Towards Smart Organizations: Big Data- & Artificial Intelligence-driven Solutions in IoT Era

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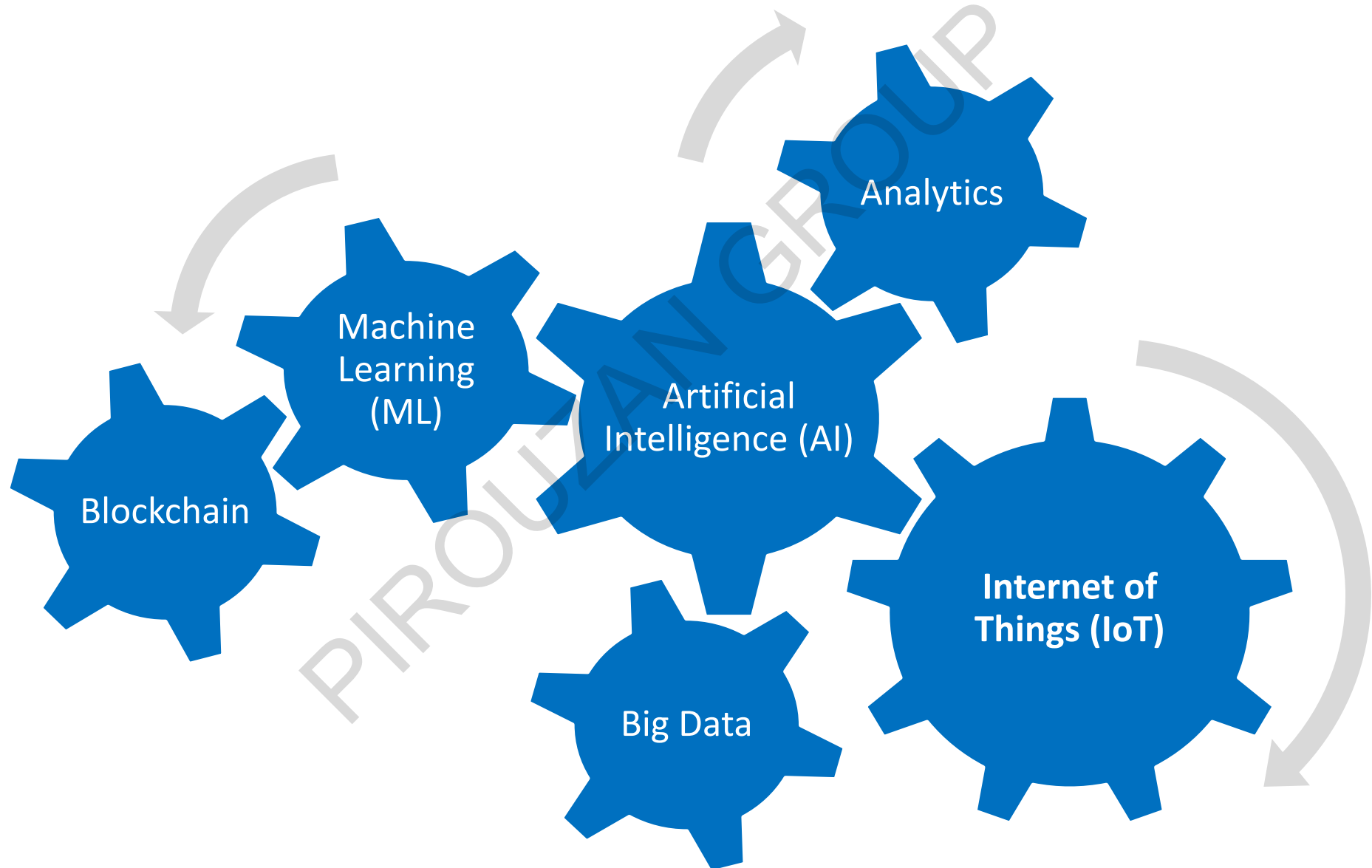
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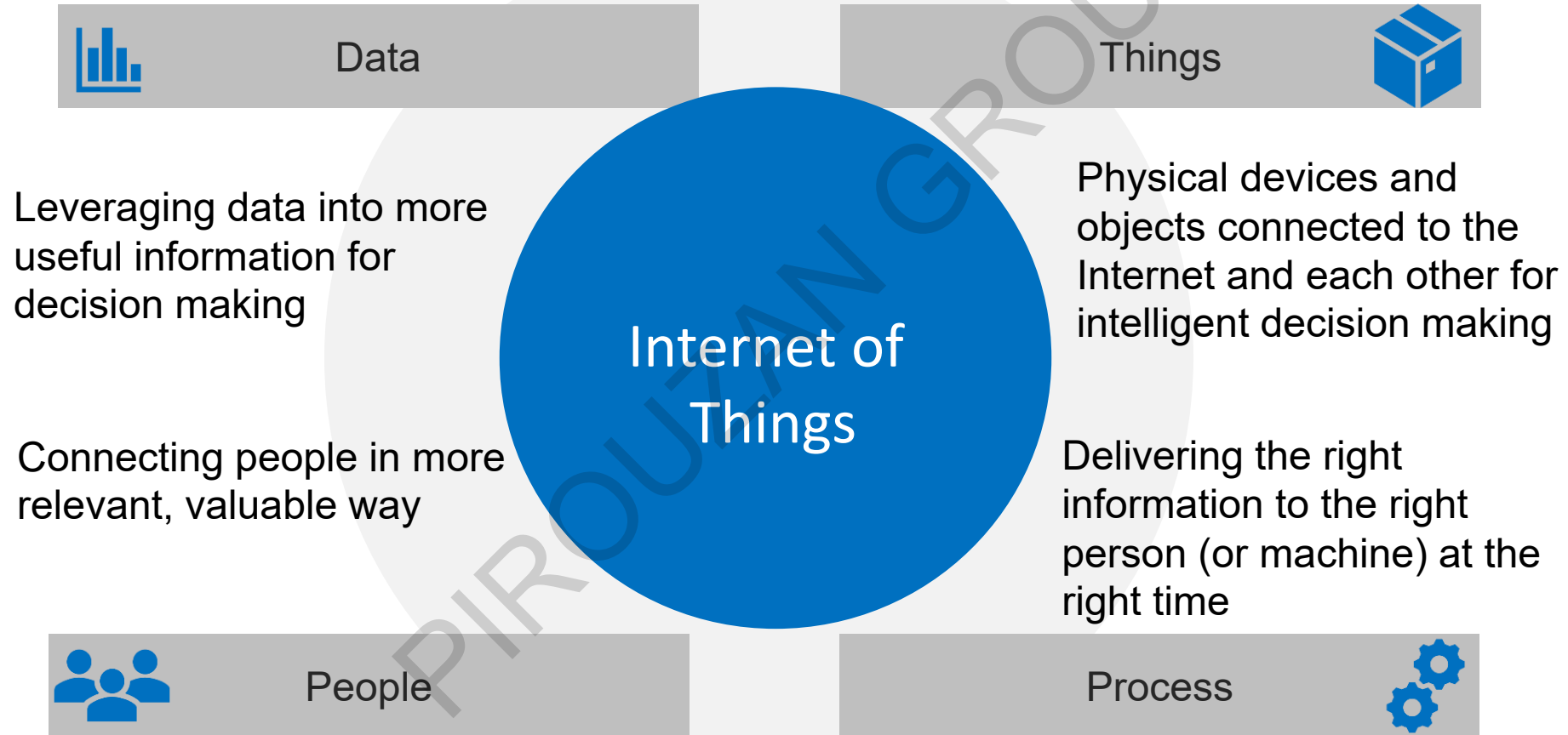
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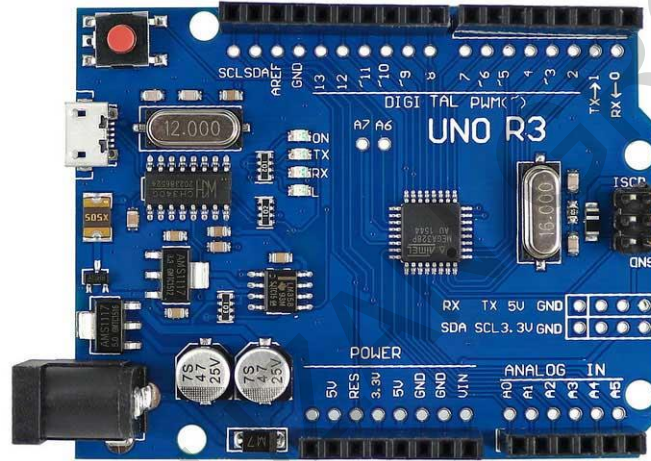
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Internet of Things (IoT)

Data

Leveraging data into more useful information for decision making

Things

Physical devices and objects connected to the Internet and each other for intelligent decision making

Internet of Things

Connecting people in more relevant, valuable way

Delivering the right information to the right person (or machine) at the right time

People

Process

Device

Computational Intelligence

Network Connection

Intelligent Device

IoT Device
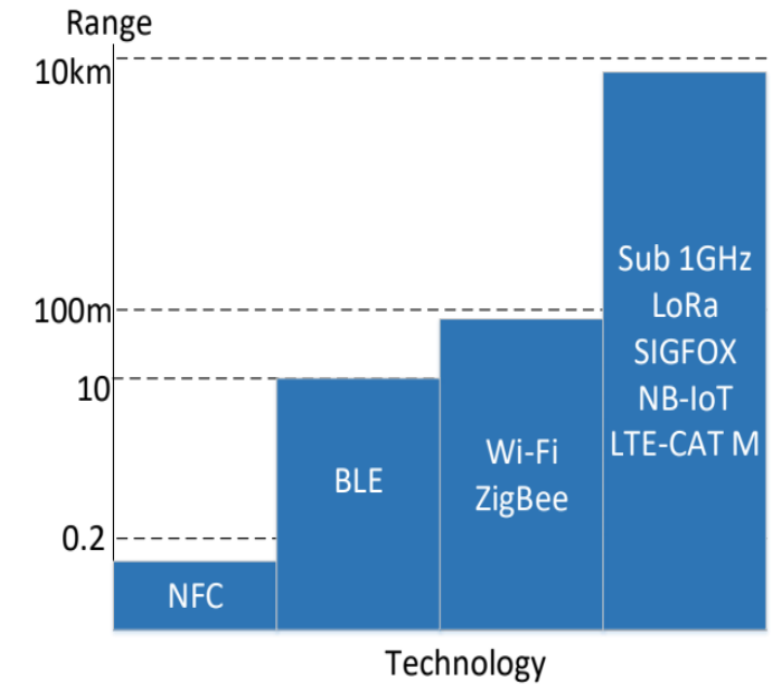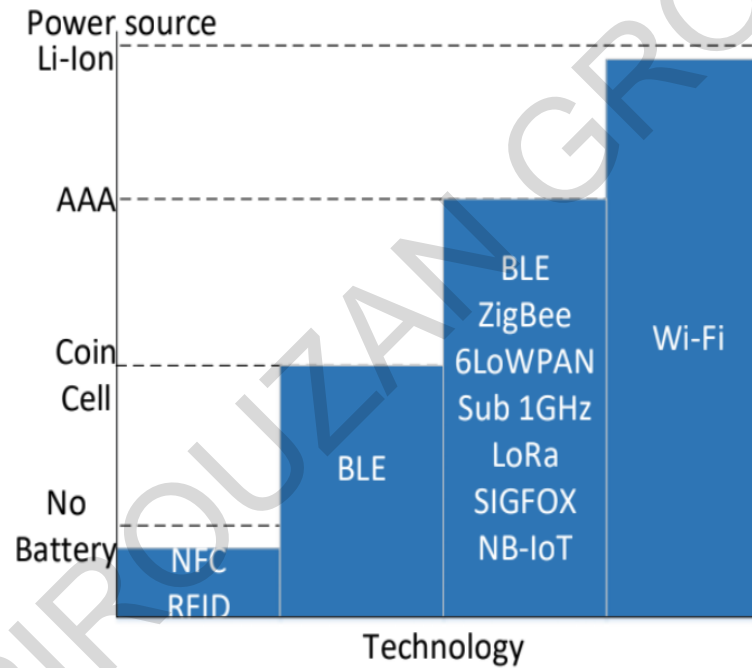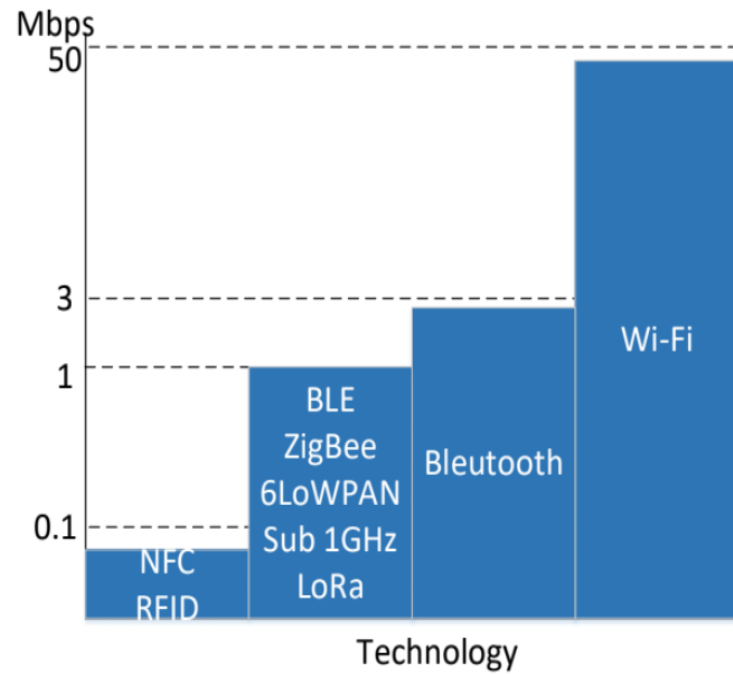
Maximum Throughput, Power source, and Range

