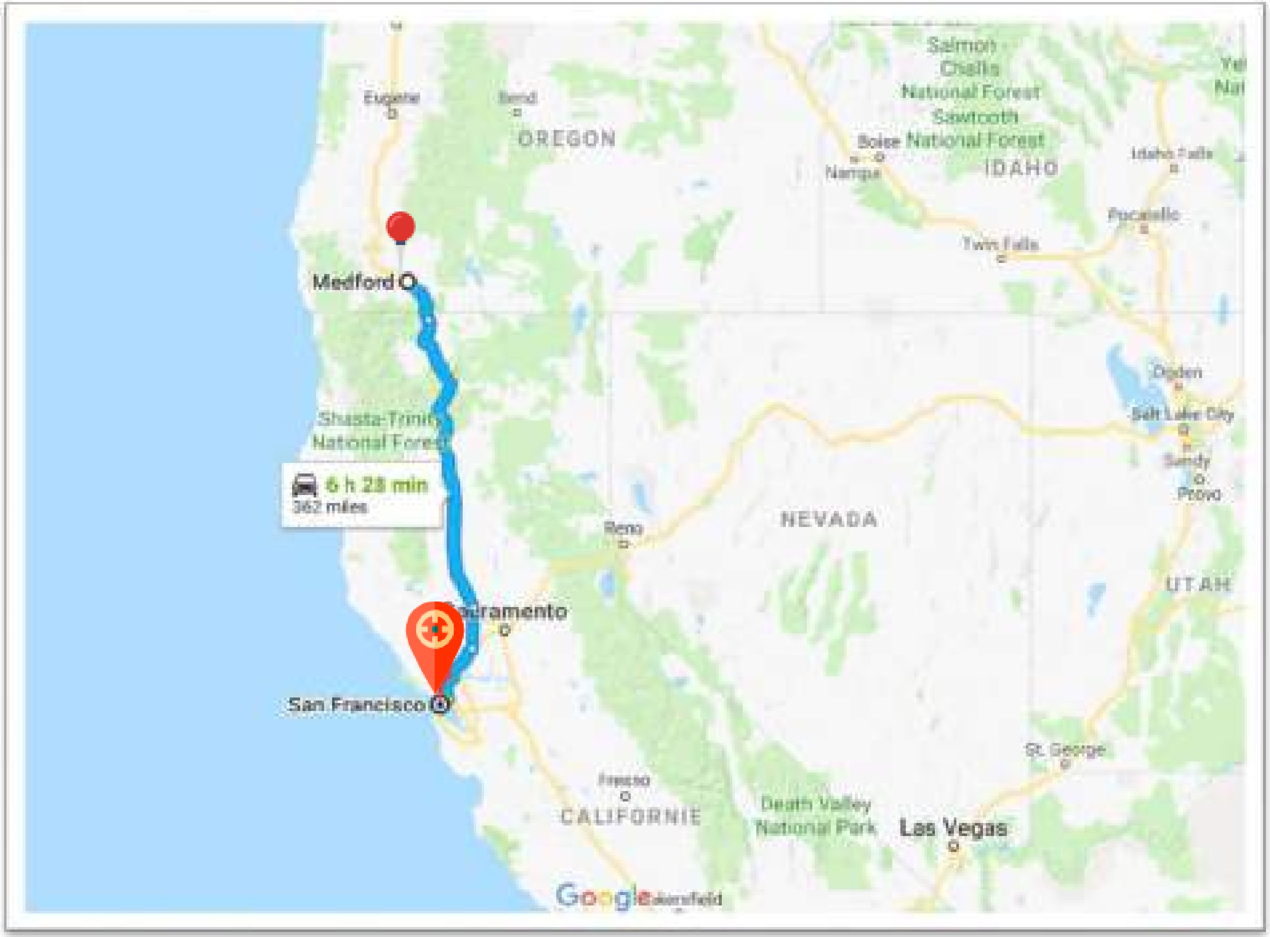
OpenJaw

WHAT WE DO:

# LOOKING FOR A SMART CAR

# PAST RM SOLUTIONS → NON CONNECTED CAR

# RM AIMS AT GUIDING YOU FROM …




CURRENT REVENUE

TO

MAXIMUM REVENUE

ACHIEVED THANKS TO THE
OPTIMAL PRICE(S)

# WAS IT EASY TO GET TO OPTIMAL REVENUE ?

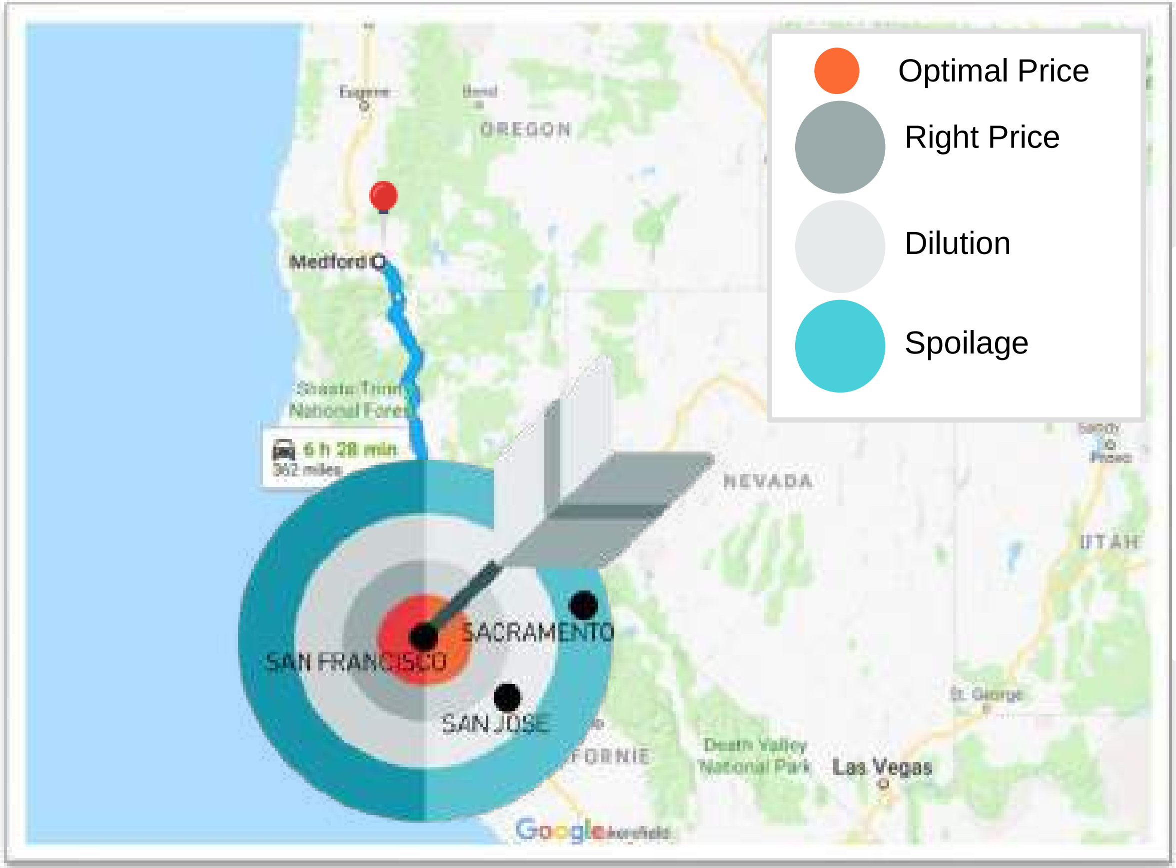
WHEN THERE WAS ONLY EMPTY MOTORWAY?
WHEN COMPETITION WAS LIMITED?
WHEN CUSTOMERS USED TO BE FAITHFUL?

# YES, JUST FOLLOW THE GPS

USING **NOT ONLINE HISTORICAL MAP**

AND AN **OPTIMISER**

# WHAT IF HISTORICAL MAP WAS NOT UP TO DATE ?




→ IN SAN JOSE, OR A BIT FURTHER, IN **SACRAMENTO**?

→ **HIGH** TECHNOLOGY ESSENTIALLY BASED ON **INTERNAL** DATA

→ REACTS **SLOWLY** TO **CHANGE** IN THE ENVIRONMENT

# WHAT IF HISTORICAL MAP WAS NOT UP TO DATE ?

**Ursula Silling**
do things differently - XXL Solutions

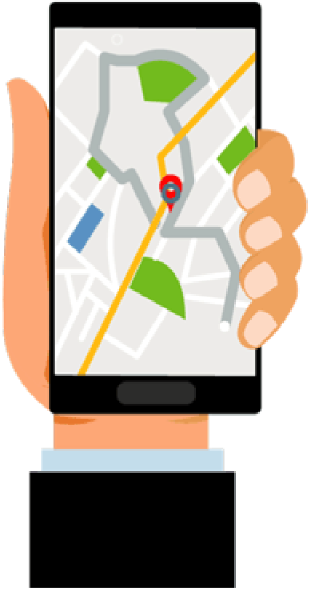
The past is less and less a faithful mirror of the future

In the digital world RM has become even more important than befor ...see more


**The past is less and less a faithful mirror of the future**
xxlsolutions.us

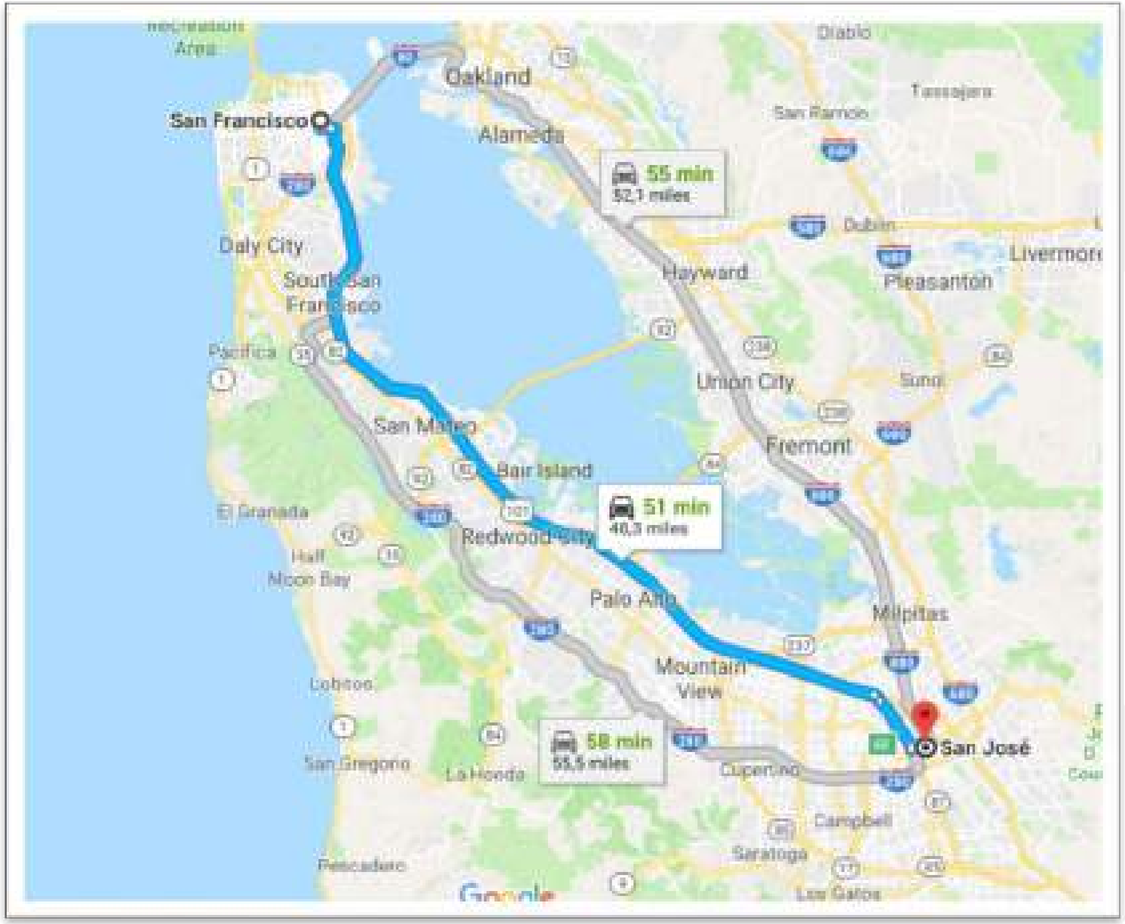
- → DEMAND HAS ACCESS TO UNIVERSAL PRICE OFFERS
- → DEMAND IS LESS AND LESS FAITHFUL
- → MARKETS ARE MOVING FASTER AND DO NOT FOLLOW A QUIET STRAIGHT ROAD

# THE ROAD MAYBE SNAKY, BUSY AND HASARDOUS



WANTED : A SMART CAR WITH **CONNECTED REAL TIME** GPS

# A SMART CAR ABLE TO ADAPT




→ ITS **GOAL** TO THE WEATHER AND YOUR MOOD

→ ITS **ITINERARY** TO ENVIRONMENTAL CHANGE

→ ITS **DRIVING STYLE** TO THE ROAD TYPE AND TO THE TRAFFIC

# A MACHINE WITH INTERNAL AND EXTERNAL SENSORS



- → MORE AND MORE DATA IS NECESSARY FOR TAKING THE RIGHT PRICE & RM DECISIONS
- → BOTH INTERNAL AND EXTERNAL DATA
- → BOTH PAST AND CURRENT
- → REQUIRED: PROCESSING AND MAPPING OF BIG DATA

Manage dynamic, tactical and strategic pricing moves

YIELDIN

# A MACHINE WHICH ADAPTS ITS GOAL


→ PERFORMANCE IS NOT ALWAYS EQUAL TO LAST PLANNED ONES →**ADJUST YOUR OBJECTIVES**

→ IF YOU CAN TRANSFORM LOW **REVENUE** FLIGHT IN MID **REVENUE** FLIGHT → YOU WIN

# A MACHINE WHICH ADAPTS ITS DRIVING STYLE


→ ADAPTS ITS **SPEED** TO **DEMAND** PRESSURE
→ ADAPTS ITS **SPEED** TO SAFETY DISTANCE WITH **COMPETITORS**

# A MACHINE WHICH SPEAKS, EXPLAINS


→ EXPLAINS THE SITUATION
→ EXPLAINS WHAT ACTIONS WILL HANDLE IT

# A MACHINE WHICH REMINDS YOU WHO DRIVES


→ WHAT IS **AUTO** AND MANAGED BY THE **MACHINE**
→ WHAT IS **MANUAL** AND IS UNDER THE **PILOT** RESPONSIBILITY

# A MACHINE WHICH DRAWS ATTENTION, STEERS ACTIONS


→ DISPLAYS CRITICAL **SITUATIONS** TO BE **MONITORED**
→ DISPLAYS **ACTIONS** TO BE **UNDERTAKEN**

# AI : HUMAN AND MACHINE DRIVING TOGETHER

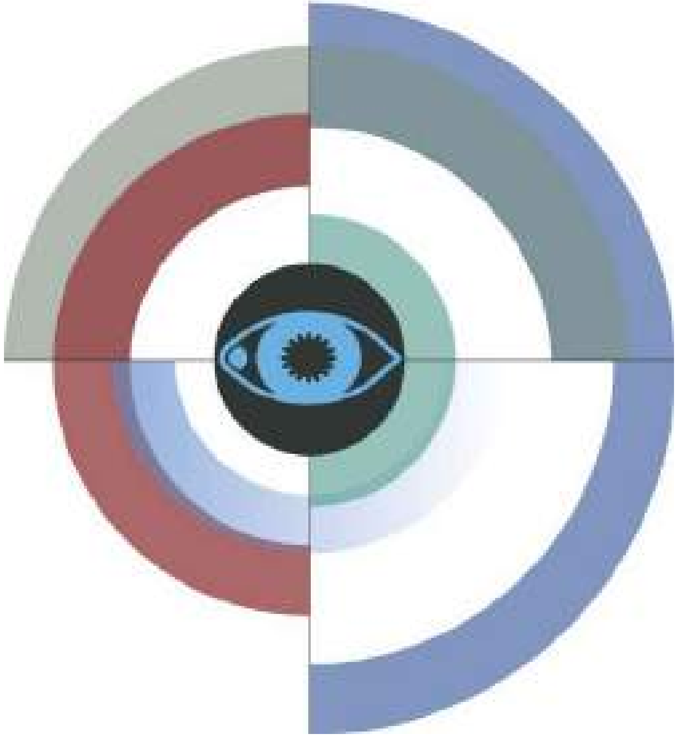

→ WITH FULL AUTOMATED PILOT, HUMAN MAY LOSE REACTION ABILITIES

→ THIS IW WHY AIRBUS WOULD LIKE TO:

✓ ADD MORE PILOT ACTIVITY IN THE COCKPIT

✓ SOME KEY INFORMATION ON THE WINDSCREEN USING PFD (PRIMARY FLIGHT DISPLAY)

# AI / ML PHILOSOPHY



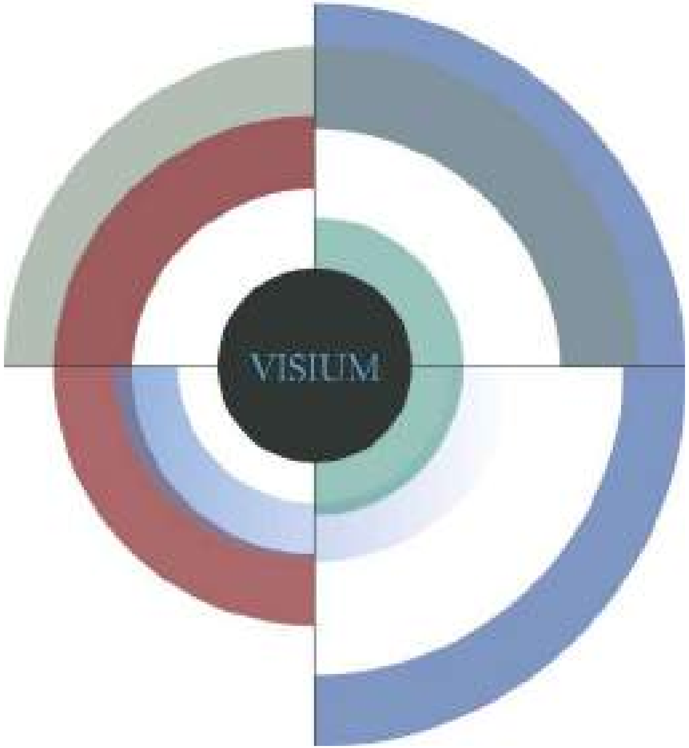
MACHINE SHOULD BE ABLE TO

→ SPY IT ALL
→ THINK FASTER
→ DRIVE IT ALL
→ RECOMMEND

HUMAN SHOULD BE ABLE TO

→ UNDERSTAND
→ KNOW HOW
→ DRIVE IT ALL
→ VALIDATE

# MACHINE LEARNING → ABILITY TO




MACHINE SHOULD BE ABLE TO

→ LOG ALL THE PAST
→ REWIND ALL SITUATIONS AND ACTIONS

SHALL IT AUTOMATICALLY CHANGE

→ SETTINGS?
→ WAY OF DRIVING?

# ML : SET OPTIMAL SAFETY DISTANCES

PRICE EFFICIENCY: SET OPTIMAL COMPETITIVE PRICE RANGE FOR INSTANCE FOR “LATE BOOKING LOW FLIGHTS”

→ MACHINE CAN DECIDE OPTIMAL PRICE RANGES / SEASONS, COMPETITORS, COMPETITOR CURRENT PRICES, LEAD TIME RANGES
→ ISSUE : LOCAL OPTIMUM

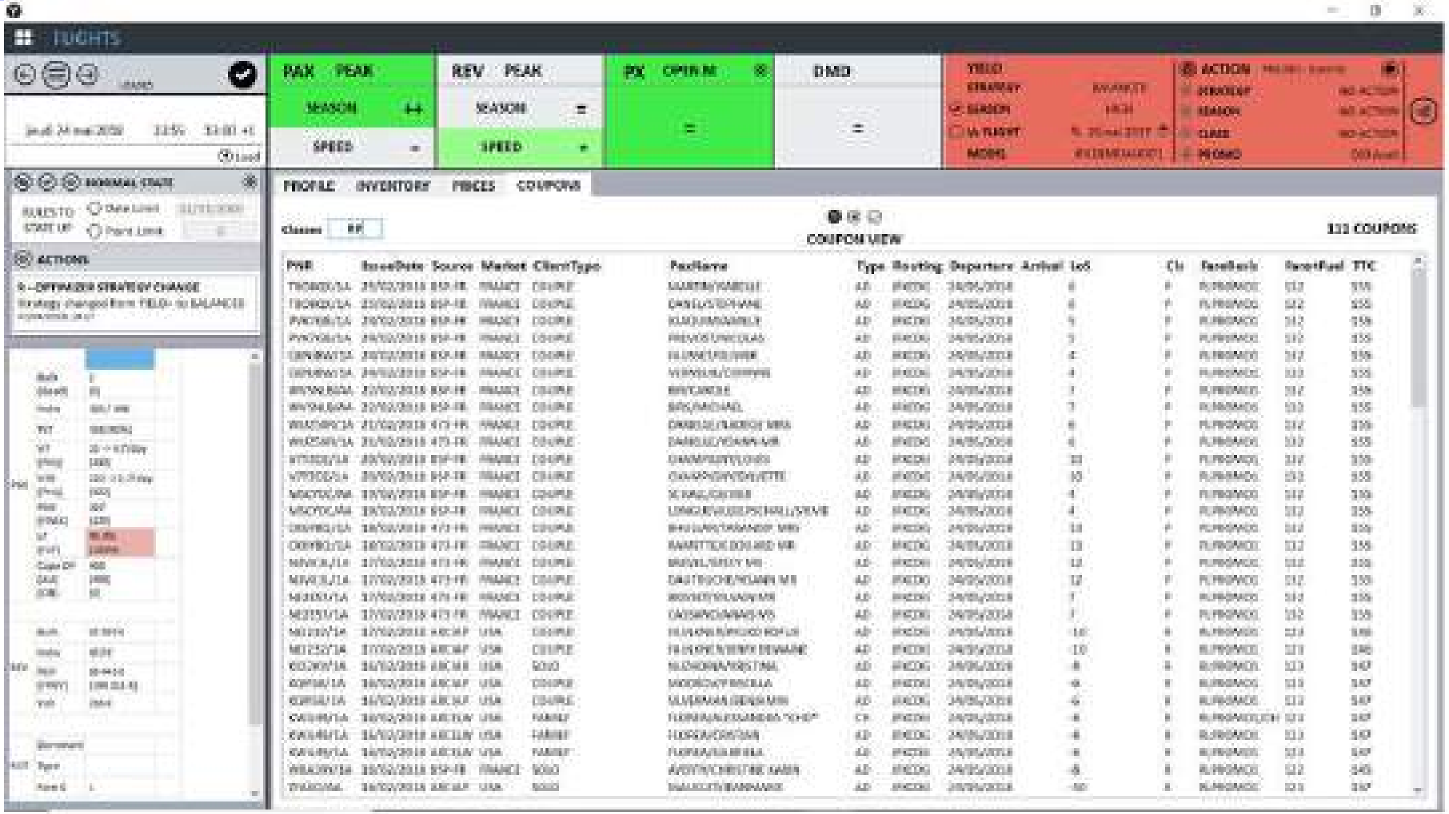
# ML: THE BASIC IS REWIND

ABILITY TO **DETECT PAST** SPOILAGE OR DILUTION

# AI : BIG DATA RM AND SALES

→ RM WILL MOVE FROM **INVENTORY** DATA TO COUPONS OR PNR DATA
→ ONE TO MANY → **TO FEW** →TO ONE RM ⇔ **RM & CRM** TOGETHER
→ USE THE POWER OF BIG DATA

# AI : RM AND SALES → RM & CRM




NEED TO KNOW WHO IS ON YOUR FLIGHT, TYPE OF CUSTOMER, LOS, DISTRIBUTION CHANNEL
→ **REAL TRUE REVENUE**!

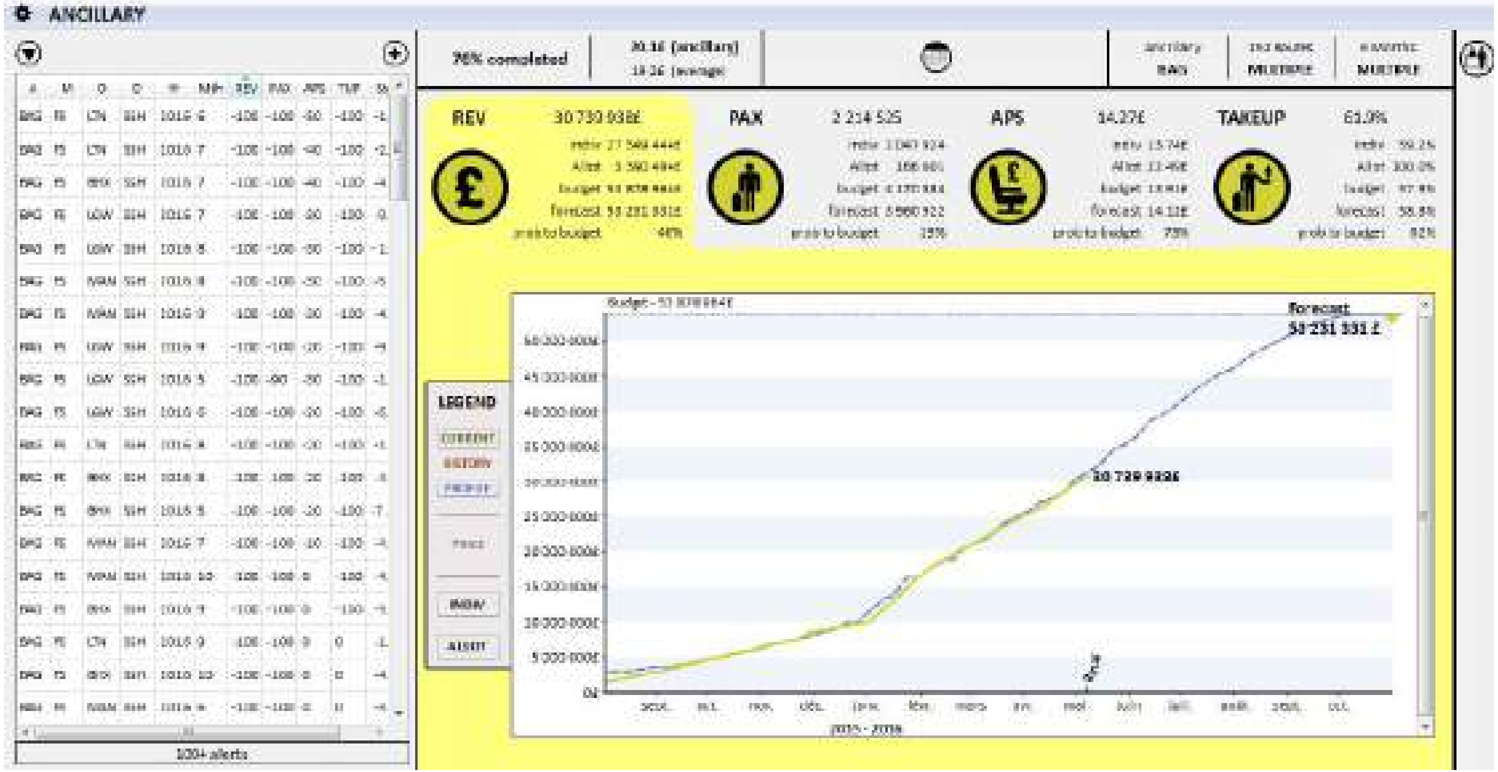
# LOOKING FOR THE INVISIBLE SMART CAR

# AI : RM AND SALES → ONE TO FEW RM

RM SET THE ENVELOPPE OF DISCOUNT, COMMERCIAL DECIDES WHAT TO DO WITH IT

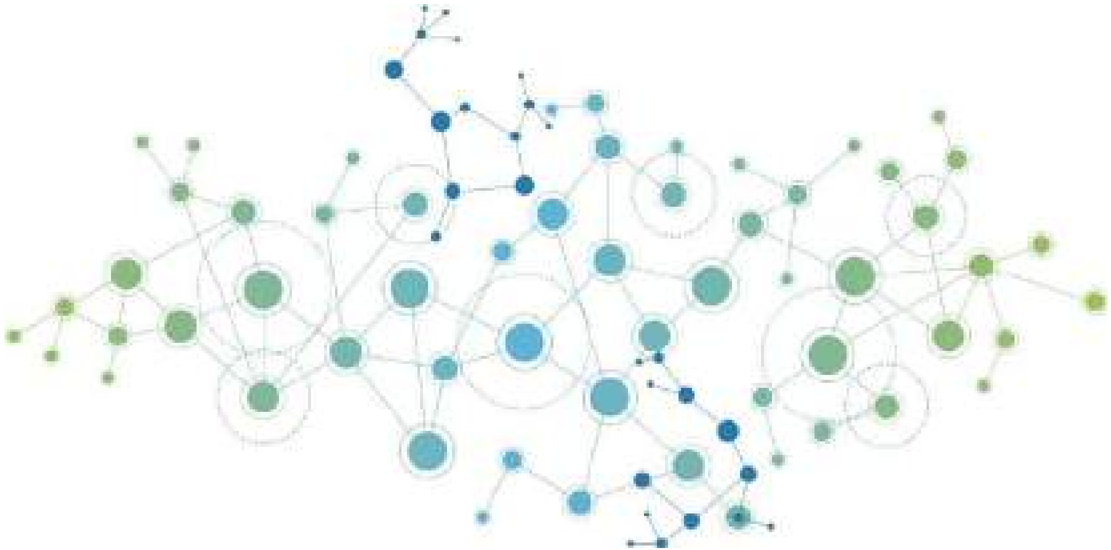

→ CUSTOMISED SPECIAL OFFERS

# AI : RM AND SALES → ONE TO FEW RM




→ MANAGE ANCILLARY REVENUE BY DYNAMIC PRICING⇔ KNOW YOUR CUSTOMERS!