Device Layer
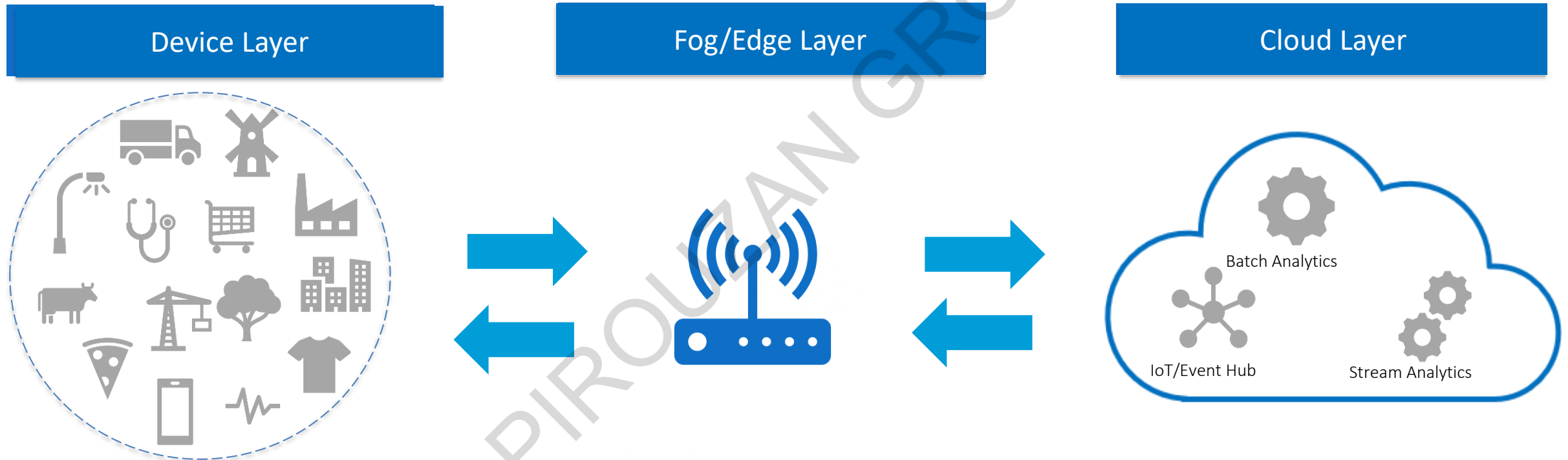
Fog/Edge Layer

Cloud Layer

Batch Analytics

IoT/Event Hub

Stream Analytics

THE IOT REFERENCE MODEL PUBLISHED BY THE IOT WORLD FORUM, 2014

CONSUMES AND SHARES THE APPLICATION INFORMATION

7 Collaboration & Processes (ACROSS DIFFERENT INDUSTRIES)

INTERPRETS DATA, MONITORS, CONTROLS, REPORTS BASED ON ANALYSIS

6 Application (REPORTING, PROCESSING, AND ANALYTICS)

ADAPTS MULTIPLE DATA FORMATS & ENSURES CONSISTENT SEMANTICS

5 Data Abstraction (AGGREGATION & ACCESS)

CAPTURES DATA & STORES

4 Data Accumulation (INGESTION & STORAGE)

REDUCTION & CONVERT DATA INTO READY TO STORE & PROCESS DATA

3 Fog/Edge Computing (DATA ELEMENT ANALYSIS & TRANSFORMATION)

RELIABLE & TIMELY TRANSMISSION OF DATA

2 Connectivity (COMMUNICATION & PROCESSING UNITS)

GENERATING DATA

1 Physical Devices & Controllers (THE "THINGS" IN IOT)

IoT Use Cases

Smart Energy	Connected Assets	Smart Health	Connected Markets	Smart People Building & City	Connected Factories
■ Smart meters ■ Digital oil field ■ Delivery ■ Refinement ■ Wind/solar management	■ Asset tracking ■ Asset insights ■ Smart car ■ Usage-based insurance ■ Remote monitoring	■ Hospital-Centered System ■ Patient-Centered System ■ Wearable sensors ■ Anomaly prediction	■ Market insights ■ Product recommendation	■ Smart waste management ■ Smart water ■ Smart building accessories e.g., lock ■ Smart traffic management	■ Predictive maintenance ■ Digital twins ■ Quality assurance ■ Product insights ■ Supply networks ■ Inventory optimization

Management, Processing, Analytics, and Machine Learning

Data Ingestion & Storage: IoT/Event/Stream Hub and Data Lake

Big/Smart Data

Variety

Structured, unstructured, semi-structured

3 V's

Batch, real-time, stream processing

Terabytes of data

Velocity

Volume

Structured

CSV, Columnar Storage ,**Strict data model structure**

Unstructured

Audio, video, images. Meaningless without adding some structure

Semi-Structured

JSON, XML, sensor data, social media, device data, web logs. **Flexible data model structure**
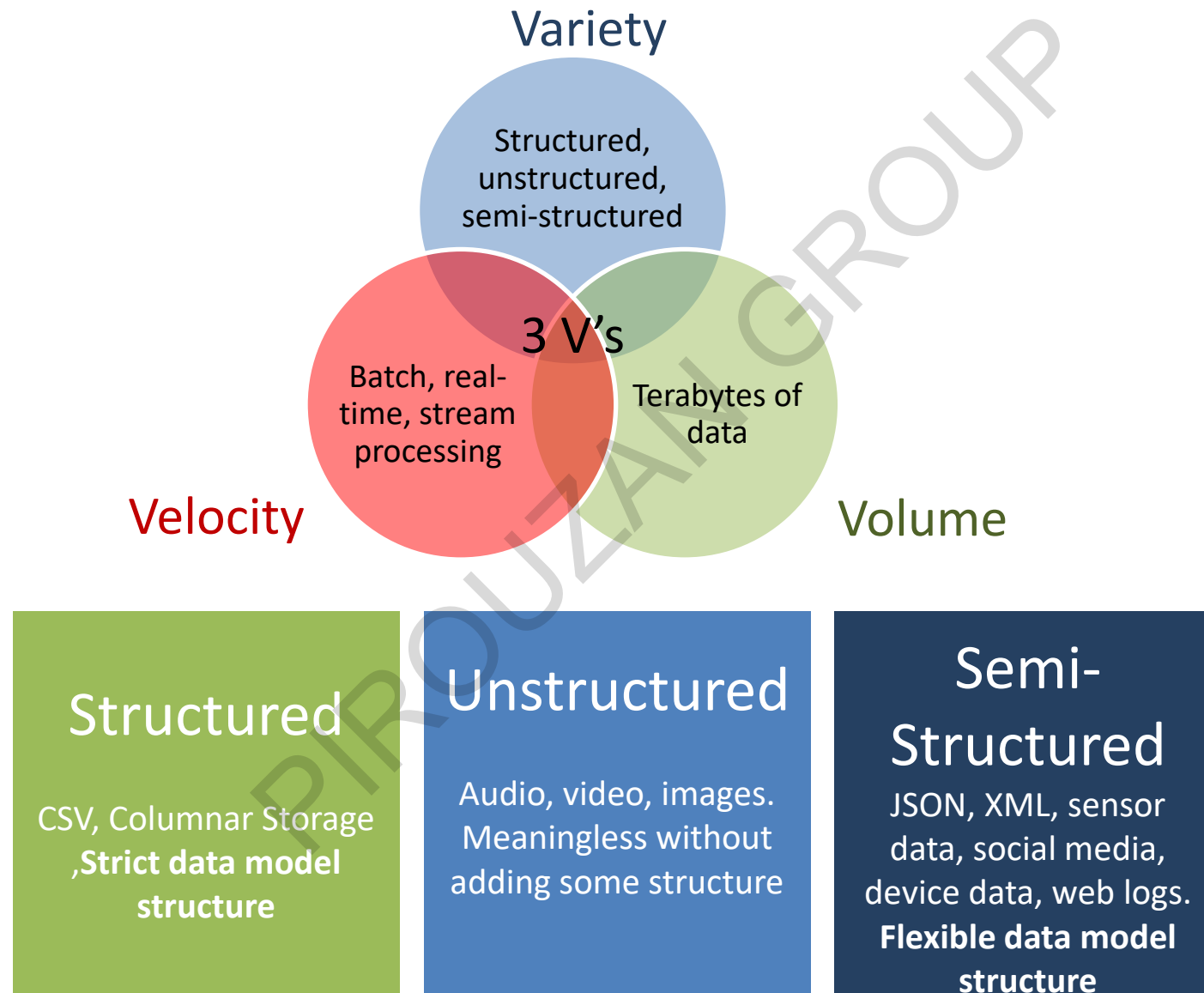
- Old Technology was based on a **Problem Driven** Methodology
  - Save some specific data
  - Archive and never visit the rest again
  - SQL Databases (e.g., SQL Server)
- Schema on Write (Extract, Transform, Load (**ETL**)):
  - Structured is applied to the data only when it's **Write!**

- New Technology is based on a **Data Driven** Methodology
  - Store all the data!
  - Extract value from data
  - No-SQL Databases (e.g., Hadoop)
- Schema on Read (Extract, Load, Transform (**ELT**)) :
  - Structured is applied to the data only when it's **Read!**

Artificial Intelligence & Machine Learning

AI is applied when a machine mimics cognitive functions that human associate with other human minds such as learning and problem solving

Understands

Learn and understand text, voice, image, etc.

Reasons

Based on learn phase, it concludes, and solves problem

Interacts

Bridge the gap between man & machine

Artificial Intelligence (AI)

Data Science

Machine Learning (ML)

- Fuzzy logic

- Reinforcement Learning
- Learning on chip/edge
- Cognitive
- Vision
- Speech
- Natural Language Processing (NLP)

- Predictive analytics
- Data based classification models

- Rule engine

- Customer analytics
- Risk scoring
- Visualization

- Infuse intelligence to machines
- Mimic human intelligence

- Use of statistical methods to find patterns in data
- Processes and systems to extract knowledge or insights from data

Five years ago, we struggled to find 10 AI-driven IoT-based business applications

In five years, we will struggle to find 10 that don't !

Blockchain

What is Blockchain?

A digital ledger or a database with a single version of the truth that maintains a continuously growing list of data records or transactions.

SHARED PUBLICLY
Servers of nodes maintain the entries (blocks) and every node sees the transaction data stored in the blocks when created

DECENTRALIZED
There is no central authority required to approved transactions and set rules

SECURE
The database is an immutable and irreversible record

TRUSTED
Distributed nature of the network requires computed servers to reach a CONSENSUS, which allows for transactions to occur between unknown parties

AUTOMATED
The software is written so that conflicting or double transactions do not become written in the data set and transactions occur automatically

GROWING APPLICATIONS
It can be used more than the transfer of currency; contracts, records, and other kinds of data can be shared
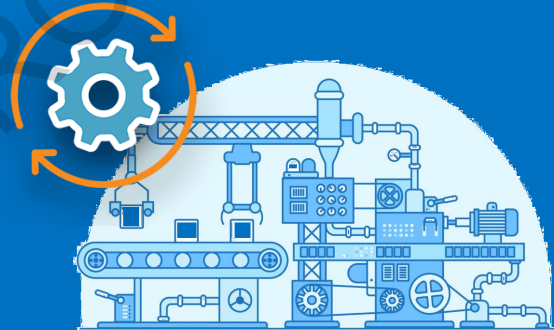
Logistics

(Artificial Intelligence Driven IoT Solutions for Logistics)

In a general business sense, logistics is the management of the flow of things between the point of origin and the point of consumption in order to meet requirements of customers or corporations.