# AI : RM AND SALES → RM & CRM & PSS MANAGING TOTAL REVENUE



→ WANTED: VERY FREE AND DYNAMIC PRICING

→ REQUIRED : HIGH CONNECTIVITY AMONG RM, PSS, CRM, ATPCO, ETC

www.yieldin.com

contact@yieldin.com
20 Avenue Kléber
75116 Paris

# Networking Lunch in Restaurant

# AI is Hard at Work, Simplifying the Industry Already

Mario Louca
Executive Director, Global Industry Leader Europe,
IBM Global Travel & Transportation Industry

Track Sponsor

OpenJaw

# Air Cargo Rules & Regulations Compliance

Mario Louca
Executive Director, Global Industry Leader
IBM Global Travel & Transportation

IBM Watson

# The need for a Virtual Compliance Agent

- **Increasing complexity of rules and regulations** on all compliance fields in the industry
- **Reduced visibilty** by increased separation of departmental responsibilities
- **Information overload** - limitations on the human capabilities to cope
- **Multiple systems and information sources** to access
- **Increased focus of regulators on compliance** and enforcement
- Recent developments show **possible prosecution of individuals** involved in the cargo supply chain

***THE NEED FOR 100% COMPLIANCE BECOMES VITAL***

# Watson for Regulatory Compliance

- IBM has engaged with a major European airline and IATA to conduct a Proof of Concept on using cognitive technologies to determine cargo compliance

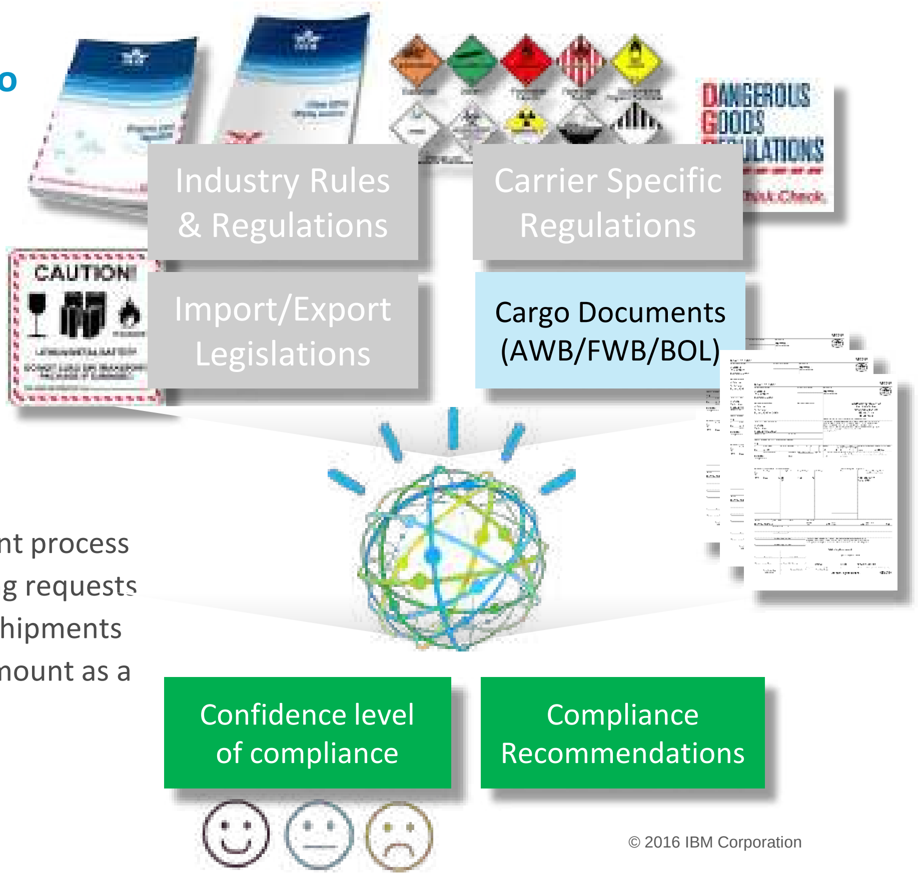
- The solution is powered by Watson (IBM's Cognitive Platform), with focus on rules for Lithium Battery identified in IATA Dangerous Goods Regulations (DGR)

- The solution was built on the knowledge base of the airline and IATA

# The Use Case for Cargo Rules & Regulations Compliance

## A cognitive compliance supporting tool that performs cargo declaration checks quickly, safely and securely

- Performing cargo declaration checks quickly, safely and securely
- Utilizing cognitive (AI) technology to determine cargo compliance
- Trained to develop a knowledge base in compliance for cargo:
  - ✓ Rules & Regulations manuals
  - ✓ carrier policies
  - ✓ relevant legislation




## The immediate benefits:

- **Lowering the false positives** - avoiding fines while delaying the shipment process
- **Increasing responsiveness of sales and compliance agents** with booking requests
- **Reducing and optimizing the time spent on repairs** of non-compliant shipments
- **Reducing or eliminating fines** due to non-compliance by reduce fine amount as a result of lower false positives

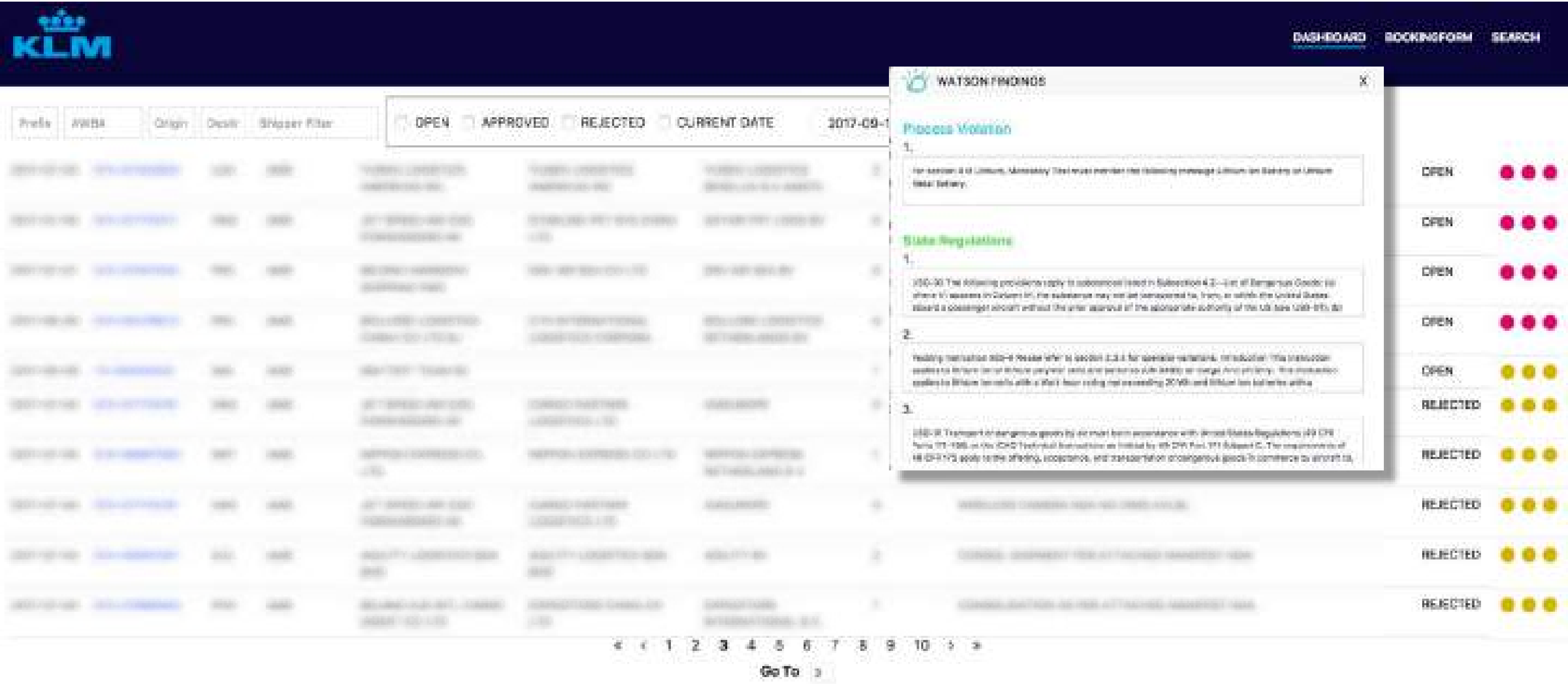
# What was the POC Objective

## Build an MVP for Hazardous & Dangerous Goods

## With Scope:

- Read and Interpret FWB and FHL information of the booking
- Read and Interpret IATA Manual Lithium Battery Shipping Guidelines and Military Goods/Dual Purpose Data (Commodity, Shipper, Consignee)
- Two levels of decision support for the compliance officer:
  - Compliance Flag (red-yellow-green) which summarizes violation
  - Drill Down to relevant IATA LBSG sections with detailed information on rules & policies violated **and resolvement**
- Takes into account Country/State and Carrier Regulations
- Captures Feedback of compliance officer to improve the system
- Shows details of Shipper history of cargo compliance - can be used for profiling

# The Dashboard - Virtual Compliance Officer



# Watson Findings and the learning process

**Watson Findings**

**Process Violation**

1.

For section II of Lithium, Mandatory Text must mention the following message Lithium Ion Battery or Lithium Metal Battery.....

✓ Agree X Disagree

**State Regulations**

1.

[ score: 0.21032925 ] HKG-02 English must be used in addition to the language which may be required by the State of origin, and each language must be given equal prominence (see 5.4, 7.2.2).....

✓ Agree X Disagree

**Other Regulations**

1.

[ score: 0.73416424 ] Packing Instruction 967–II Please refer to section 2.3.4 for operator variations. Introduction This instruction applies where the equipment contains lithium ion cells with a Watt-hour rating in excess of 20 Wh or lithium ion batteries with a Watt-hour rating in excess of 100 Wh .....

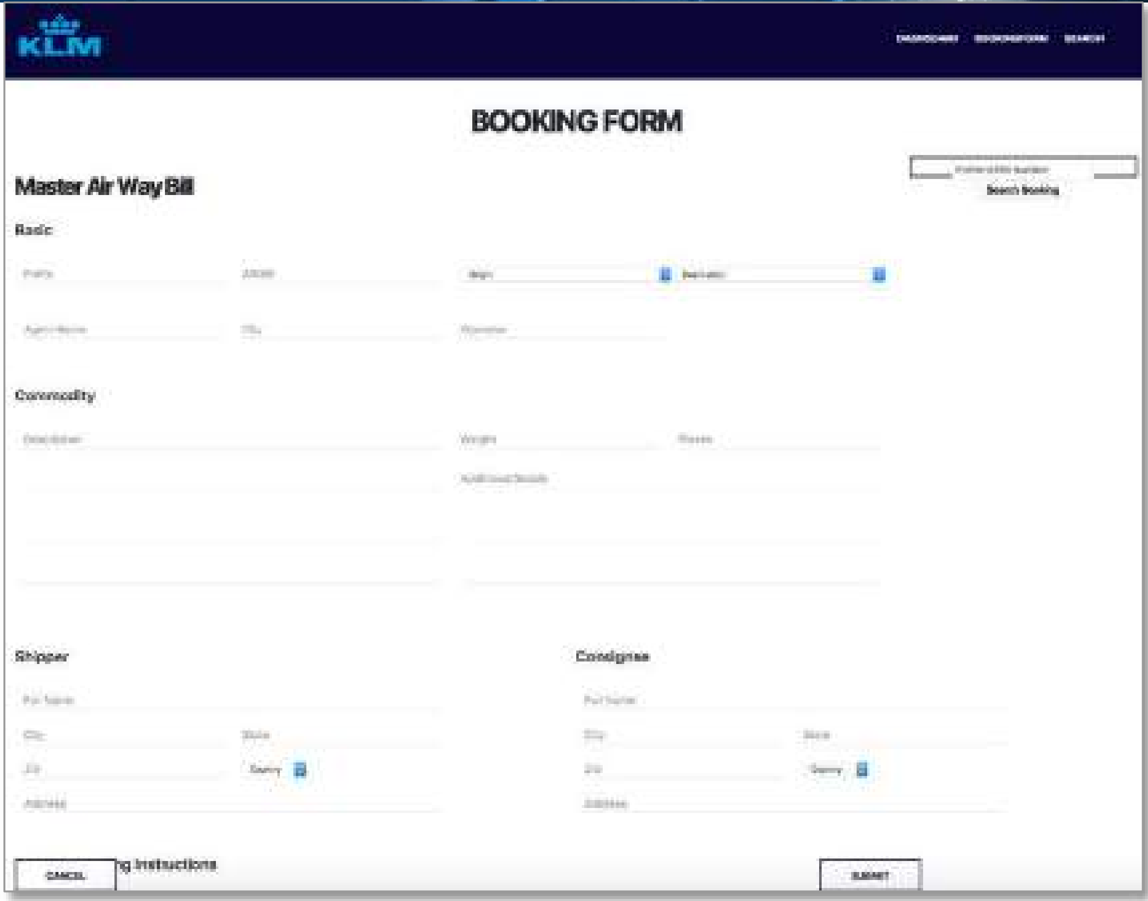
✓ Agree X Disagree

2.