IoT in Logistics

The use of IoT results in better efficiency

Real-time asset & fleet management

End-to-end visibility to delivery process

Inventory tracking & analytics

Environmental Intelligence & Storage conditions control

Cargo integrity monitoring

Workforce monitoring

Smart labels

Smart Energy Management
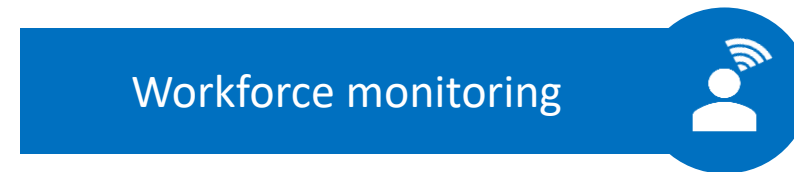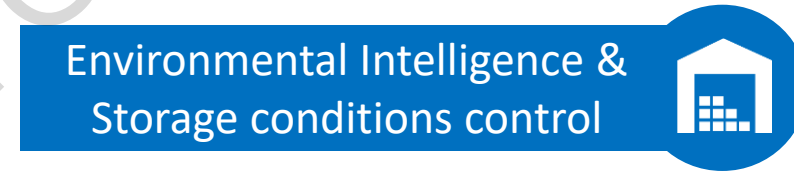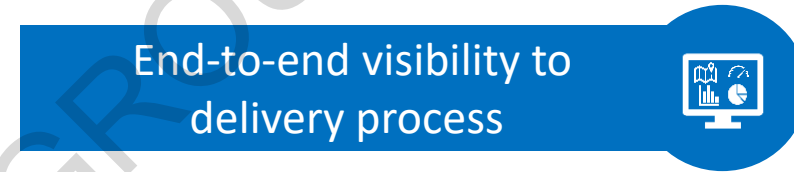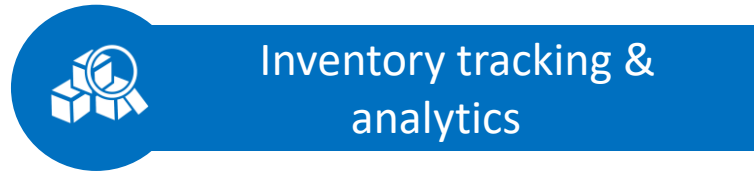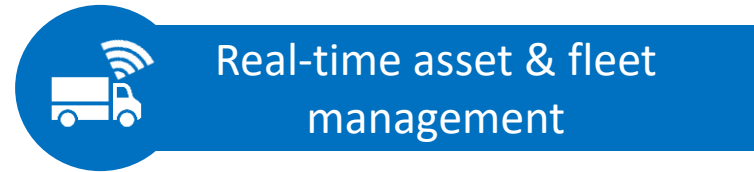
CASE: Port of Rotterdam- IoT to Digitize Operations

PROBLEM

As the largest port in Europe, the Port of Rotterdam handles over 461 million tones of cargo and more than 140,000 vessels annually. The port relied on traditional radio and radar communication between captains, pilots, terminal operators, tugboats and more to make key decision on port operations. To improve the efficiency and safety, the port would like to begin its digital transformation

SOLUTION

Sensors are being installed across 42-kilometers of land and sea - spanning from the City of Rotterdam into the North Sea - along the Port's quay walls, mooring posts and roads. These sensors will gather multiple data streams including water (hydro), weather data, tides and currents, temperature, wind speed and direction, water levels, berth availability and visibility. A centralized dashboard application collects and process real-time sensor readouts

RESULT

Port of Rotterdam operators will also be able to view the operations of all the different parties at the same time, making that process more efficient. In fact, shipping companies and the port stand to save up to one hour in berthing time which can amount to about 80,000 US dollars in savings

CASE: DHL- Item-level Tagging

PROBLEM

With critical cargo and packages, DHL wants it shipped without any problems. And when problems do occur, DHL needs to know why. With sensitive loads pharma-products, it's important to maintain a stable environment to prevent spoilage and adhere to environmental regulations and also validate the shipment process to comply with regulation

SOLUTION

- DHL Smart Sensor RFID: measures temperature data during the course of transportation

- DHL Smart Sensor GSM: measures temperature, location, humidity, shock and light data during the course of transportation

RESULT

- Real-time visibility to the LOCATION
- Quality & integrity control for sensitive goods
  - ENVIORMENTAL conditions monitoring
- Transparency with customers in real-time
- Security of the packages
- Supply chain optimization

CASE: FedEx's IoT Response to Supply Chain Optimization

PROBLEM

According to FedEx: Visibility is a prerequisite to logistics and supply chain agility and responsiveness. It requires tracking the location of a shipment not only at the transportation level, but also at a unit and item level. Location tracking is good protection against shipment theft or loss, but companies need a deeper level of visibility for their packages

sense(a)ware.sm

powered by FedEx

SOLUTION

FedEx developed IoT-inspired SenseAware, a sensor-based logistics (SBL) solution. SBL uses sensors to detect the shipment's environmental conditions while warehoused or in transit and sends the data — via wireless communication devices — to a management software system where the data is collected, displayed, analyzed and stored

RESULT

SBL provides intelligence that can help enterprises coordinate and manage product, information and financial flows

Big data in Logistic

Real-time route optimization	Demand & supply forecasting	Price planning	Inventory planning	Production planning
Omni-channel customer analytics	Strategic Network Planning	Risk Evaluation & Resilience Planning	Anomaly Detection	Operational Capacity Planning

ORION—or On-Road Integrated Optimization and Navigation—is a route-optimization system that analyzes a collection of data points including the day's package deliveries, pickup times, and past route performance to create the most efficient daily route for drivers
UPS saves US$50 million a year by reducing daily travel resulting (on average six miles daily for each driver) resulting in significant fuel savings

Problem:

- Natural disasters, adverse weather, political unrest, cargo theft – all these events can cause disruption in a supply chain and logistics
- DHL needs a solution to provide insight into risk events and their impact on increasingly complex supply chains and help identify risk bottlenecks and supply chain pain points using historic and forward-looking risk information

Solution:

- DHL Resilience360 is an innovative, cloud-based supply chain risk management platform that helps companies to visualize, track and protect their business operations
- The solution facilitates intuitive supply chain visualization, tracks shipments and ETAs across different transport modes and enables near real-time monitoring of incidents capable of disrupting supply chains
- DHL solution easily integrates with business systems and helps companies keep track of risk in combination with their business performance indicators. It enables companies to better ensure business continuity, building risk profiles based on over 30 risk databases

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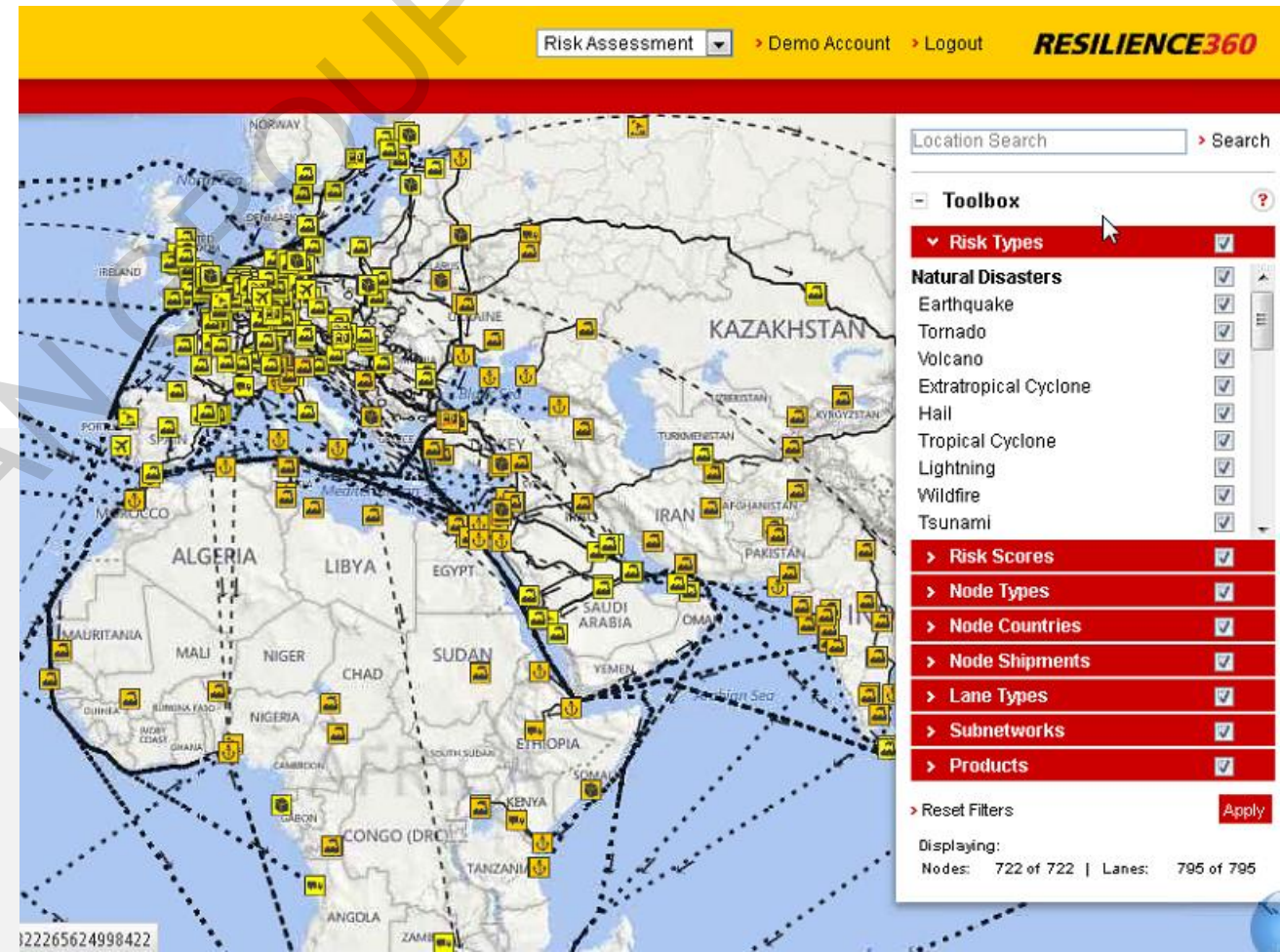
✓ Demand Forecasting

✓ Outsource the shopping list to an algorithm so you don't need to worry about it
✓ An advanced prediction technique to anticipate customer demand for specific products, in specific locations during specific time-ranges (Demand Forecasting)
✓ Prediction-based inventory adjustments
✓ Deliver products to customers before they place an order.

✓ Porsche uses AI and Data Analytics to Forecast Your Waiting Time at each Electric Car Charging Station

Artificial Intelligence in Logistic

Quality Control

Anomaly Detection

Workforce Monitoring

Security

✓ Quality control
  ▪ Surface defects - scratches, cracks, integrity
  ▪ Dimensional control relative to standards/tolerances
  ▪ Packaging - shape, color
  ▪ Verification of the presence of the logo
✓ Automatic sorting packages
  ✓ Size, color, etc.
✓ Augmented reality for safety & order picking

Speed is everything. News is only news if it is fresh, not if it is old hat. Axel Springer (Das Bild, Die Zeit, etc.) is replacing laser scanners with image-based ID reading equipment from Cognex.

Problem:
Intense schedules, remote locations, long hours and repetitive tasks leave mining equipment operators especially prone to the dangers of fatigue. Even the smallest lapse in concentration can put operational people at risk and cost millions of dollars to the owners.