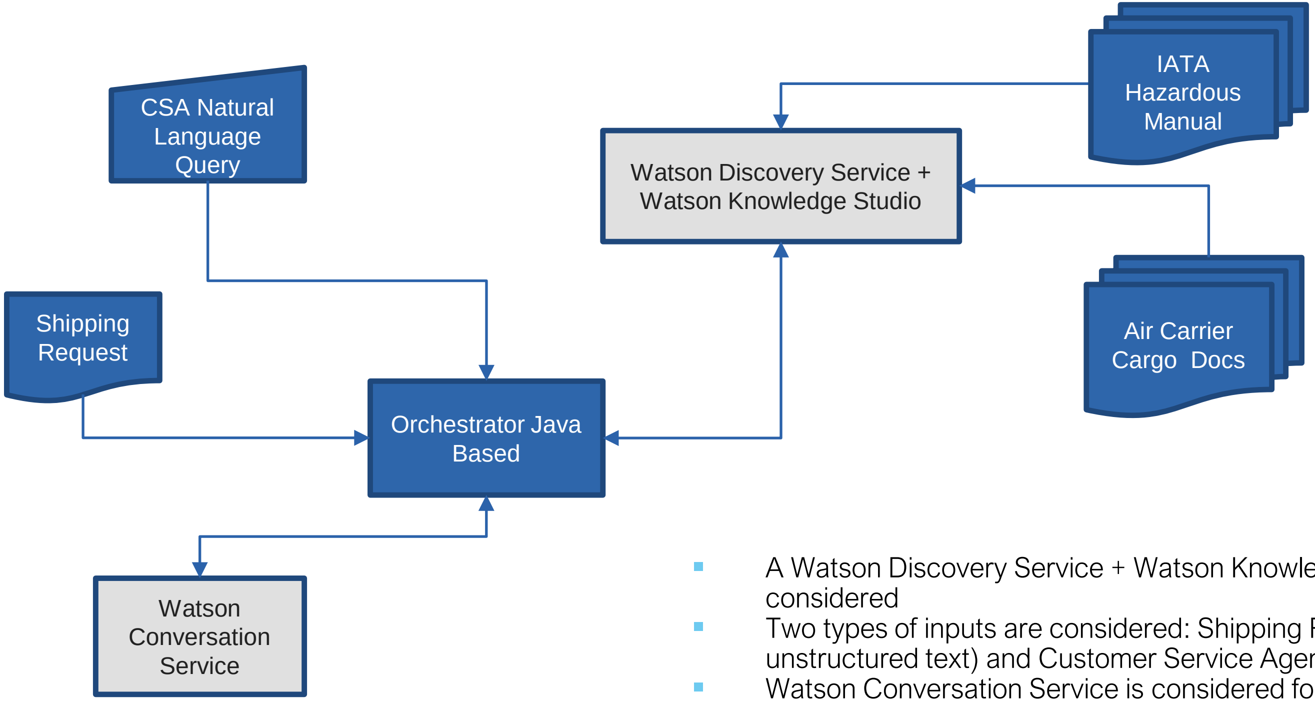
[ score: 0.66647196 ] Packing Instruction 965–II Please refer to section 2.3.4 for operator variations. Introduction This instruction applies to lithium ion or lithium polymer cells and batteries (UN 3480) on Cargo Aircraft Only. This instruction applies to lithium ion cells with a Watt-hour rating .....

CANCEL SUBMIT

# Bookings can be entered via a form or consumed in real time when integrated with a CMS

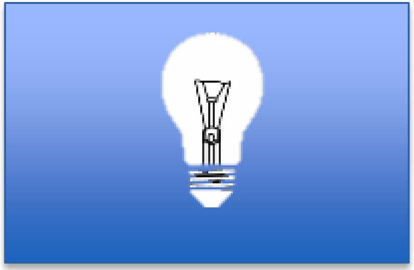


# High Level Solution Overview




- A Watson Discovery Service + Watson Knowledge Studio based solution has been considered
- Two types of inputs are considered: Shipping Request ( mix of structured and unstructured text) and Customer Service Agent (CSA) natural language query
- Watson Conversation Service is considered for processing natural language chat

# Step by Step development of the Virtual Compliance Agent



## Step 1: Proof of Concept Ideation

Define the scope jointly with:
- IATA
- the Air Cargo Carrier
- IBM

Key consideration:
- Solution requirements

Objective:
- Learn how cognitive works and can be used by KLM Cargo to improve compliance

## Step 2: PoC Build & Deliver

- Data Ingestion & Output
- Technology Proof & Assessment of Full Scope

Objective:
- Improved compliance by finding faster non-compliant shipment bookings
- Improve productivity

## Step 3 – Full solution build

- Customization and prepare for Deployment
- Final set of requirement Requirements
- Business Value Case
- Deployment Project Plan

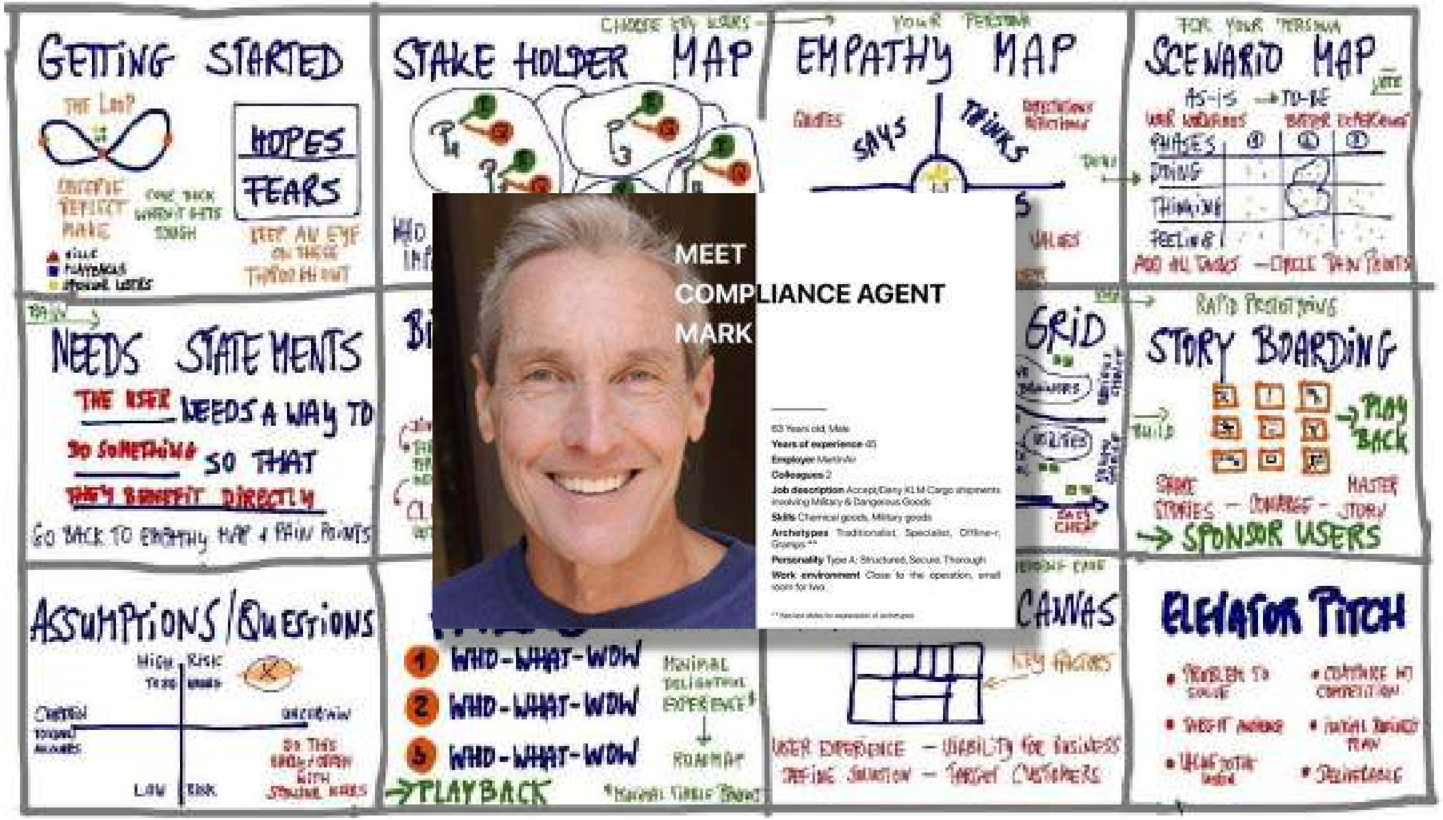
## Step 4 - Implementation

- Full Solution Deployment
- Integrating into business process and IT landscape
- Continue to add enhancements

Objective:
- Increase compliance by monitoring more bookings with the Watson Compliance Advisor

# POC based on Design Thinking Workshop for one Persona

Learn how cognitive capability can be used by an  Air Cargo Carrier to support compliance process



# The PoC Journey – Steps 1 and 2

**A 12 week engagement:**

- 6 weeks to agree on scope, define the requirements and built the Dashboard
- 6 week to teach Watson in real time

19/6 & 20/6
Step 1
Proof of Concept
Ideation

30/6
Approve
Scope

3/7
Step 2
Start Build &
Deliver

20/7
Step 2
Review
Sprint I

3/8
Step 2
Review
Sprint II

17/8
Step 2
Review
Sprint III

31/8
Step 2
Review
Sprint IV

14/9
Step 2
Review
Sprint V

06/10
Step 2
Final
Briefing

# POC Results after 12 weeks trial

**Lithium shipments:**

- 75% accuracy for Lithium shipments with the first 12 weeks of training
- Further training of Watson Compliance has increased accuracy to beyond 90%

**Military Goods shipments:**

- For a selected set of non-compliant shipments, we could identify 90% of non-compliant shipments

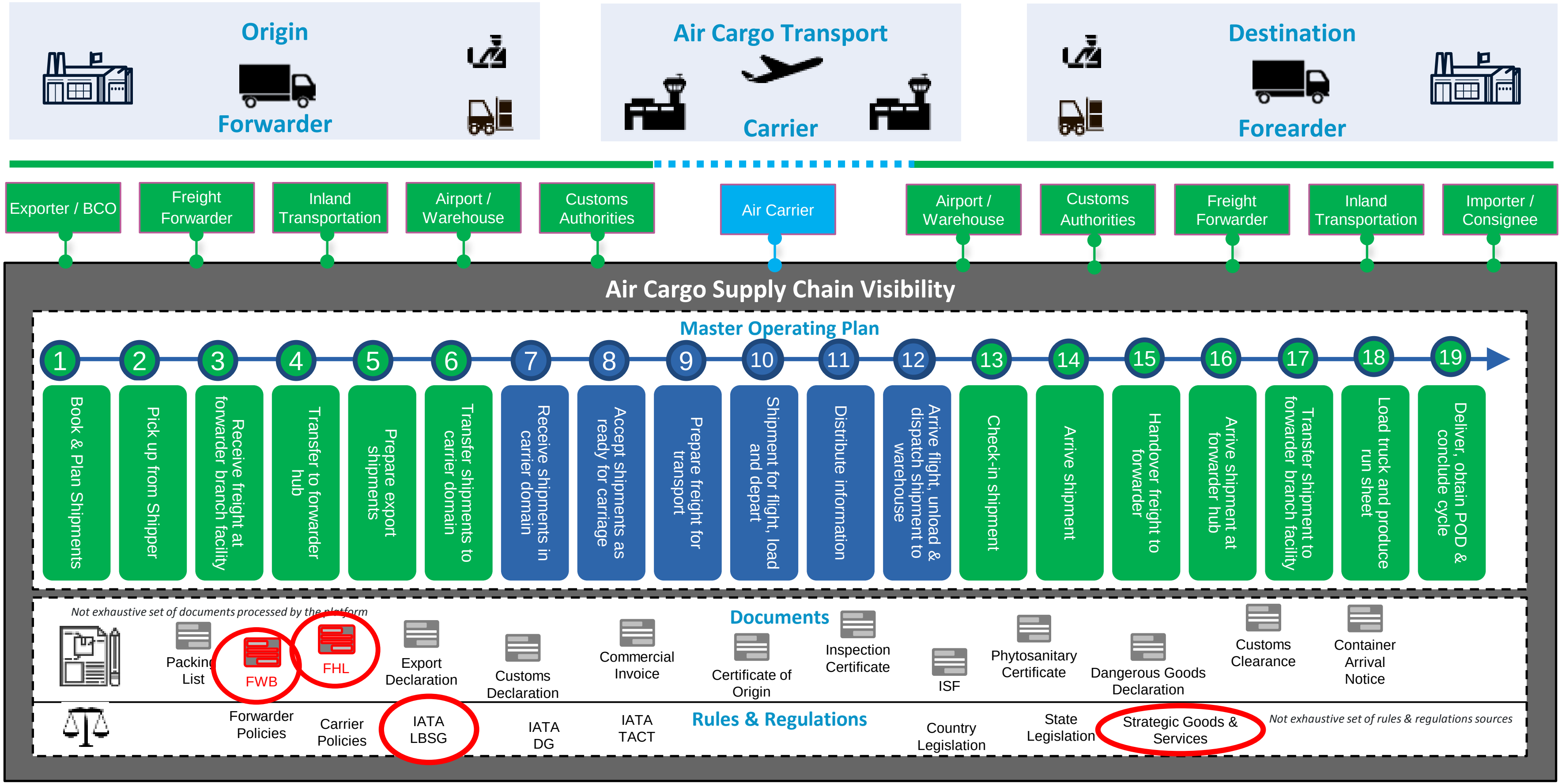
**Watson Findings with confidence score:**