Solution: in collaboration with seeing machines a holistic video analytic platform is implemented that:
- Alerts operators the instant that they stop paying sufficient attention to vehicle operation
- Real-time event data is then transmitted to a specialist 24-hour facility where trained personnel can implement best practice risk mitigation processes
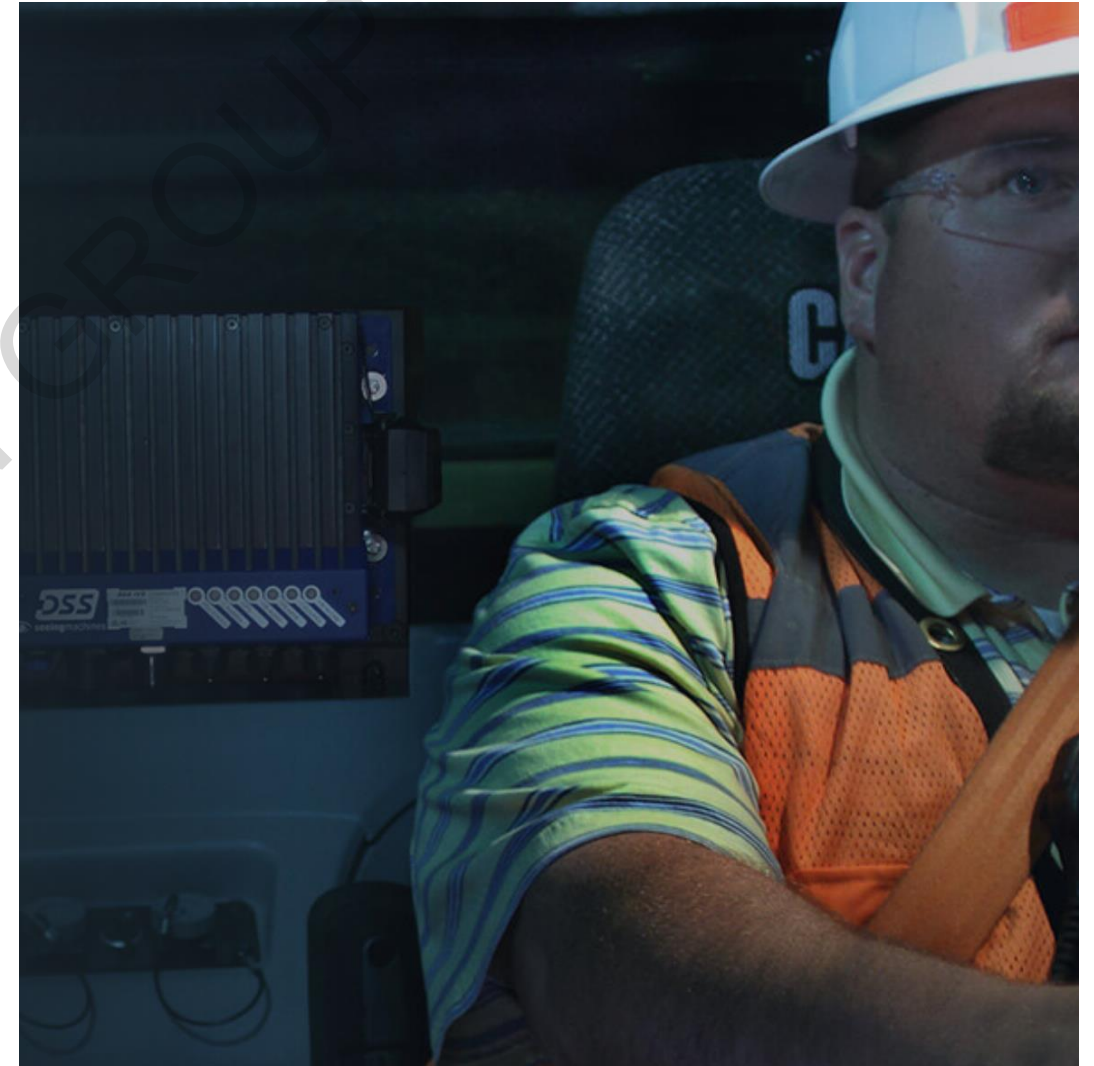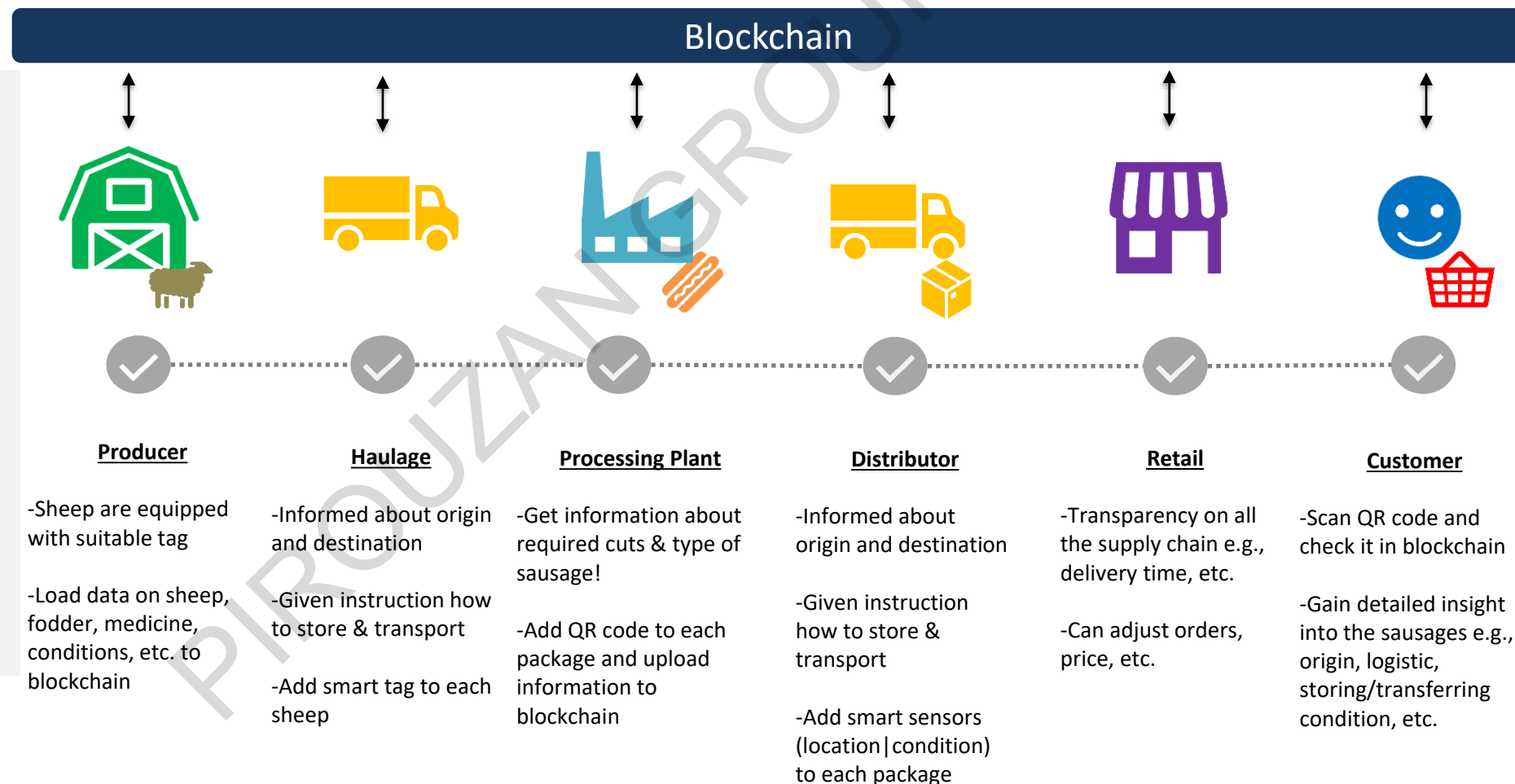
Blockchain in Logistic

| End-to-End Visibility | Smart Contract | Payment Integration | Inventory Management |

Blockchain

- End-to-end visibility
- Traceability & transparency
  - Entire view
  - What, when, where! How
- Smart contract
- Reduce delays from paper work
- Identify issues faster
- Safer transaction
- Improve inventory management
- Payment integration
- Reduce error and fraud

Producer

-Sheep are equipped with suitable tag

-Load data on sheep, fodder, medicine, conditions, etc. to blockchain

Haulage

-Informed about origin and destination

-Given instruction how to store & transport

-Add smart tag to each sheep

Processing Plant

-Get information about required cuts & type of sausage!

-Add QR code to each package and upload information to blockchain

Distributor

-Informed about origin and destination

-Given instruction how to store & transport

-Add smart sensors (location|condition) to each package

Retail

-Transparency on all the supply chain e.g., delivery time, etc.

-Can adjust orders, price, etc.

Customer

-Scan QR code and check it in blockchain

-Gain detailed insight into the sausages e.g., origin, logistic, storing/transferring condition, etc.

Problem: participants in the food industry supply chain each have their own information silos. Food can only be traced one step at a time.

Solution: Walmart and IBM began collaboration on a blockchain to accurately record the following:

- Farm origin data
- Batch number
- Factory and processing data
- Expiration dates
- Storage temperatures
- Shipping details

Result: Food tracking that would usually take seven days could be done in 2.2 seconds with blockchain.
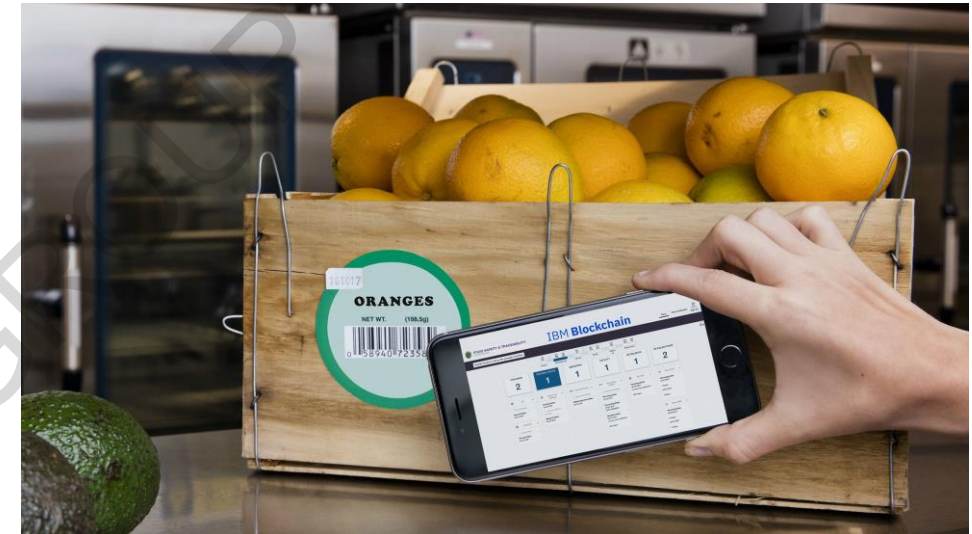
Problem:
- One shipment from East Africa to Europe can go through nearly 30 people and involve more than 200 different communications
- One lost form or late approval could leave the container stuck in port
- Documentation can be as much as a fifth of the total cost of moving a container

Solution: In collaboration with IBM, Maersk is developing a blockchain platform to achieve:
- **A shipping information pipeline:** end-to-end supply chain visibility to enable all actors involved in managing a supply chain to securely and seamlessly exchange information about shipment events in real time
- **Paperless Trade:** digitize and automate paperwork filings by enabling end-users to securely submit, validate and approve documents speeding up approvals and reducing mistakes
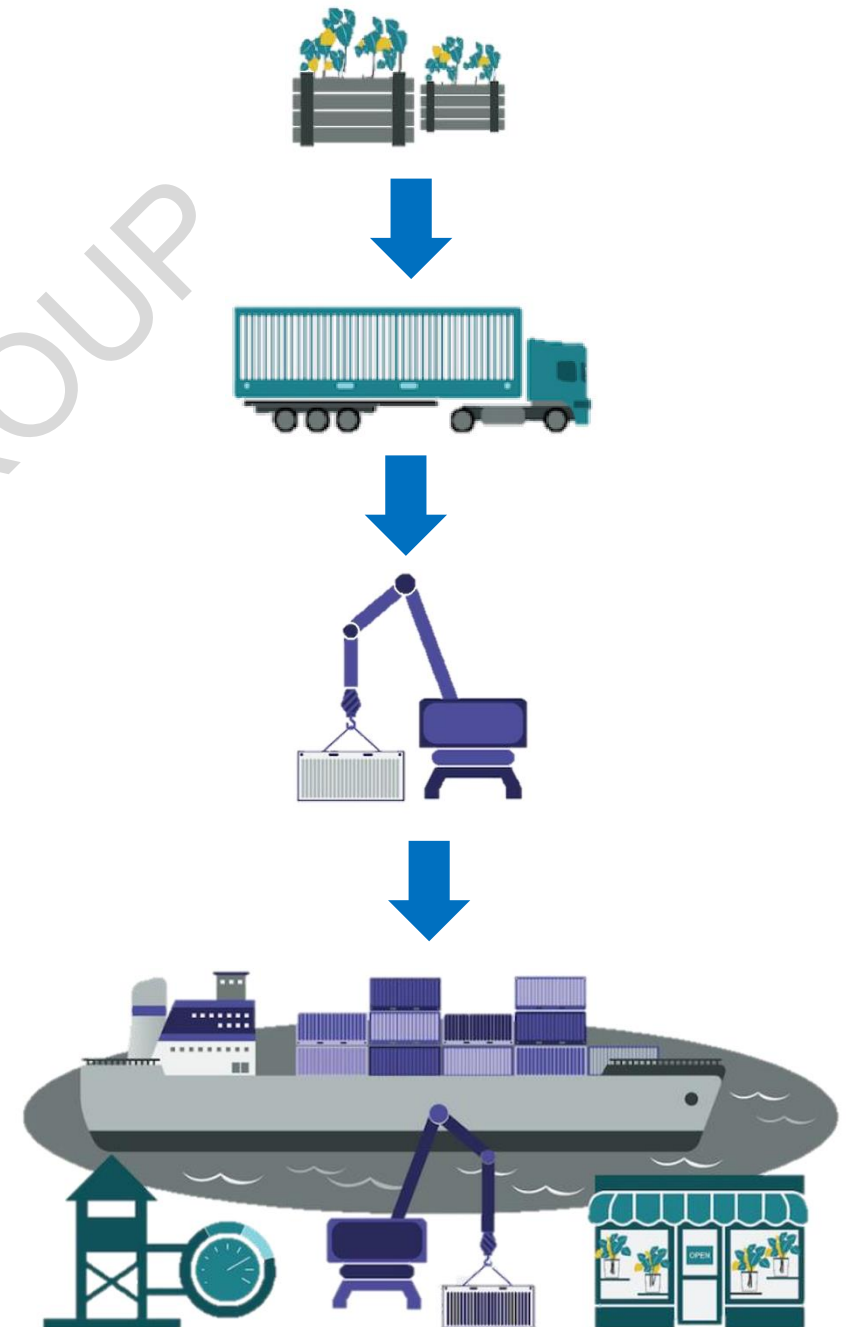
Predictive Maintenance (PM)