- The confidence score of the Findings goes up or down based upon “Agree” or “Disagree” in real time

**MOP Process steps impacted:**

- Watson can add value at different steps in the MOP process.
- Main events of impact are:
    1. Booking process
    2. And documentation and physical Acceptance

# Future Scope Opportunities…..



# Thank you!

# Privacy and AI in the Age of GDPR

Kevin Iverson
CTO, Journera

Track Sponsor

OpenJaw

# AI and Privacy

## Can AI and ML Help to Comply with GDPR and Other Data Privacy and Security Frameworks?

Kevin Iverson

ADS 2018

JOURNERA

# About me

- Kevin Iverson
  kiverson@journera.com
- CTO @ Journera
- Background
  - 9 years @ Orbitz
  - 5 years @ various small-big companies focused on using data in Real Estate, Consumer Reviews, and Commercial Construction and Architecture

# JOURNERA

## Secure platform for real-time data exchange


**Publish and Subscribe APIs**
Work with data easily via standardized APIs providing one-to-many connectivity and advanced data normalization

**Permissions Architecture**
Any data used to enhance a traveler's experience requires explicit permission from the Publisher - no data flows to subscribers without proper permissions in place

**Cryptographically-enforced**
All sensitive personal data is cryptographically hashed so that it is unreadable and unrecoverable - even for Journera employees

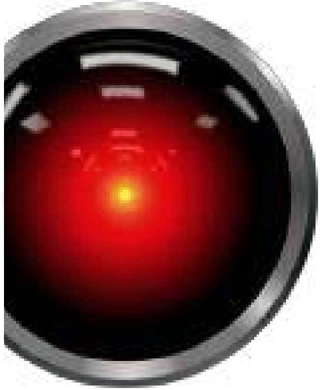
**Relationship-based**
Both Publisher and Subscriber must know a traveler to use the platform - Journera cannot be used for customer acquisition or selling travelers' contact information

**Compliant**
Journera is Privacy Shield and GDPR compliant, adhering to the highest standards of global privacy practices

# AI and Privacy – The Negative

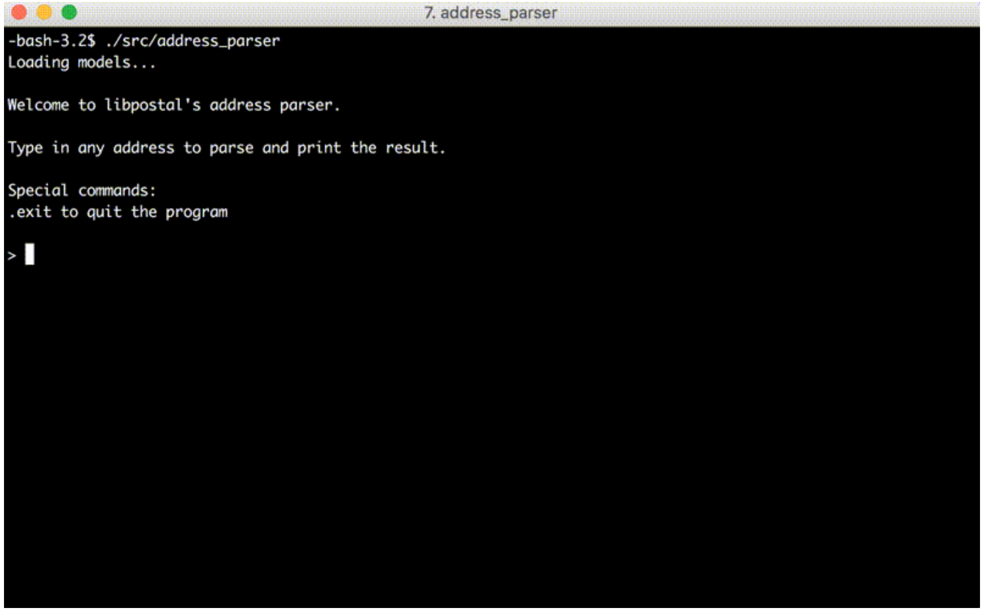
- Big data
  - More data the better
- Black box
  - Not always possible to know why a decision is made
- Surfacing new insights
  - How did they know that?
- Reverse engineering risks
  - Pulling source data out of models

# AI and Privacy – The Positive Negative

# Data Minimization and Privacy by Design

- **Challenge: Balance privacy and appropriate use**
- Passwords
  - Plain text -> Hashed
  - Great for exact matches
- Can also work for "standard" formats
  - Exact match after normalization
  - Phone, government ID, etc
- Harder for less structured data – addresses



# Data Minimization

**Challenge: Creating good synthetic test data is hard**

- Testing with representative data is critical for complex data systems
- Masking can help, but so can AI

# Analyzing data

- **Challenge: Privacy-preserving data analysis is hard**
- Differential Privacy

# The
# ~~End~~
# Beginning

:-)

kiverson@journera.com

# “Moving the Needle” in the Airline Front Office


Mark Roboff

VP, Aerospace & Automotive

SparkCognition


Track Sponsor

OpenJaw

sparkcognition™

# Moving the Needle with AI

## Applications in the Airline Front Office

Mark Roboff
*Vice President, Aerospace & Automotive*

# AI Systems Work Like A Human Brain

Process Information

Draw Conclusions

Codify Instincts and Experience Into Learning

# AI systems

Significant benefits for the industrial world

Improved Accuracy

Scalability

External Factors

Adaptability

Security

In-Context Remediation

# Global commercial aviation

## A remarkable transformation of its own

- After nearly a decade of of growing profit, major airline CEOs are saying the “boom/bust” cycle which has defined the industry over the last thirty years has come to an end
- Pundits are quick to point out as key factors:
    - *Industry consolidation*
    - *Low oil prices and other favorable externalities*
- But that is only part of the story

# Analytics and optimization

**Critical to the turnaround**

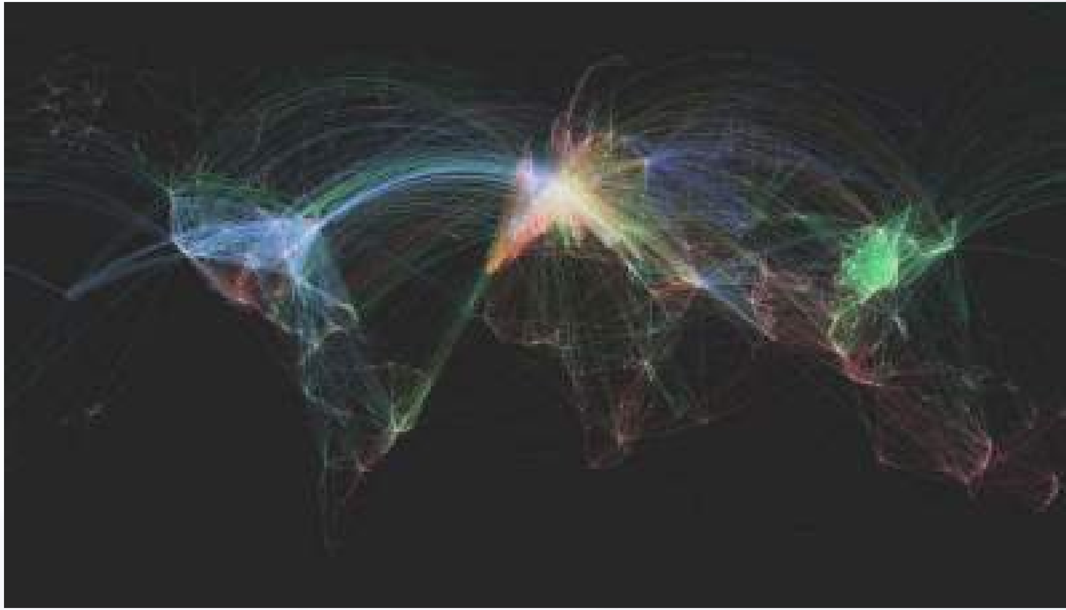
- Capacity Optimization
- Revenue Management
- Pricing Prediction
- Customer Segmenting

*It's no accident that most planes are full today*

# Equilibrium is re-established

## New approaches are needed to forge ahead

- Improved Forecasting
- Hyperlocal Pricing
- Market Prescience
- Smarter Segmenting



# AI and revenue management

**AI will power the next generation of revenue management**

Weather & Environmental Data

Social Media

Hyperlocal Event & Traffic Patterns

**Imagine being able to automatically consider, ingest, and integrate volatile and voluminous external data sources:**

1. The AI augmented data scientist
2. Can scale model development
3. And keep pace with accelerated change

# The building blocks of AI

## Beyond machine learning algorithms

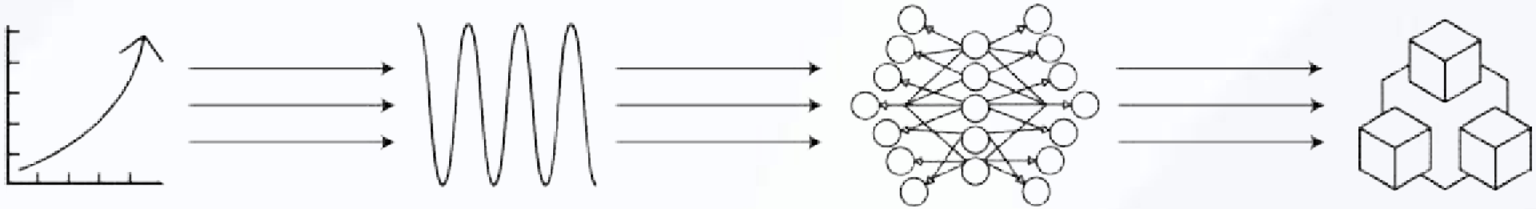
**Automated Model Building (AMB) and Infinite Learning**

**Natural Language Processing and Vision**

**Deep Learning and Reasoning Algorithms**

**Powerful Visualization with Evidential Insights**

# Accelerating and achieving scale



**Preprocessing**

- *Scaling*
- *Imputation*
- *One-Hot Encoding*
- *Balancing*

**Feature Generation**

- *Time Domain*
- *Fourier Domain*
- *Risk Index*

**Feature Selection**

- *Raw Features*
- *Generated Features*

**Model Building**

- *Classification*
- *Regression*
- *Clustering*
- *Anomaly Detection*

***SparkCognition uses advanced AI and genetic algorithms to drive model maintenance automatically***

# Who we are

SparkCognition is an enterprise AI company with software solutions that help customers

**Analyze increasingly complex data stores**

**Reveal actionable insights**

**Identify and automate optimal responses**

***Closed Series B funding of $56.5M in venture capital in February 2018***

# Customers, partners, and awards

**Customers**

Invenergy
DOVER
DUKE ENERGY
Honeywell
BOEING
DEFENSE INNOVATION UNIT EXPERIMENTAL
FLOWSERVE
MHPS
ARMY BE THE BEST
U.S. DEPARTMENT OF ENERGY

**Partners**

IBM
Google
OSIsoft.
ptc
GE
NATIONAL INSTRUMENTS
Deloitte.
relayr.

**Awards**

FROST & SULLIVAN
NOKIA Open Innovation Challenge 2015
CNBC DISRUPTOR 50 2017
THE AI 100
Gartner 2015 Cool Vendor
RED HERRING 100
50 2016 Fastest-Growing Companies in Central Texas
AUSTIN A-LIST

# Thank you

sparkcognition™

**Mark Roboff**
*Vice President, Aerospace & Automotive*
mroboff@sparkcognition.com

# Discover SITA's Secret Cookbook of an AI Project for Baggage!

Caroline Camilli-Gay
Program Manager, SITA Labs

Track Sponsor

OpenJaw


# AN AI COOKBOOK FOR BAGGAGE

By: Caroline Camilli-Gay Program Manager SITA Lab
with Patrick Valente, Data Scientist SITA

IATA

SITA

# THE 6 STEPS TO A RECIPE

| Steps | Food recipe | AI recipe |
|---|---|---|
| 1 | Shop for ingredients | Data collection |
| 2 | Unpack and wash | Data aggregation |
| 3 | Ingredient preparation | Feature engineering |
| 4 | Mix and cook | Machine learning approach |
| 5 | Taste and adjust seasoning | Model tuning |
| 6 | Eat and enjoy | Data interpretation |



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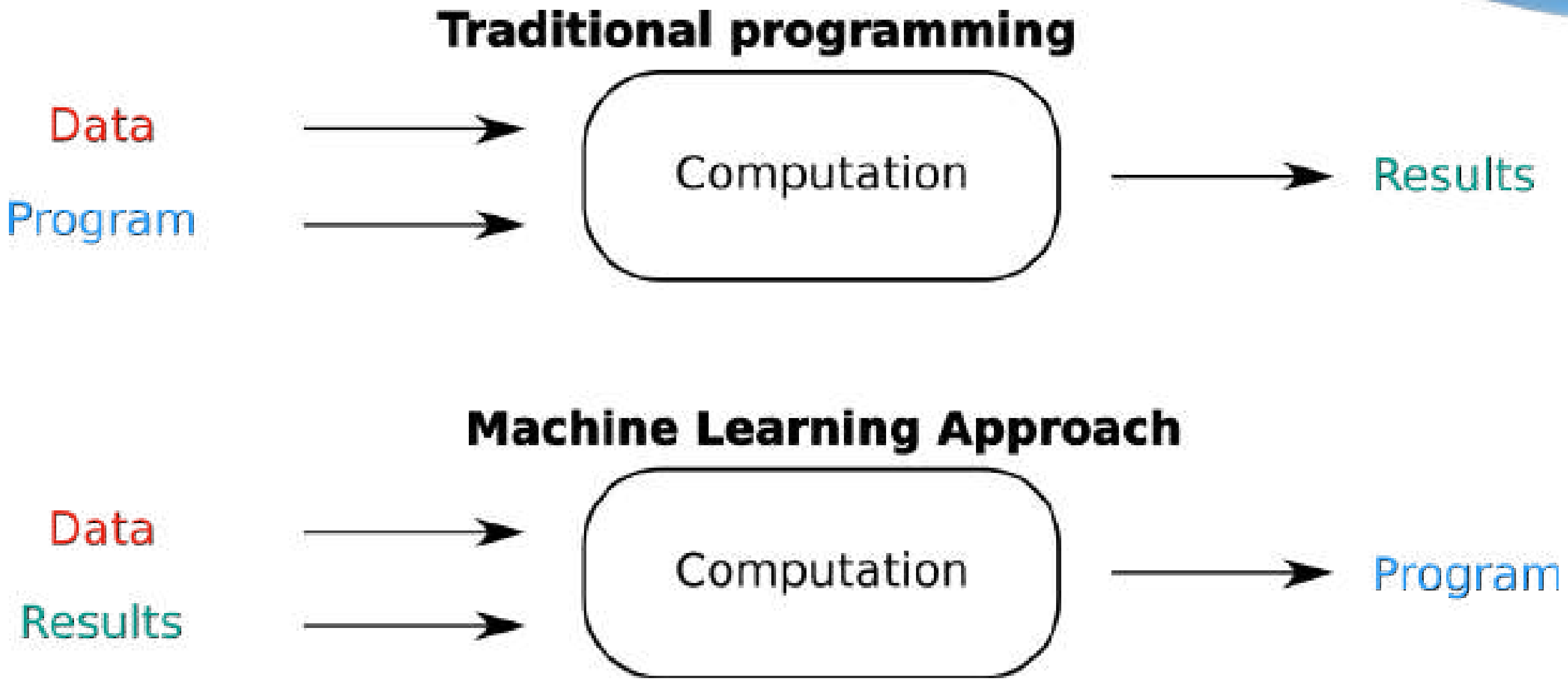
# DO YOU REALLY NEED TO COOK?