(Artificial Intelligence Driven Maintenance:
From Device, Edge, To Cloud)

An unreliable machine results in waste of time, money, and very bad impression

and unfortunately sometimes so many lives

That is why, we preventively keep maintaining ALL PARTS!!! Considering the fact that we cannot forecast which part will fail in future!
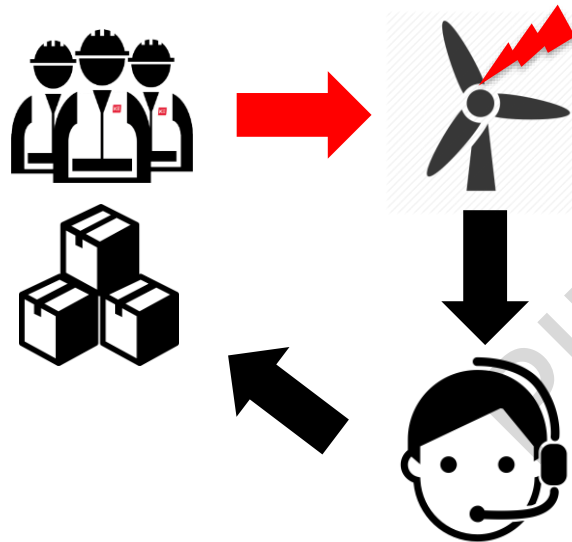
Traditional Corrective Maintenance

- Faults are reported by end-user

- Afterwards, inventory and the team should be scheduled and dispatched
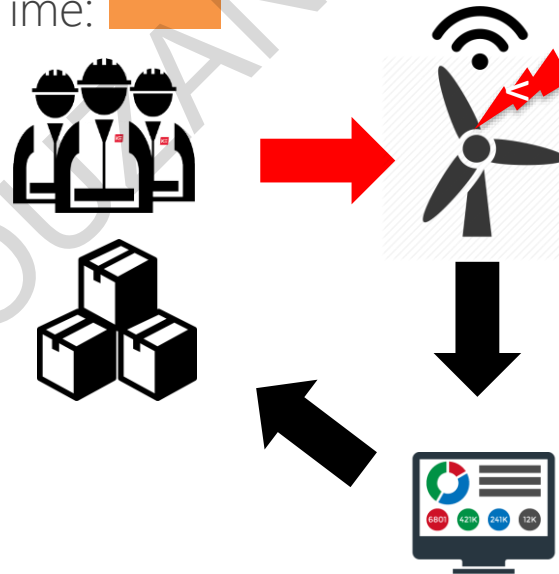
Time:

Real-time Monitoring (IoT)

- Faults are detected by connected sensors in near real-time

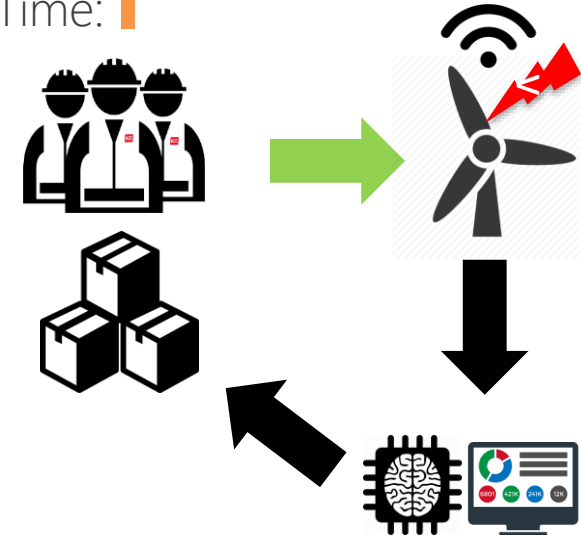- Afterwards, inventory and the team should be scheduled and dispatched

Time:

Machine Learning (Prediction)

- Faults are predicted before they really occur
- There is enough time to schedule the team and inventory in advance

Time:

Business Statistics

20% ✓ Total cost of poor quality amounts to 20% of sale (American Society of Quality)

5%-20% ✓ Poor maintenance strategies can reduce plant capacity by 5-20% (Deloitte)

$50 Billion ✓ Unplanned downtime costs manufacturers approximately $50 billion per year (Deloitte)

2%-3% ✓ Warranty costs to companies amount to approximately 2-3% revenues (Warranty Week)

Up to 16% ✓ Up to 16% of manufactures have adopted IoT strategies! (McKinsey)
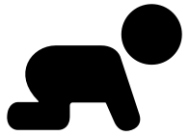
5%-40% ✓ Predictive Maintenance reduces the cost by 5%-40% (McKinsey)

3%-10% ✓ Predictive Maintenance reduces the equipment capital investment (3%-10%) by extending the life time of the machine (McKinsey)

Reliability Model of a Machine over Time (Bathtub Curve)

1

Early Life

✓ Machine learning based root-cause analysis is used to improve the manufacturing process and the quality of products

2

Normal/Random

✓ Machine learning driven maintenance is usually used in this phase
✓ Machine learning can
  ✓ Postpone the wear-out
  ✓ Forecast the failure
  ✓ Change unplanned maintenance to planned maintenance

3

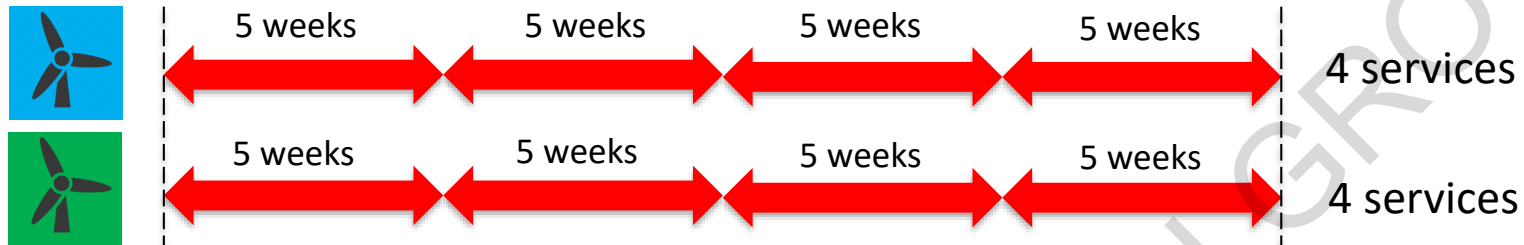## Wear-out

✓ To comply with the specification and manual of the machine, it is recommended to perform a maintenance at this phase

Standard (Planned) Maintenance

| 5 weeks | 5 weeks | 5 weeks | 5 weeks | 4 services |

| 5 weeks | 5 weeks | 5 weeks | 5 weeks | 4 services |

Predictive Maintenance

| 15 weeks | | 5 weeks | 2 services |

| 10 weeks | 4 weeks | 6 weeks | 3 services |
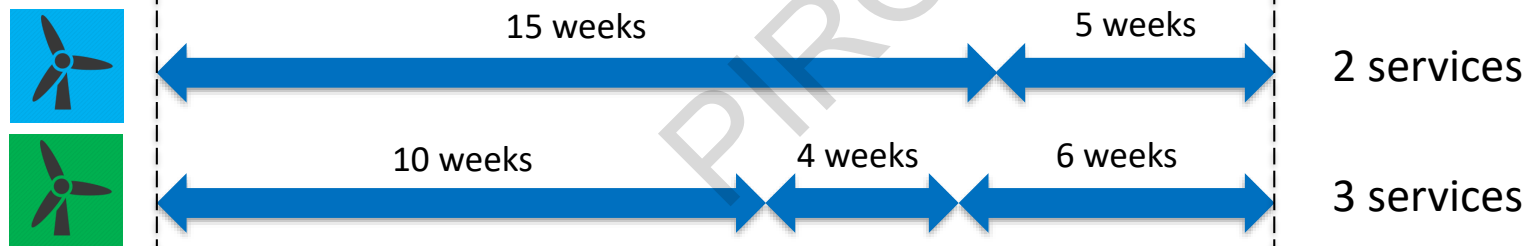
- ✓ Understand nature and nurture of each machine

- ✓ Dynamically schedule the maintenance services

- ✓ Customize the maintenance service for each machine individually

Use Cases of Predictive Maintenance

Aerospace

- When this component of airplane will fail?
- How much delay will cause due to a specific mechanical issue?

Utilities

- Which/when breakers of the smart grid will be broken?
- Which/when my vending machine or ATM will fail?
- What is **remaining useful life** of my machines?

Manufacturing

- What is the root cause of this failure?
- How can I decrease my warranty cost?
- How can I create a new business model e.g., pay per use?
- How can I spend my maintenance wisely?

Transportation & Logistics

- When do I need to replace my break disk?
- Which/when will elevator doors fail?
- How can I reduce the high costs of unscheduled maintenance of cranes?
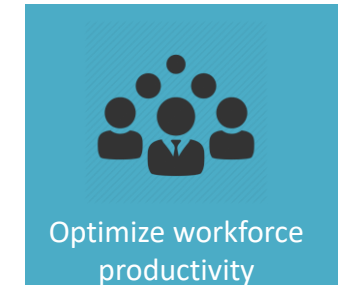
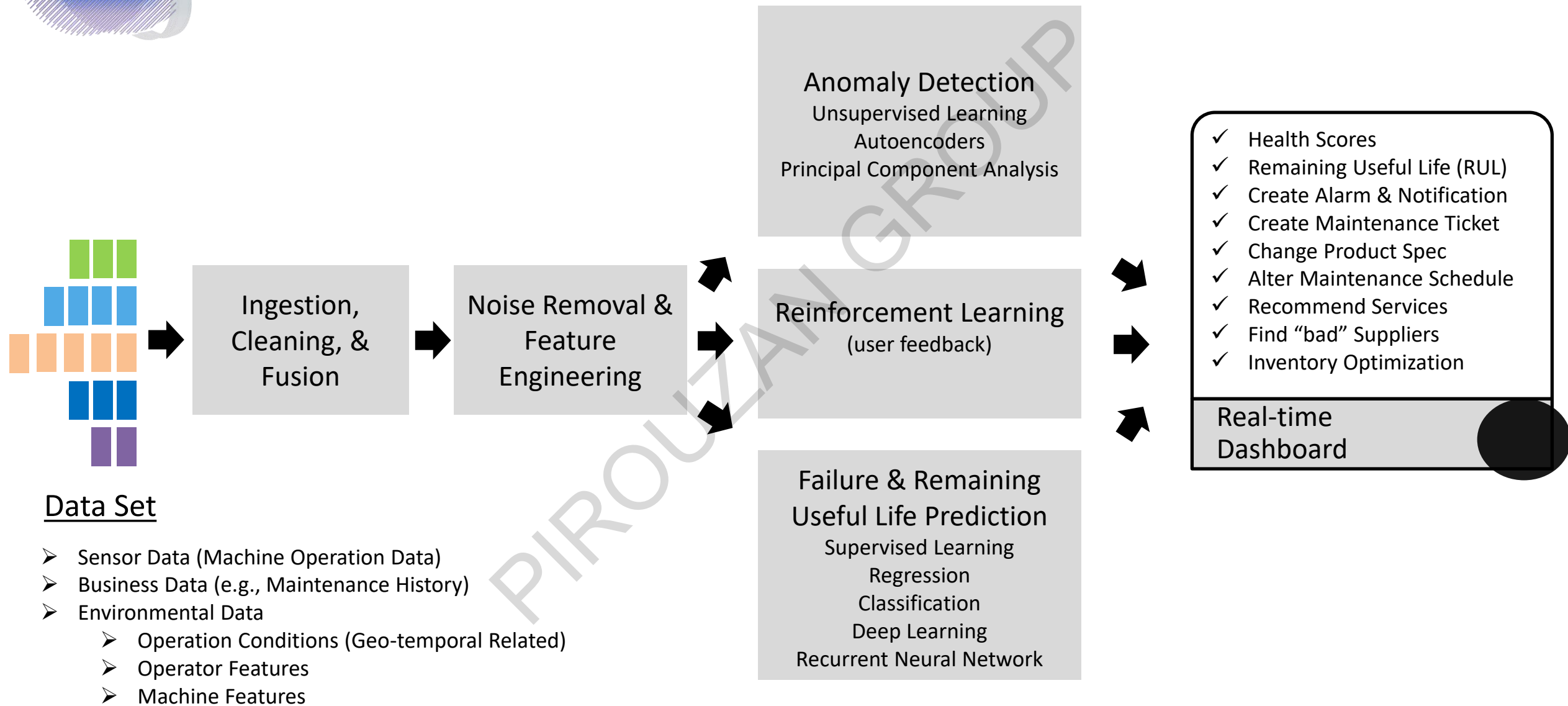**Machine Learning (Predictive Maintenance)**

IoT/Event/Stream Hub and Data Lake

✓ Opportunity to analyze real time monitoring data
✓ Maintenance costs can be reduced because of better planning; parts can be ordered and shipped in advance without disrupting the equipment run time
✓ Unscheduled downtime can be significantly reduced thereby leading to improved productivity and output
✓ Product inventory maintenance based on upcoming maintenance
✓ Operations & Maintenance teams can address equipment issues before they become problems and significantly affect operations
✓ OEMs and operators can fix the issue in the first-visit, since they already localized the root cause of the problem remotely!
✓ OEMs can reduce the warranty cost by root cause analysis methods to improve the production line accordingly
✓ OEMs can have new business model e.g., offer pay per use!