… if all you need is a glass of wine

# WHAT DO YOU NEED AI FOR?




*Source: recast.ai*

# 1

-

## SHOP FOR INGREDIENTS

## SELECT YOUR DATA

| Steps | Food recipe | AI recipe |
|---|---|---|
| 1 | Shop for ingredients | Data collection |
| 2 | Unpack and wash | Data aggregation |
| 3 | Food preparation | Feature engineering |
| 4 | Mix and cook | Machine learning approach |
| 5 | Taste and adjust seasoning | Model tuning |
| 6 | Eat and enjoy | Interpretation |

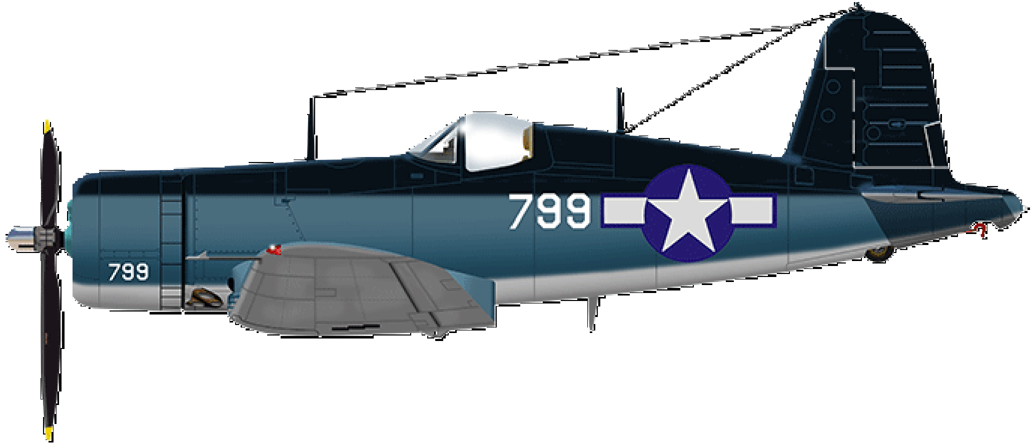
# SELECT YOUR INGREDIENTS / DATA

- Top quality ingredients taste better
- You need the right quantities
- Peas and beans vs beans and peas

- Quality data
- Data sample of sufficient size
- Consistent definition of data

# WHAT IS DATA QUALITY?

An illustrating story of Abraham Wald



# WHERE SHOULD PLANES BE ARMOURED?

| Section of plane | Bullet holes per square foot |
|---|---|
| Engine | 1.11 |
| Fuselage | 1.73 |
| Fuel system | 1.55 |
| Wings | 1.80 |

*Source: the power of mathematical thinking by Jordan Ellenberg*

# 3 KEY RULES FOR DATA QUALITY

- Data sample must be a **random** extract of the statistical population
  - Beware of the survivors' bias
  - Representative of full population
- Data must be **consistent** (same definition across spectrum)
  - Green peas don't taste the same as chick peas
  - There are many types of baggage data
  - RP1745 is not applied consistently by all airlines and airports
- Data sample must be of **sufficient size**

# WHAT DATA QUANTITY?

- 100,000 data points is a good start
- But you need a bigger sample if:
  - You have many parameters
  - You want to analyse sub-categories, extreme cases, seasonality

- Be aware of your computing power
  - More is not always better
  - Data size x 2 => computing power x 4
  - Data size x 3 => computing power x 9

# 2

-

# UNPACK AND WASH

# AGGREGATE YOUR DATA

| Steps | Food recipe | AI recipe |
|---|---|---|
| 1 | Shop for ingredients | Data collection |
| 2 | Unpack and wash | Data aggregation |
| 3 | Food preparation | Feature engineering |
| 4 | Mix and cook | Machine learning approach |
| 5 | Taste and adjust seasoning | Model tuning |
| 6 | Eat and enjoy | Interpretation |

# UNPACK AND WASH

# DATA AGGREGATION & CLEANING

{"airport":"MAD","eventDateTimeLocal":"2016-05-02T22:20:20.838+02:00","eventDateTimeUTC":"2016-05-
02T20:20:20.838Z","eventCode":"EXPECTED","eventType":"BAG_EXPECTED","eventDescription":"Bag
Expected","bagTagNumber":"0996111264","bim":"BSM\r\n.V/1TMAD\r\n.F/UX1061/03MAY/MXP/Y\r\n.I/UX0072/02
MAY/CCS/Y\r\n.N/0996111264001\r\n.S/Y/01A/C/004/004\r\n.W/K/2/46\r\n.P/SMITH/JOHNMR\r\nENDBSM","inboun
d":{"airlineCode":"UX","fltNum":"0072","date":"02MAY","airportCode":"CCS","classOfService":"Y"},"outbound":{"airlin
eCode":"UX","fltNum":"1061","date":"03MAY","airportCode":"MXP","classOfService":"Y"},"messageType":"BSM","ba
ggageSourceIndicator":"T","passenger":{"lastName":"SMITH","firstName":"JOHNMR","numberOfPassengers":""},"ba
gWeightDetails":{"indicator":"K","numberOfCheckedBags":"2","checkedWeight":"46"},"tagType":"0","sequenceNumb
er":"004","seatNumber":"01A","paxstatus":"C","bagType":"0"}

{"airport":"MAD","eventDateTimeLocal":"2016-05-03T02:20:41.844+02:00","eventDateTimeUTC":"2016-05-
03T00:20:41.844Z","eventCode":"EXPECTED","eventType":"BAG_EXPECTED","eventDescription":"Bag
Expected","bagTagNumber":"0996111264","bim":"BSM\r\nCHG\r\n.V/1TMAD\r\n.F/UX1061/03MAY/MXP/Y\r\n.I/UX0
072/02MAY/CCS/Y\r\n.N/0996111262001\r\n.N/0996111264001\r\n.S/Y/01A/C/004/004\r\n.W/K/2/46\r\n.P/SMITH/J
OHNMR\r\nENDBSM","inbound":{"airlineCode":"UX","fltNum":"0072","date":"02MAY","airportCode":"CCS","classOfS
ervice":"Y"},"outbound":{"airlineCode":"UX","fltNum":"1061","date":"03MAY","airportCode":"MXP","classOfService":"Y
"},"messageType":"BSM","messageSubType":"CHG","baggageSourceIndicator":"T","passenger":{"lastName":"SMIT
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}

{"airport":"MAD","eventDateTimeLocal":"2016-05-03T14:49:09.710+02:00","eventDateTimeUTC":"2016-05-
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ssenger
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OHNMR\r\nENDBSM","inbound":{"airlineCode":"UX","fltNum":"0072","date":"02MAY","airportCode":"CCS","classOfS
ervice":"Y"},"outbound":{"airlineCode":"UX","fltNum":"1061","date":"03MAY","airportCode":"MXP","classOfService":"Y
"},"messageType":"BSM","messageSubType":"CHG","baggageSourceIndicator":"T","passenger":{"lastName":"SMIT
H","firstName":"JOHNMR","numberOfPassengers":""},"bagWeightDetails":{"indicator":"K","numberOfCheckedBags":"
2","checkedWeight":"46"},"tagType":"0","sequenceNumber":"004","seatNumber":"01A","paxstatus":"B","bagType":"0"
}

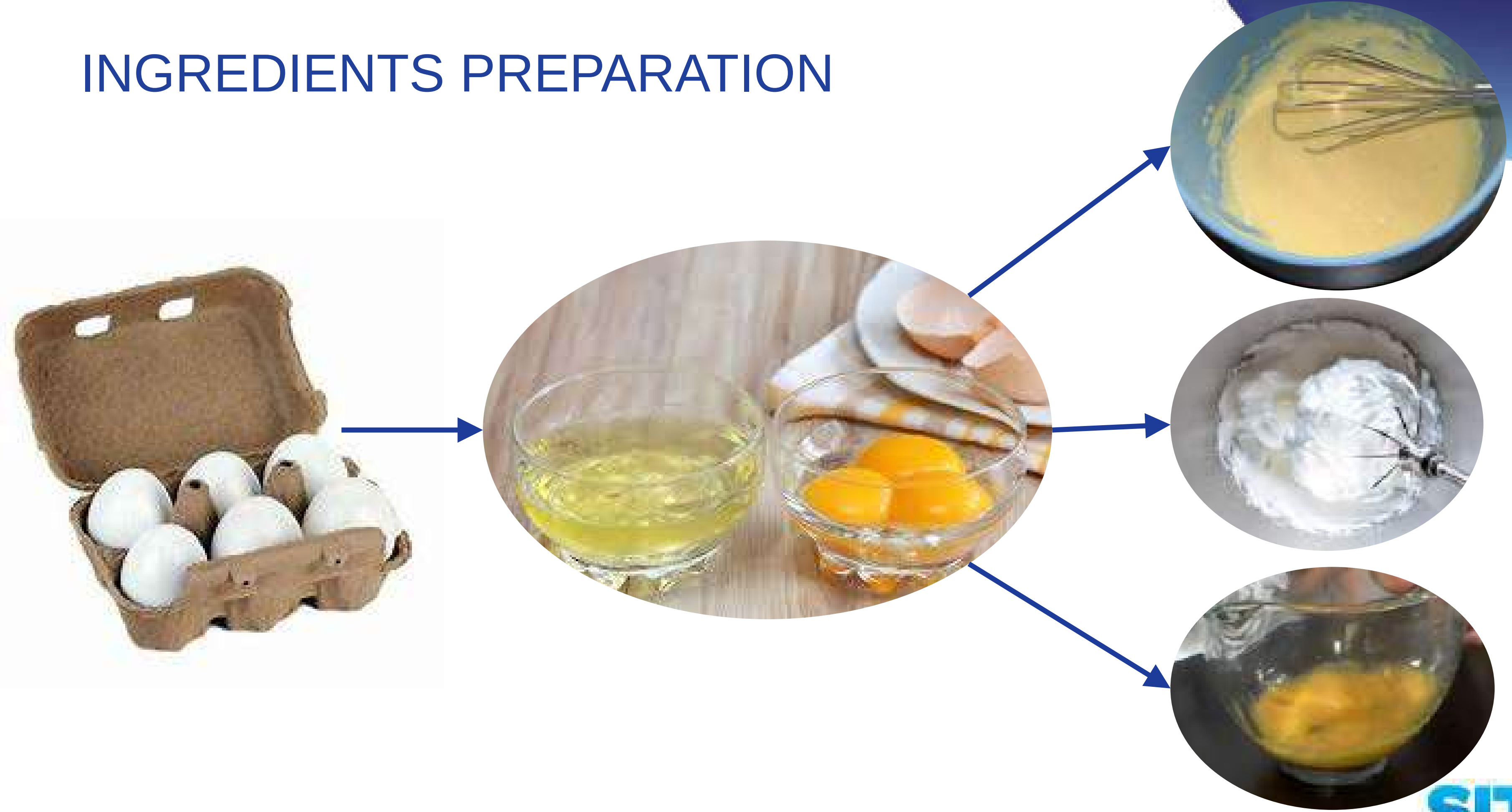
| .F | .S | .W | … |
|---|---|---|---|
| UX1061 | Y,01A | K,46 | … |

# 3
# -
# FOOD PREPARATION

# FEATURE ENGINEERING

| Steps | Food recipe | AI recipe |
|---|---|---|
| 1 | Shop for ingredients | Data collection |
| 2 | Unpack and wash | Data aggregation |
| 3 | Food preparation | Feature engineering |
| 4 | Mix and cook | Machine learning approach |
| 5 | Taste and adjust seasoning | Model tuning |
| 6 | Eat and enjoy | Interpretation |