Optimize asset lifetime & availability	Lower risk	Decrease loss of services
Optimize labor and operations cost	Decrease planned & unplanned maintenance	Improve customer satisfaction
Improve fuel cost efficiency	Smarter inspection & replacement	Optimize workforce productivity

Anomaly Detection
Unsupervised Learning
Autoencoders
Principal Component Analysis

Ingestion, Cleaning, & Fusion

Noise Removal & Feature Engineering

Reinforcement Learning
(user feedback)

Failure & Remaining Useful Life Prediction
Supervised Learning
Regression
Classification
Deep Learning
Recurrent Neural Network

- ✓ Health Scores
- ✓ Remaining Useful Life (RUL)
- ✓ Create Alarm & Notification
- ✓ Create Maintenance Ticket
- ✓ Change Product Spec
- ✓ Alter Maintenance Schedule
- ✓ Recommend Services
- ✓ Find "bad" Suppliers
- ✓ Inventory Optimization

Real-time Dashboard

Data Set

- ➤ Sensor Data (Machine Operation Data)
- ➤ Business Data (e.g., Maintenance History)
- ➤ Environmental Data
    - ➤ Operation Conditions (Geo-temporal Related)
    - ➤ Operator Features
    - ➤ Machine Features

❑ Regression

✓ It is used to find "Remaining Useful Life (RUL)" of the machine based on the given inputs (e.g., sensor data)

✓ How many more cycles the machine can work?

❑ Binary Classification

✓ Classify/categorize the future status of the machine based on the given inputs such as sensor data

✓ Will the Machine fail in next **w** cycles (time)?

❑ Multiclass Classification

✓ Will the machine fail within the window **[1, w0]** cycles or fail within the window **[w0+1, w1]**?
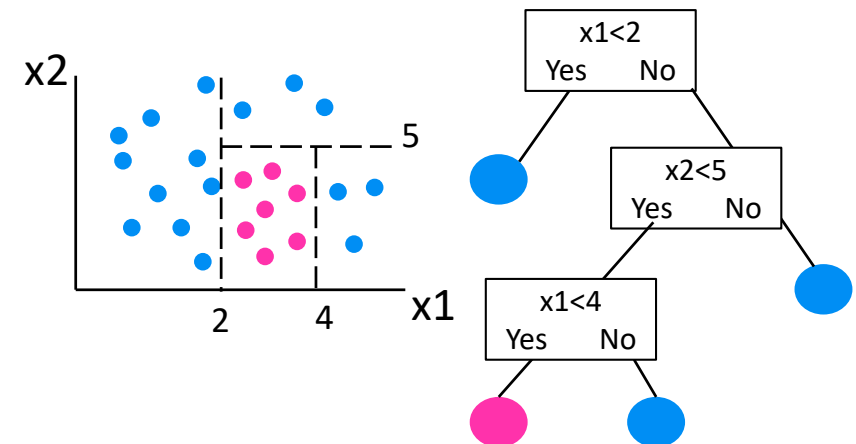
Regression

Find: Y=f(x) e.g., X = input = Sensor data, Y = output = RUL

Y (RUL)

x
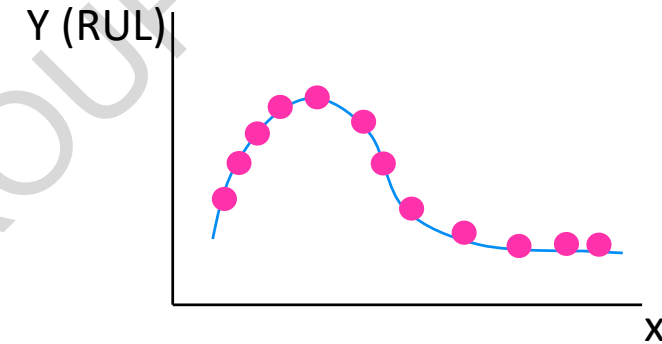
Classifier (Decision Tree)

Input: Sensor data; Group1 (Will fail): ● Group2 (Will not fail): ●

x2

5

2   4   x1

x1<2
Yes   No

x2<5
Yes   No

x1<4
Yes   No

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Anomaly Detection (Autoencoders)

- ✓ It is typically used for the purpose of dimensionality reduction.
- ✓ Output layer having the same number of nodes as the input layer, and with the purpose of reconstructing its own inputs.
- ✓ Do a feed-forward pass to compute activations at all hidden layers, then at the output layer to obtain an output x'. Measure the deviation x' from the input x (typically using squared error).
- ✓ The algorithm is trained to learn the normal behavior of your data.
- ✓ Having a distribution of the reconstruction error, if the value of the error does not lie in a right-sided (upper) confidence interval with confidence level α it is marked "faulty".

Human brain consists of millions of neurons
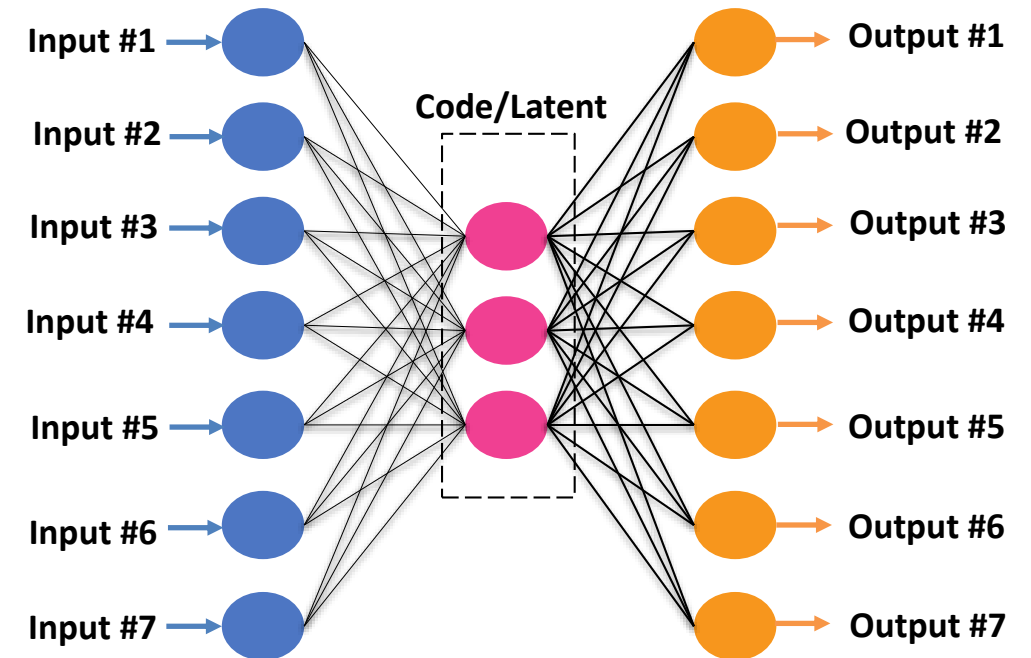
Autoencoders consist of several digital neurons

Jet Engine ID

Time (cyle)

Data
(e.g., sensor, setting, config, maintenance history)

id	cycle	setting1	setting2	setting3	s13	s18	s19	s20	s21	RUL	label1	label2
1	1	0.45977011	0.16666667	0	0.2058824	0	0	0.71317829	0.7246617	191	0	0
1	2	0.6091954	0.25	0	0.2794118	0	0	0.66666667	0.73101353	190	0	0
1	3	0.25287356	0.75	0	0.2205882	0	0	0.62790698	0.62137531	189	0	0
1	4	0.54022989	0.5	0	0.2941176	0	0	0.57364341	0.66238608	188	0	0
1	5	0.3908046	0.33333333	0	0.2352941	0	0	0.58914729	0.70450152	187	0	0
1	6	0.25287356	0.41666667	0	0.2205882	0	0	0.65116279	0.65272024	186	0	0
1	131	0.51149425	0.41666667	0	0.3676471	0	0	0.45736434	0.62040873	61	0	0
1	132	0.68390805	0.41666667	0	0.4117647	0	0	0.30232558	0.58602596	60	0	0
1	133	0.68390805	0.33333333	0	0.3088235	0	0	0.62790698	0.4942005	59	0	0
1	134	0.41954023	0.5	0	0.3676471	0	0	0.41860465	0.53728252	58	0	0
1	135	0.40229885	0.58333333	0	0.3529412	0	0	0.5503876	0.5249931	57	0	0
1	136	0.67241379	0.41666667	0	0.3382353	0	0	0.48062016	0.38069594	56	0	0
1	165	0.55747126	0.83333333	0	0.5294118	0	0	0.34883721	0.4400718	27	1	1
1	166	0.37356322	0.25	0	0.5	0	0	0.37209302	0.34631317	26	1	1
1	187	0.22988506	0.5	0	0.5882353	0	0	0.21705426	0.2595968	5	1	2
1	188	0.11494253	0.75	0	0.5147059	0	0	0.28682171	0.08920188	4	1	2
1	189	0.46551724	0.66666667	0	0.6617647	0	0	0.26356589	0.30171223	3	1	2
1	190	0.34482759	0.58333333	0	0.6911765	0	0	0.27131783	0.23929854	2	1	2
1	191	0.5	0.16666667	0	0.6176471	0	0	0.24031008	0.32491025	1	1	2
1	192	0.55172414	0.5	0	0.6470588	0	0	0.26356589	0.09762497	0	1	2

Multi-class Classification

Binary Classification

Remaining Useful Life

1 or 2: Alarm
1: Warning
0: Ok

❑ Accuracy depends on so many parameters such as:
- ✓ Predefined window size (how many cycles in advance we want to create an Alarm)
- ✓ Machine learning algorithms and the corresponding complexity
- ✓ Size and quality of data
- ✓ How the missing values are handled

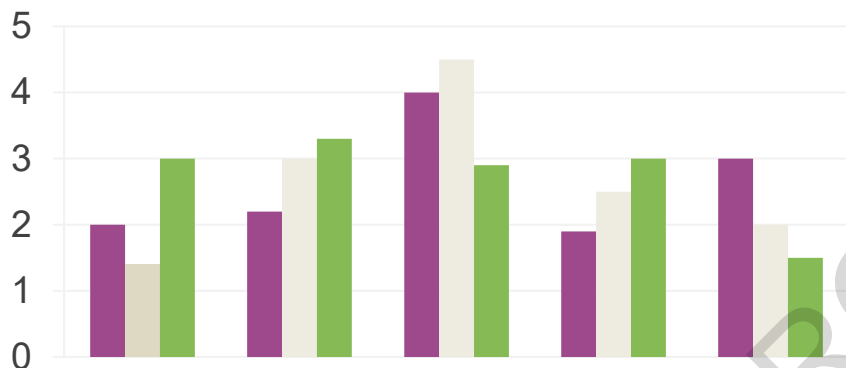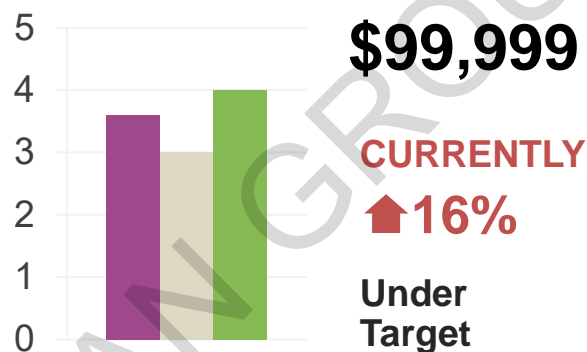❑ Beside Accuracy, we need to consider Precision, Recall, and F-score

Sam PIROUZAN GROUP
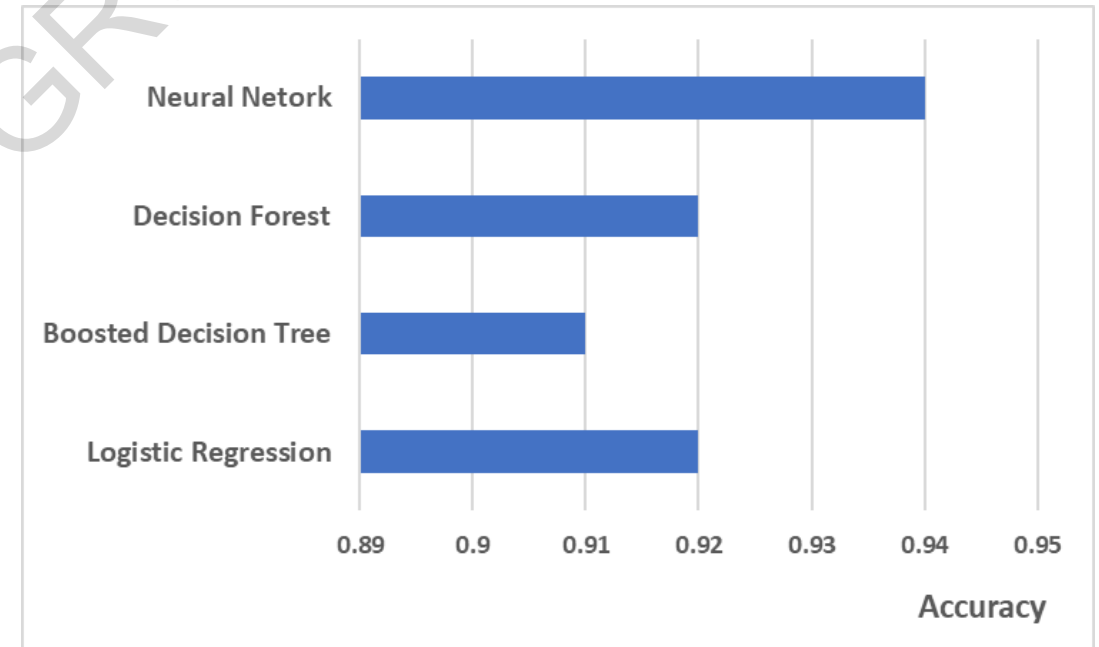
⚠ 5 Risks

3 Machines need maintenance in 2 weeks

2 Machines will fail in 1 day

Machine Capacity

Maintenance Cost

$99,999

CURRENTLY

▲**16%**

Under Target

Performance

83%

Maintenance Tickets

2 Days Ago — Machine #3 — **MON 00/00**

3 Days Ago — Machine #102 — **TUE 00/00**

10 Days Ago — Machine #308 — **FRI 00/00**

Remaining Useful Life

Category 4
Category 3
Category 2
Category 1
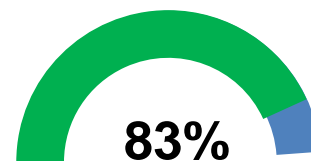
Probability of Failure

Machine #1 — **74%**

Machine #2 — **63%**

Machine #3 — **32%**

Engagement Methodoloy

| 1) Scope (1-2 weeks) | 2) Analysis (4-8 weeks) | 3) Implementation (3-12 months) | 4) Test (2-6 months) |

1
- Define Scope

2
- Find Critical Points with help of stakeholders
- Prepare Operation & Maintenance Manual
- Practical Predictive Maintenance Methodology

3
- Design Architecture (Sensor, Edge, Cloud)
- Implementation of Sensors, Edge, Connectivity
- Cloud: ingestion, storage, processing, visualization
- Find best machine learning algorithm
- Scale the machine learning algorithms

4
- Acceptable Results?
- Periodic measurement of parameters
- Evaluate the system

There is no one-approach-fits-all

Each Predictive Maintenance is unique

Are you ready for AI-driven IoT-based CUSTOMER JOURNEY!?

AI, ML, and Big Data for Customer Analytics and Digital Transformation

PIROUZAN GROUP

Insurance
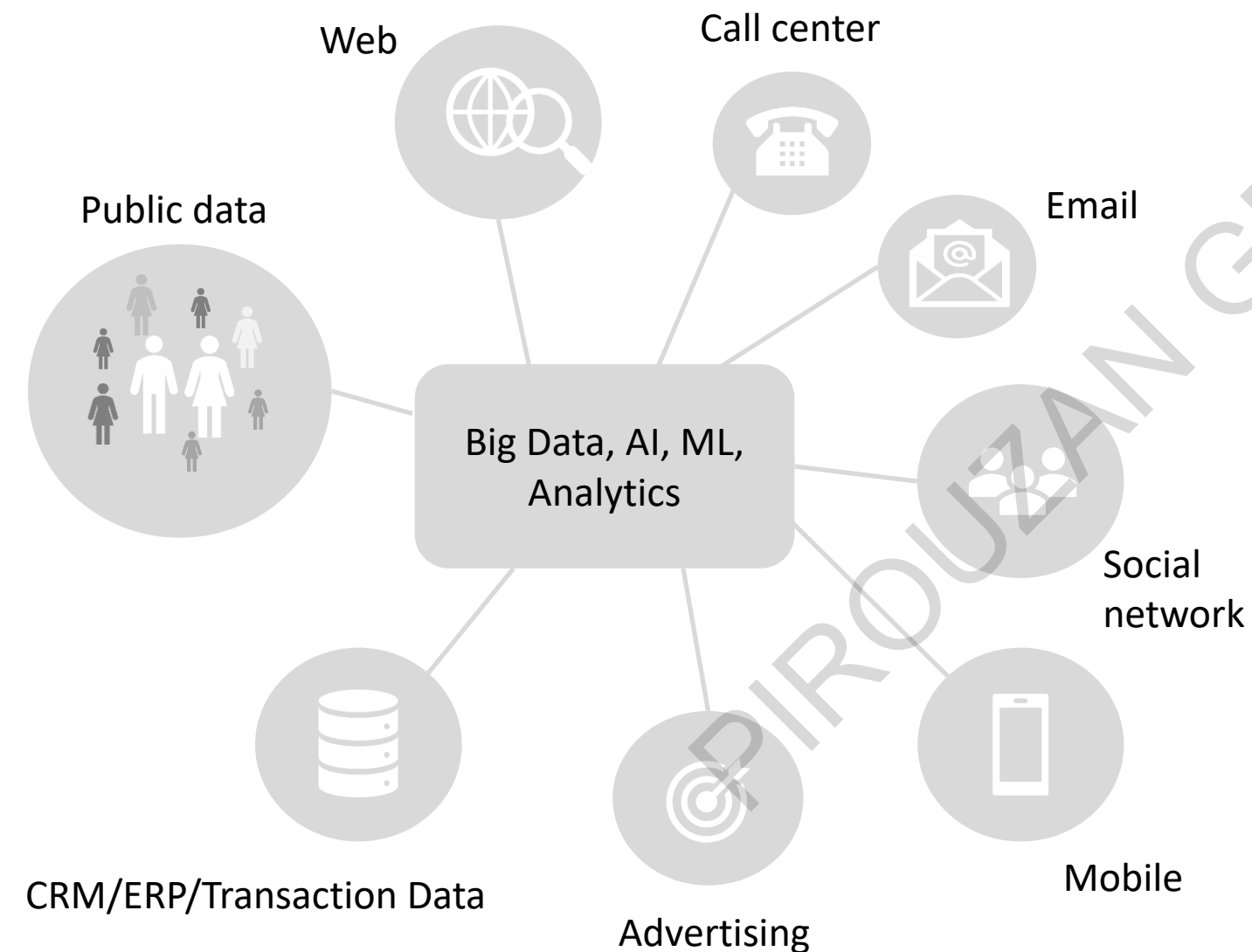
Banking

Utilities
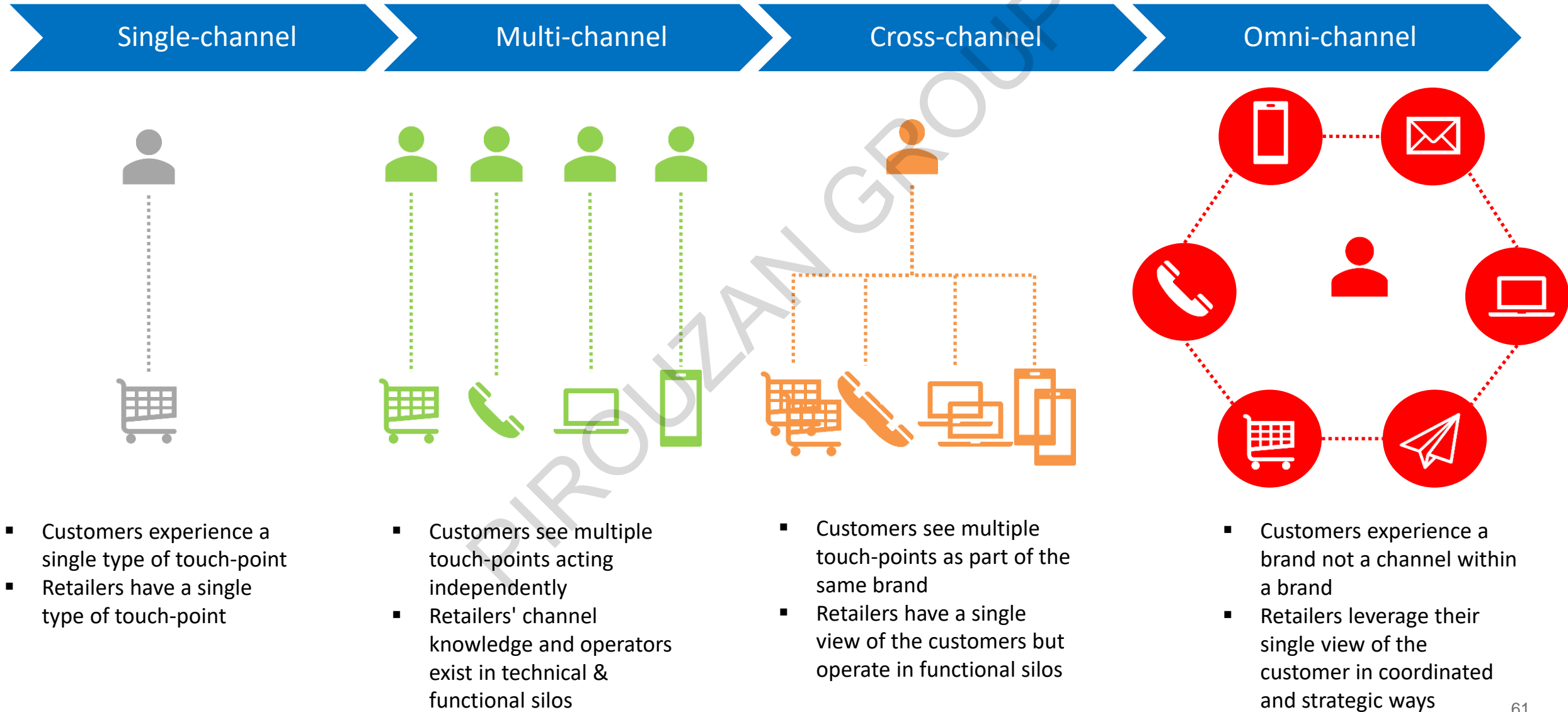
Transportation

Manufacturing

Healthcare

Hospitality

Retail

AI, ML, and Big Data Deliver Omni-channel Insights

Web

Call center

Public data

Email

Big Data, AI, ML, Analytics

Social network

- 85% of generated data by 2020 are unstructured!
- AI, ML, and Big Data techniques can rapidly correlate, aggregate, and analyze your data and gain actionable insights
- AI, ML, and Big Data techniques can quickly combine and enrich your existing data sets with 3rd party data

CRM/ERP/Transaction Data

Advertising

Mobile

The Evolution from Single-channel to Omni-channel

Single-channel	Multi-channel	Cross-channel	Omni-channel

- Customers experience a single type of touch-point
- Retailers have a single type of touch-point

- Customers see multiple touch-points acting independently
- Retailers' channel knowledge and operators exist in technical & functional silos

- Customers see multiple touch-points as part of the same brand
- Retailers have a single view of the customers but operate in functional silos

- Customers experience a brand not a channel within a brand
- Retailers leverage their single view of the customer in coordinated and strategic ways

Social Media Assessment

- Are we invest on right marketing channels
- What is the "share of voice" and "reachability" of our marketing strategy

Social Media Segmentation

- What kind of audiences we have?
- Geographic, demographics
- Influence score
- Recommenders

**Assess**

Segment

Discover

Social Media Discovery

- Find meaningful insight about prospective customers
- Discover new ideas, trends, etc.
- Topic analysis
- What users say about our brand and campaign?
- Sentiment analysis

✓ Improve customer satisfaction
✓ Identify patterns and trends
✓ Make smarter decision