# INGREDIENTS PREPARATION





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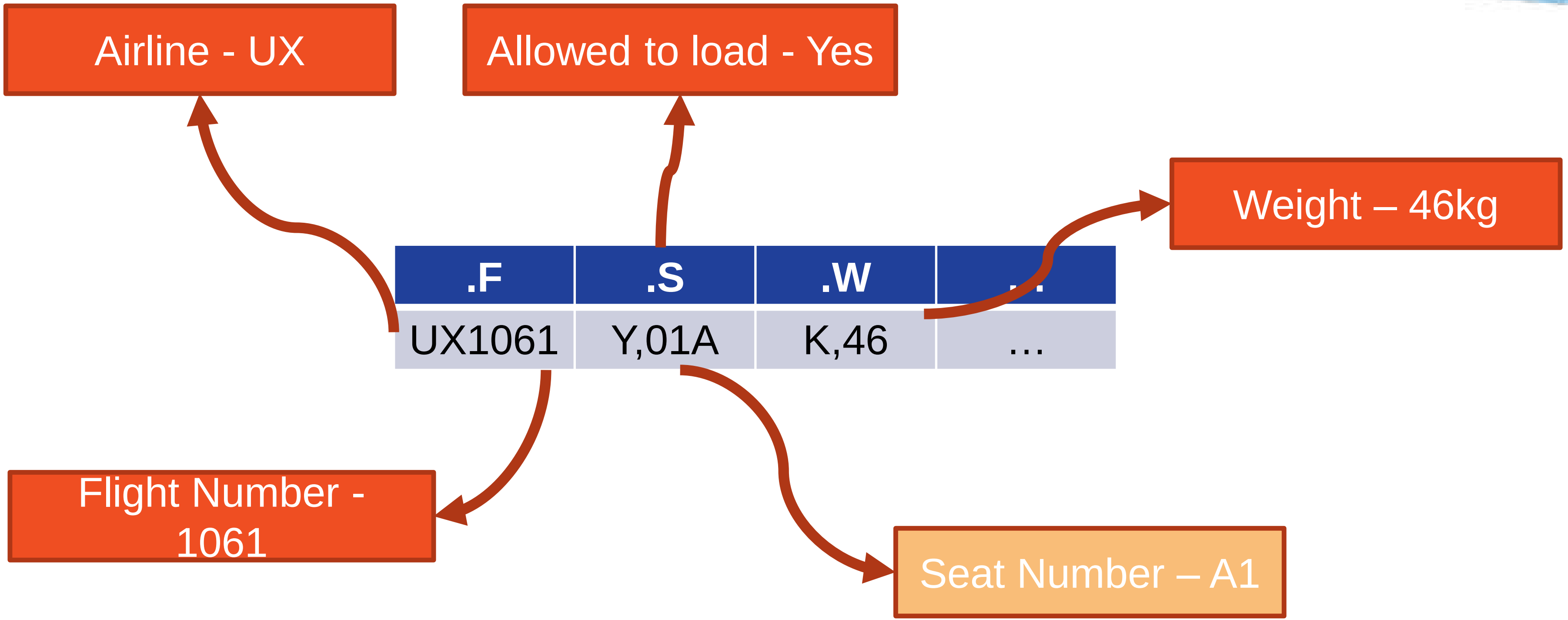
# FEATURE ENGINEERING



# 4

# -

# MIX AND COOK

# MACHINE LEARNING APPROACH

| Steps | Food recipe | AI recipe |
|---|---|---|
| 1 | Shop for ingredients | Data collection |
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| 5 | Taste and adjust seasoning | Model tuning |
| 6 | Eat and enjoy | Interpretation |

# MIX AND COOK



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# ML APPROACH – YOUR OBJECTIVES

| What are you trying to do? | What is it called? | Example |
|---|---|---|
| Predict a category | Classifying | Bag Conveyability |
| Predict a quantity | Regression | Number of mishandled bags |
| Detect an anomaly | Anomaly detection | Characteristics of an unusual bag journey |
| Discover structure / patterns in data | Clustering | Types of airlines (high or low performance) |

 

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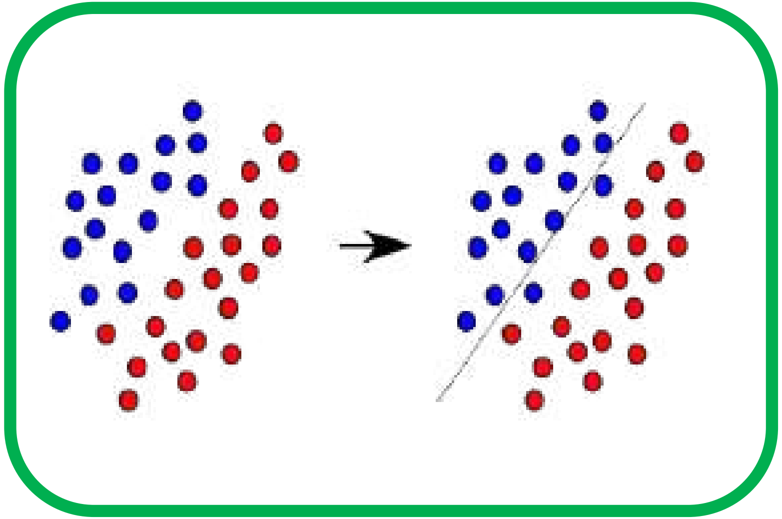
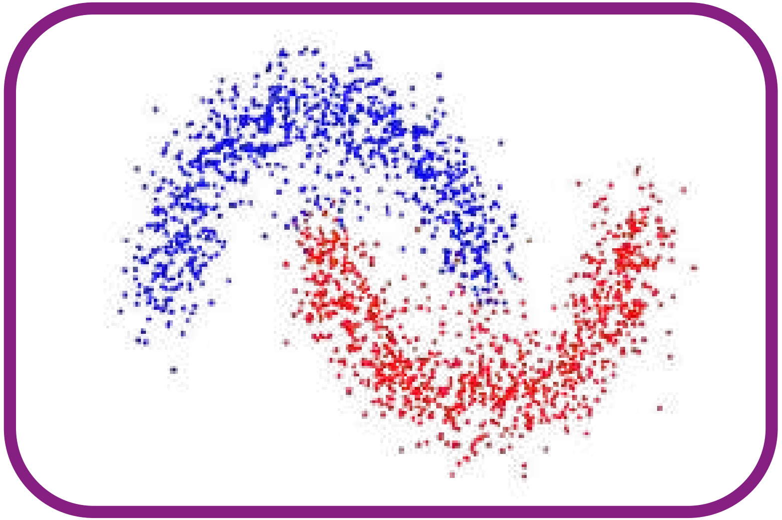
# SUPERVISED AND UNSUPERVISED LEARNING

Labelled data



Non labelled data



Source: recast.ai & blog.statsbot.com

# PICK UP YOUR ALGORITHM AND RUN IT

**Regression Algorithms**

- Linear/Nonlinear Regression
- Decision Trees(CART)
- Random Forest
- General Additive Models(GAM)
- Ridge/LASSO Regression
- Support Vector Regression
- Neural Net Regression
- Stepwise Generalized Linear Model
- Neural Nets with Bayesian Reg.
- Multivariate Adaptive Splines
- Meta-Learners
- Elastic Net

**Classification Algorithms**

- Logistic Regression
- Decision Trees
- Random Forest
- Naive Base
- K-Nearest Neighbors
- Linear/Quadratic Discriminant Analysis
- Gradient Boosting
- Support Vector Machine
- Artificial Neural Networks
- Leaning Vector Quantization
- CHAID

# 5

-

# TASTE AND ADJUST SEASONING

# MODEL TUNING

| Steps | Food recipe | AI recipe |
|---|---|---|
| 1 | Shop for ingredients | Data collection |
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| 4 | Mix and cook | Machine learning approach |
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| 6 | Eat and enjoy | Interpretation |

# TASTE AND ADJUST SEASONING

1

2

3

# MODEL TUNING

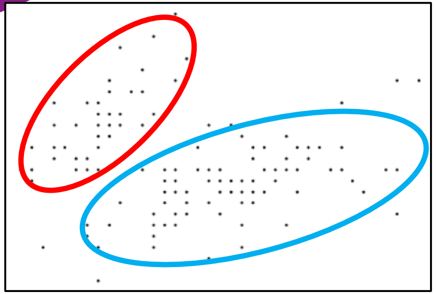
Airline - UX

Flight Number - 1061

Weight – 46kg

Seat Number – A1

| Airline | Flight # | Weight | Seat # | … |
|---|---|---|---|---|
| UX | 1061 | 46 kg | A1 | … |



Low-Cost Carrier - No

IATA member - Yes

Airline Tier - 2

# 6

-

# EAT AND ENJOY

# DATA INTERPRETATION

| Steps | Food recipe | AI recipe |
|---|---|---|
| 1 | Shop for ingredients | Data collection |
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| 6 | Eat and enjoy | Interpretation |

# BON APPETIT!!!

## Anything you want to improve for next time?



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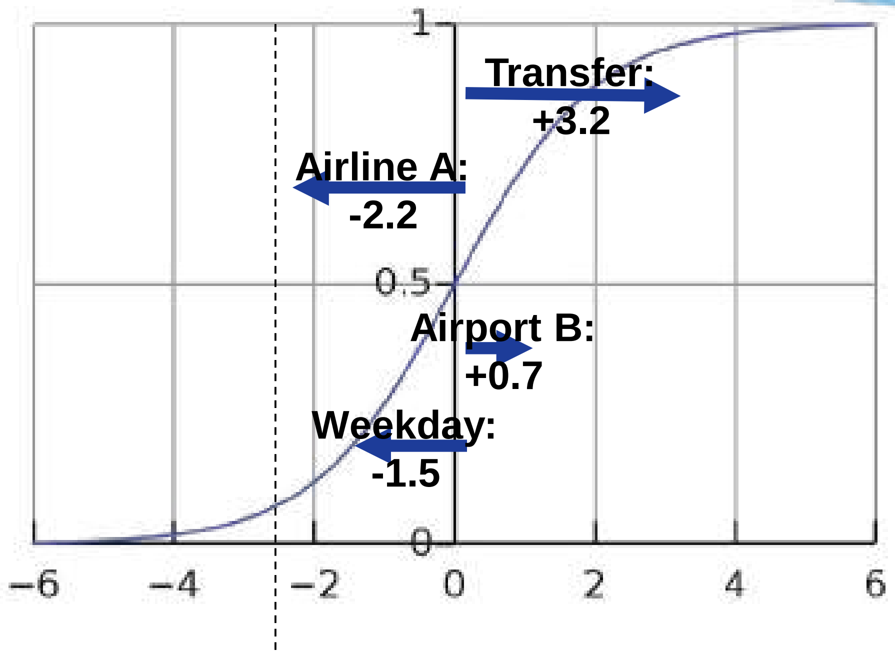
# MODEL INTERPRETATION

| Logistic Score | Probability of Mishandling |
|---|---|
| **-4** | *Very low* |
| **-2** | *Low* |
| **0** | *Medium* |
| **2** | *High* |
| **4** | *Very high* |



# 7
# -
# A FEW RECIPES

# AI WITH BAG IMAGE – CLASSIFICATION BY CONVEYABILITY

- Teaching a bag drop to recognize conveyable from non conveyable bags

# AI WITH BAG IMAGE – CLASSIFICATION BY CONVEYABILITY

conveyable

over-size

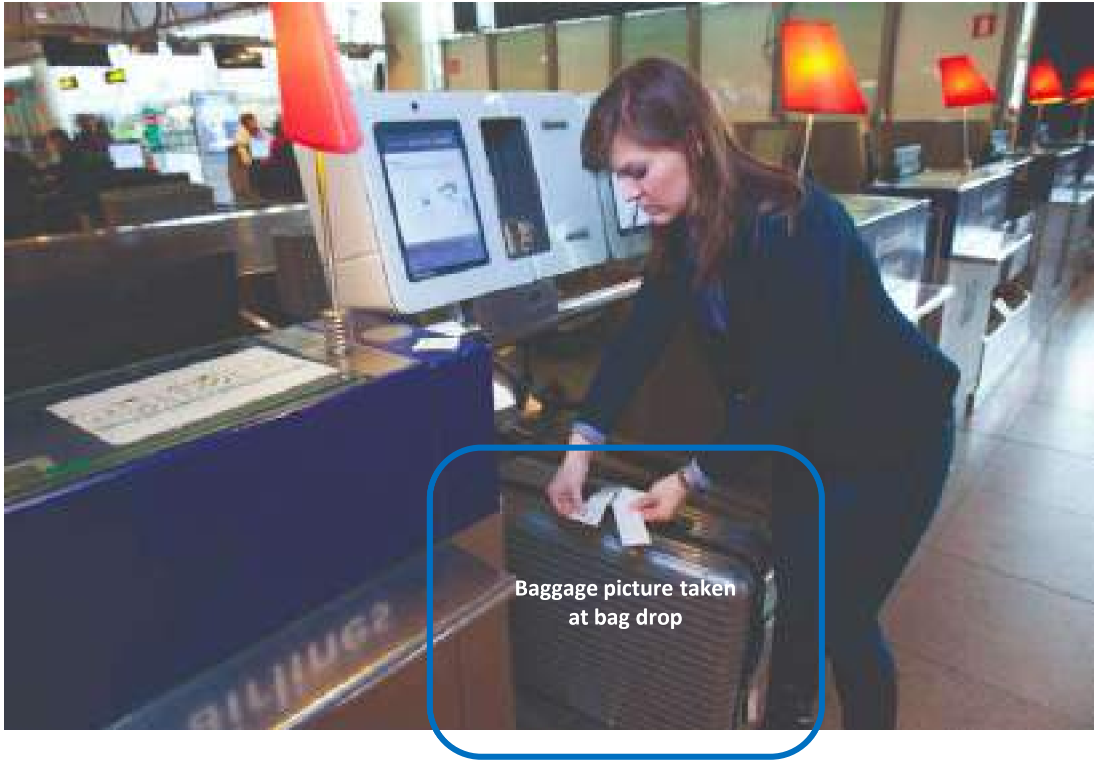
non conveyable

# AI WITH BAG IMAGE – CLASSIFICATION BY TRAY REQUIREMENTS

Requires tray

Doesn't require tray

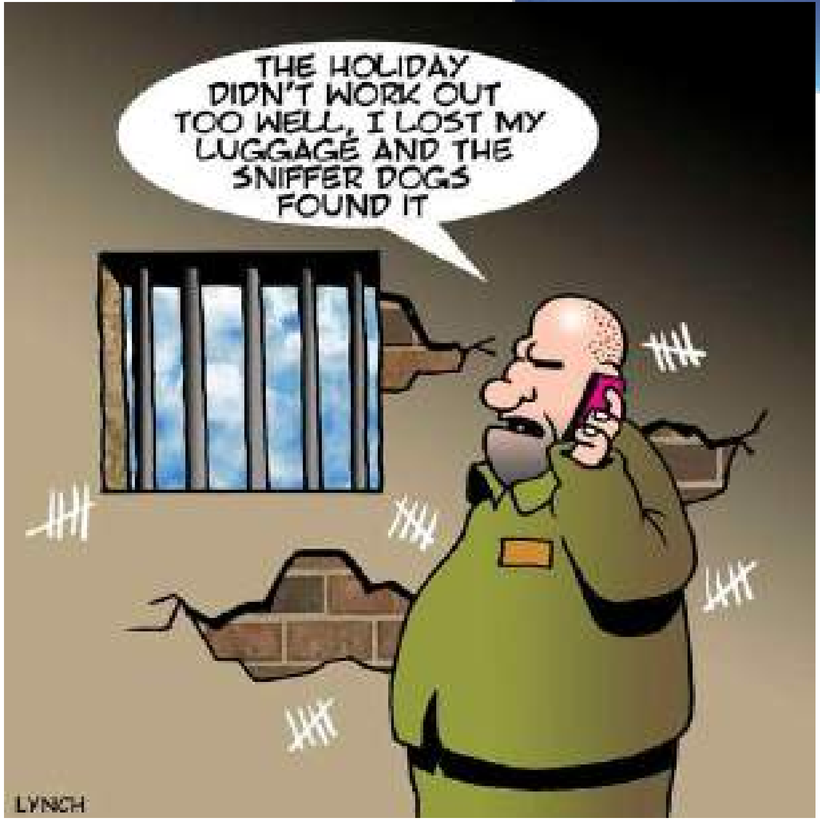
# AI WITH BAG IMAGE – CLASSIFICATION BY IATA BAGGAGE IDENTIFICATION CHART




# AI WITH WORLDTRACER DATA - BAGGAGE MISHANDLING

What are the parameters most influencing mishandling worldwide?

- Airlines?
- Regions?
- Number of legs?
- Weight of bag?
- Class of bag?
- Short connections?
- Colour of bag?



# BAGGAGE MISHANDLING FOR AIRPORTS

What are the parameters most influencing mishandling for my airport?

- Groundhandler?
- Terminal?
- Peak time? High season, low season?
- Class of bag?
- Short connections?
- Colour of bag?

# BAGGAGE MISHANDLING FOR AIRLINES

What are the parameters most influencing mishandling for my airport?

- Regions? Airports?
- Groundhandler?
- Number of legs?
- Weight of bag?
- Class of bag?
- Short connections?
- Interline partners?

# AI WITH 753 TRACKING DATA

- With 753 more and more tracking data is captured and collected
- With RFID implementation ability to have granular tracking points will increase
- What can we do with it?
    - Have in depth knowledge of baggage processing and reasons for good and bad performance – Feed continuous improvement process.
    - Detect anomalies in locations of bags or processing duration
    - Have real time information at make-up areas and improve turn-around time
    - Predict disruption due to baggage and feed airport or airline disruption model
    - Predict traffic and better manage resource allocation

# AI FOR SUPPORTING BAGGAGE SERVICES

- AI powered video analytics for trolley operations
- HKG is using an AI robotic arm to apply RFID stickers on transfer bags
- AI powered video analytics to count bags on a conveyor belt
- Ground handling robotics: delivery of bag and cargo to belts, loading and unloading the aircraft

# THANK YOU FOR LISTENING!!

Caroline Camilli-Gay
Program manager SITA Lab

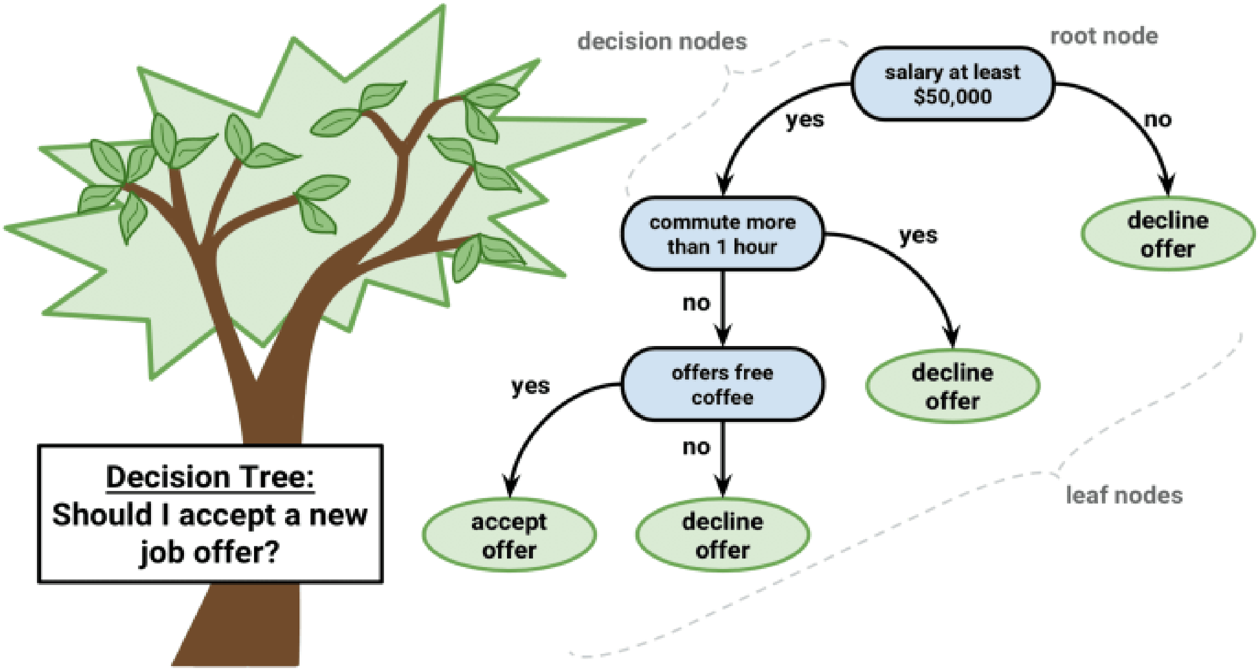
# BACK UP SLIDES

# SUMMARY OF MAIN ML ALGORITHMS

- **Linear regression** Despite an apparent simplicity, they are very useful on a huge amount of features where better algorithms suffer from overfitting.
- **Logistic regression** is the simplest classifier with a linear combination of parameters and nonlinear function (sigmoid) for binary classification.
- **Decision trees** is often similar to people's decision process and is easy to interpret. But they are most often used in compositions such as Random forest or Gradient boosting.
- **K-means** is more primal, but a very easy to understand algorithm, that can be perfect as a baseline in a variety of problems.
- **PCA** is a great choice to reduce dimensionality of your feature space with minimum loss of information.
- **Neural Networks** are a category of machine learning algorithms and can be applied for many tasks, but their training needs huge computational complexity.

Source: blog.statsbot.co

# DECISION TREES



# AI USE CASES CAN BE ORGANIZED IN 10 CATEGORIES

| | | | | |
|---|---|---|---|---|
| Deep Learning | Natural Language Processing | Computer Vision Image Recognition | Virtual Personal Assistants | Gesture Control |
| Smart Robots | Recommend. Engines & Collaborative Filtering | Context Aware Computing | Speech to Speech Translation | Video Automatic Content Recognition |

# AI USE CASES CAN BE ORGANIZED IN 10 CATEGORIES

**Deep Learning:** Algorithms that operate based on their learnings from existing data. (predictive data models and software platforms that analyse behavioural data)

**Natural Language Processing** Algorithms that process human language input and convert it into understandable representations.

**Computer Vision/Image Recognition:** Technology that process and analyze images to derive information and recognize objects from them

**Virtual Personal Assistants:** Software agents that perform everyday tasks and services for an individual based on feedback and commands.

**Video Automatic Content Recognition:** Software that compares a sampling of video content with a source content file to identify the content through its unique characteristics.

**Smart Robots:** Robots that can learn from their experience and act autonomously based on the conditions of their environment.

**Reco Engines & Collaborative Filtering:** Software that predicts the preferences & interests of users for items such as movies or restaurants, & delivers personalized reco.

**Context Aware Computing:** Software that auto becomes aware of its environment and its context of use, such as location, orientation, lighting and adapts its behavior accordingly.

**Speech to Speech Translation:** Software which recognizes and translates human speech in one language into another language automatically and instantly.

**Gesture Control:** Enable one to interact and communicate with computers through their gestures.

# Artificial Intelligence in Aviation

Houman Goudarzi
Manager, Innovation, IATA

Track Sponsor

OpenJaw

# AI REVOLUTIONIZING TRAVEL & TRANSPORTATION

Houman Goudarzi, IATA

# R&D TECHNOLOGY STREAMS

SOCIETY
TECHNOLOGY
ENVIRONMENT
ECONOMY
POLITICS

ARTIFICIAL INTELLIGENCE

BLOCKCHAIN TECHNOLOGY

DRONE & UAV TECHNOLOGY

AUGMENTED & VIRTUAL REALITY

CRYPTO CURRENCIES

BIOMETRICS & DIGITAL IDENTITY

AUTONOMOUS VEHICLES

RENEWABLE ENERGY

IATA

# AI IN AVIATION WHITE PAPER

## CUSTOMER TOUCH-POINT CAPABILITIES

- INTELLIGENT BOT ERA
- DYNAMIC RESOURCE ALLOCATION
- PERSONALIZED FULFILLMENT
- DISRUPTION DAMAGE CONTROL
- COMPLAINTS & CLAIMS MANAGEMENT

## OPERATIONAL CAPABILITIES

- OUTCOME & IMPACT PREDICTION
- CORRELATIONS OF DATA
- AGILE AND ADAPTABLE OPERATIONS
- MACHINE LEARNING

## SUPPORT & MANAGEMENT CAPABILITIES

- VALUE CHAIN RISK MANAGEMENT
- ASSET (e.g. AIRCRAFT) PROTECTION
- MAINTENANCE & SAFETY CHECKS
- SUPPLY CHAIN RISK MANAGEMENT

# AI IN AVIATION WHITE PAPER: HIGHLIGHTS (1/3)

CUSTOMER TOUCH-POINT CAPABILITIES

| SHOP | PURCHASE | PRE-FLIGHT | IN-FLIGHT | POST-FLIGHT |
|---|---|---|---|---|
| OFFER MANAGEMENT | ORDER MANAGEMENT | DEPARTURE MANAGEMENT | FLIGHT MANAGEMENT | ARRIVALS MANAGEMENT |
| CUSTOMER INFO & VALUE CHAIN | QUEUE MANAGEMENT | LOUNGE MANAGEMENT | GUEST FEEDBACK & COMPENSATION MANAGEMENT | |
| CUSTOMER EVENTS | GUEST REACCOMMODATION | | | JOURNEY EXTRAS |
| | COMMUNICATIONS MANAGEMENT | | | |

# AI IN AVIATION WHITE PAPER: HIGHLIGHTS (2/3)

OPERATIONAL CAPABILITIES

## STRATEGIZE

- BRAND MANAGEMENT
- PROD/SERVICE DEVELOPMENT
- ALLIANCE MANAGEMENT
- ALLIANCE/NETWORK PLANNING
- FLEET
- SCHEDULE MANAGEMENT
- PARTNERSHIP MANAGEMENT

## PLAN

- SALES MANAGEMENT
- REVENUE MANAGEMENT
- PRICING MANAGEMENT
- CREW PLANNING
- OPERATIONS PLANNING
- ENGINEERING

## OPERATE

- FLIGHT PLANNING

## ANALYZE

- CUSTOMER INSIGHTS

## OPERATE / ANALYZE

- BAGGAGE OPERATIONS
- GUEST OPERATIONS
- CREW OPERATIONS
- AIRCRAFT TURNAROUND
- PORT OPERATIONS
- AIRCRAFT OPERATIONS
- EMERGENCY RESPONSE

IATA

# AI IN AVIATION WHITE PAPER: HIGHLIGHTS (3/3)

SUPPORT & MANAGEMENT

## ENABLE

- PERFORMANCE & STRATEGY
- TECHNOLOGY
- PEOPLE
- FINANCE
- SUPPLIER MANAGEMENT
- INFO. SUPPORT & INSIGHTS
- ASSET/FACILITY MANAGEMENT
- SAFETY MANAGEMENT
- QUALITY MANAGEMENT
- LEGAL
- IN-EXT RELATIONSHIPS

IATA

# AVIATION BUSINESS TO AI MAPPING

HEAT MAP OF BUSINESS IMPACT

## CUSTOMER

SHOP | ORDER | PAY | EXPERIENCE

## OPERATIONS

STRATEGIZE | PLAN | EXECUT | REPORT

## SUPPORT

HR | IT | FINANC | LEGAL

| | INDUSTRY USE CASES | IATA PROJECTS |
|---|---|---|
| CUSTOMER | • CHATBOT AND VOICE DRIVEN SEARCH & BOOKING INTERFACE<br>• PERSONALIZED FULLFILMENT LEVERAGING AI MACHINE LEARNING. | |
| OPERATIONS | • DISRUPTION DAMAGE CONTROL (DELAYS, CANCELLATIONS).<br>• COMPLAINTS & CLAIMS MANAGEMENT.<br>• AUTONOMOUS VEHICLES<br>• COMMERCIAL MODELING<br>• MAINTENANCE & SAFETY CHECKS<br>• PREDICTIVE ANALYTICS & DYNAMIC RESOURCE ALLOCATION TO MINIZE QUEUES. | • AGENT FRAUD DETECTION<br>• REAL-TIME SALES MONITORING AI POC. |
| SUPPORT | • VALUE CHAIN RISK MANAGEMENT (DEFAULTS, FRAUD)<br>• SUPPLY CHAIN RISK MANAGENT (FUEL USAGE AND SUPPLY). | • IDENTIFICATION OF UNDECLARED FORMS OF PAYMENT. |

IATA

# AI WHITE PAPER CONCLUSIONS

ADOPT AI CAPABILITIES FASTER THAN NEW ENTRANTS

ALLOCATING RESOURCES TO AI RESEARCH & DEVELOPMENT

PROTECTING DIGITAL ASSETS FROM AI CONSUMERS

# IATA AIR COMPETITION

3 CHALLENGES

CASH PRIZES $17K

AIR

Airline Industry Retailing

COMPETITION

C-SUITE JURY

DEADLINE: 27TH JULY

iata.org/air-competition

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# Artificial Intelligence and Machine Learning in Aviation

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