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Brand Monitoring (II)
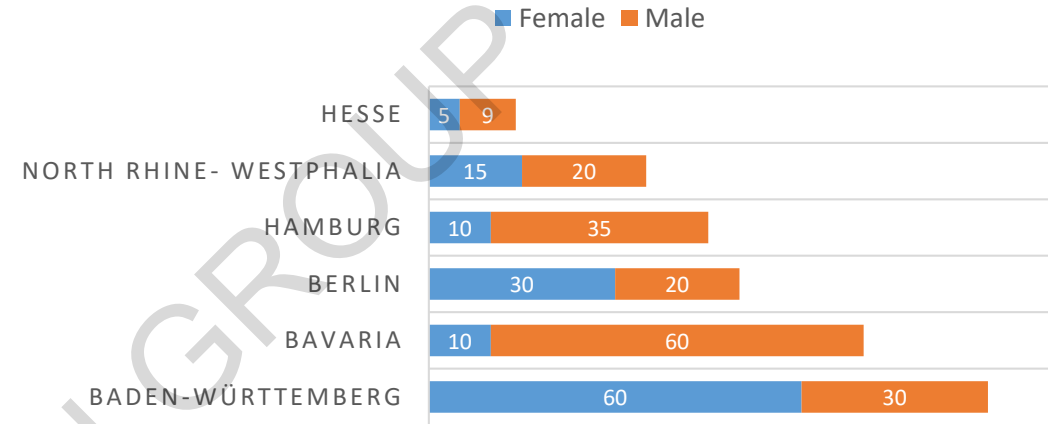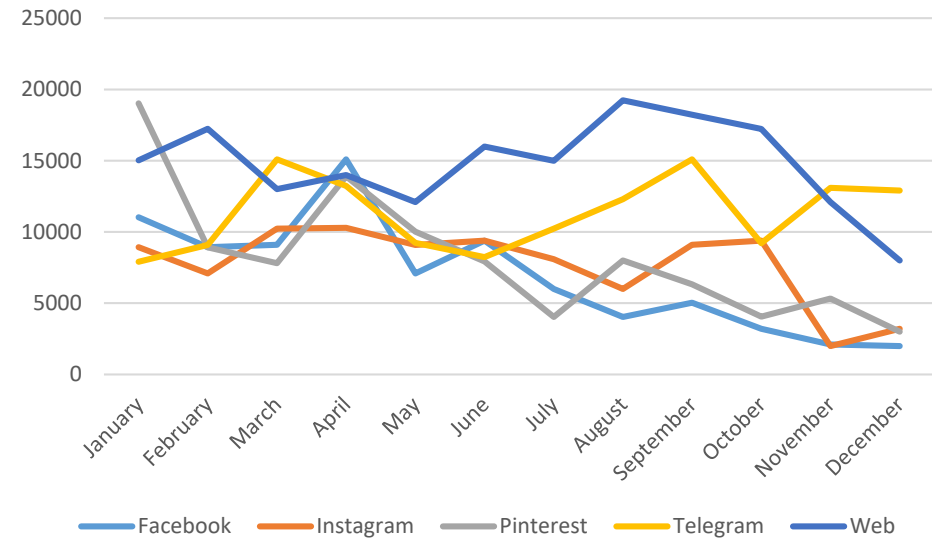## Social Network and Sentiment Analysis
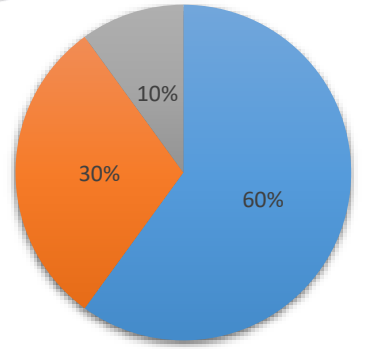
Share of voice (Author) by gender
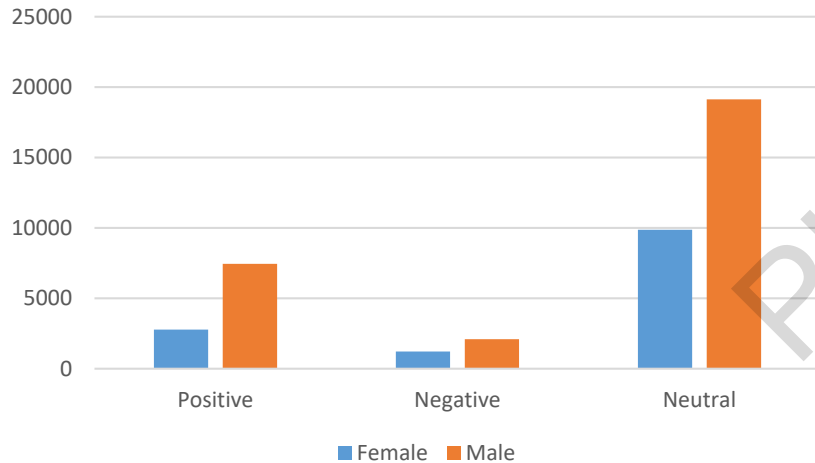
Distribution of gender across geographic

Sentiment by gender

The trend (#mention) of the brand over time in different channels

Brand Monitoring (III)

Social Network and Sentiment Analysis

can exhaust featuring bigger html bit cnn

Sport cool youtube don't comment

cnnmoney overview davidcward Sam

twitter

scene July hotel finance AOK million march

Action public answer iot pic days AI drone

Qualcomm

Automatically thanks round public ces data

Okay

Context of discussion

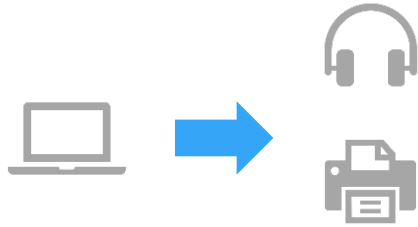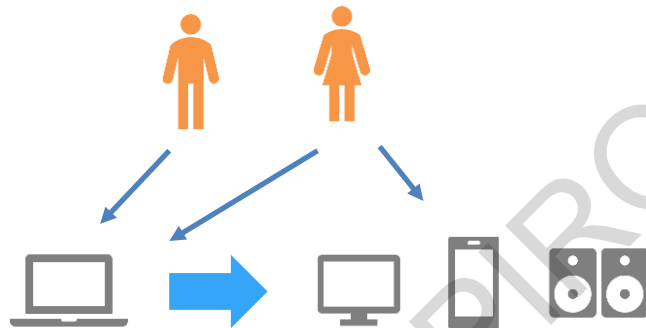|		
	Sara	20.808% Share of voice
	Alex	12.203% Share of voice
	Tara	11.309% Share of voice
	Nick	9.503% Share of voice

Influence of social media authors

Product/Service Recommendation

What else are you interested in?

**Upselling &
Item Hierarchy**

**Cross-selling &
Collaborative Filtering**

Love story

Titanic

Content-based Filtering

You and your friend like angry bird in Facebook

Social Interest Based

Image Processing & Video Analytics (I)
Real-life scenarios

Non-Registered Users

- Female: 99%
- Age (25-30): 95%
- Happy: 97%

- Customer analytics & product enhancement
- Pattern analytics for e.g., targeted advertising
- Demographic (age, gender, etc.) Analysis
- Location/product analytics: heatmap, #users, duration of stay, hot products, interaction of users, Emotion detection?
- Brand Monitoring

Registered Customers

- Sarah O'Connor: 98%
- Last visit: 7.8.2018
- Gold Customer
- Interest: Gucci, Armani
- Birthday: 21.03.1984
- Single
- Address: Dusseldorf

- Can be combined with other source of data e.g., CRM, Social networks, etc.
- Loyalty program
- Customer satisfaction
- Upselling/Product Recommendation
- Tailored marketing

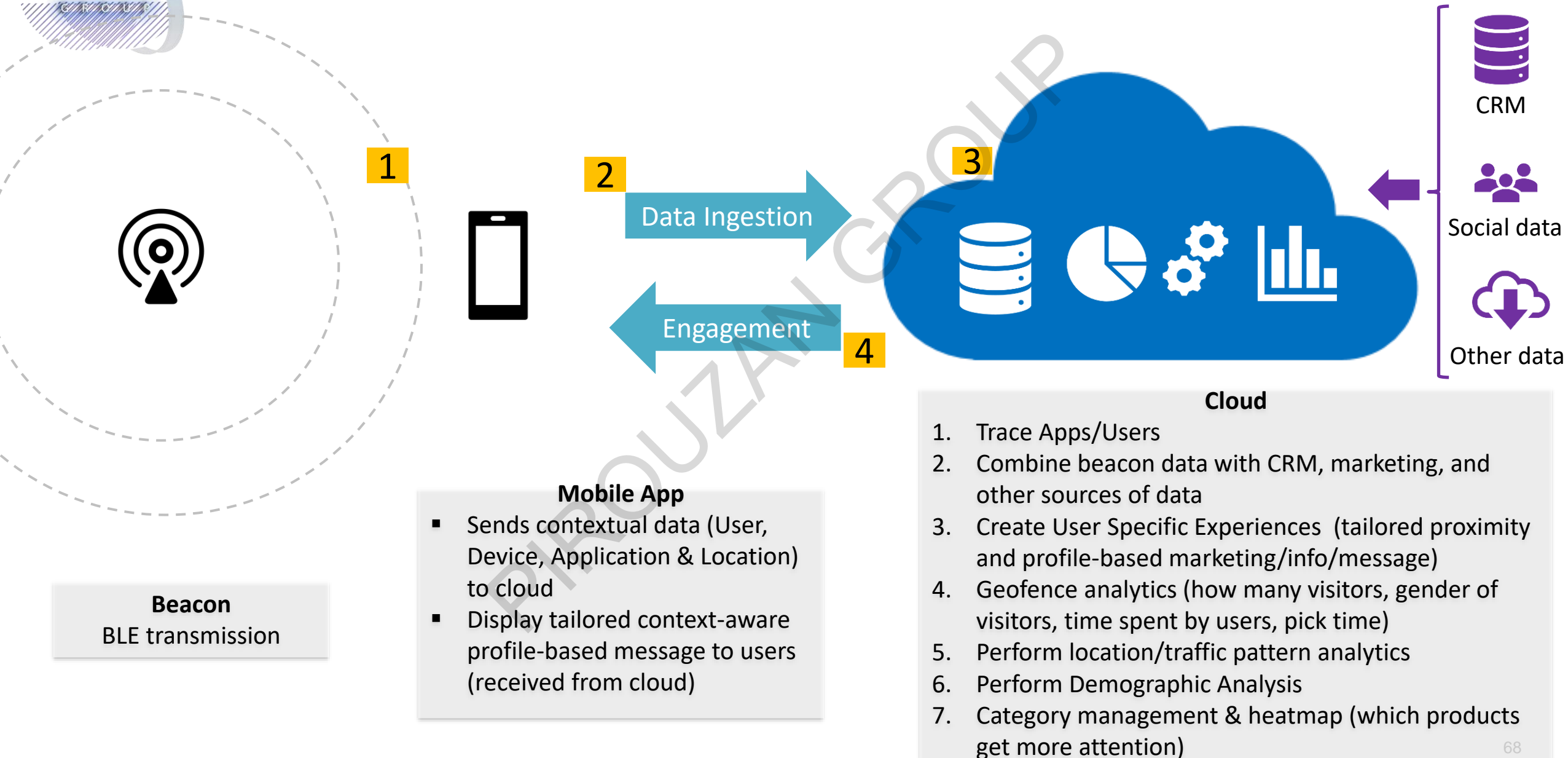Location-based Service
AI-driven Beacon (I)

Far

Near

Immediate

Bluetooth Beacon transmit small packets of data

OH! You're nearby!

... Which wake up an application on your mobile device and Lets you to calculate your location and PROXIMITY To The Beacon

AI-driven Beacon (II)

1

2 Data Ingestion →

3

← Engagement **4**

CRM

Social data

Other data

Beacon
BLE transmission

Mobile App
- Sends contextual data (User, Device, Application & Location) to cloud
- Display tailored context-aware profile-based message to users (received from cloud)

Cloud
1. Trace Apps/Users
2. Combine beacon data with CRM, marketing, and other sources of data
3. Create User Specific Experiences (tailored proximity and profile-based marketing/info/message)
4. Geofence analytics (how many visitors, gender of visitors, time spent by users, pick time)
5. Perform location/traffic pattern analytics
6. Perform Demographic Analysis
7. Category management & heatmap (which products get more attention)

68

How Categorize Customers (Customer Segmentation)?

We need to spend our budget in a wise way!

RFM Model

Recency
5 days ago

Frequency
3x month

Monetary Value
EUR 120

Current Value ↑

Low potential value
High Current Value

Grow These Customers

High potential value
High Current Value

Keep These Customers

Low potential value
Low Current Value

Should you spend money here?

High potential value
Low Current Value

Grow These Customers

Potential Value →
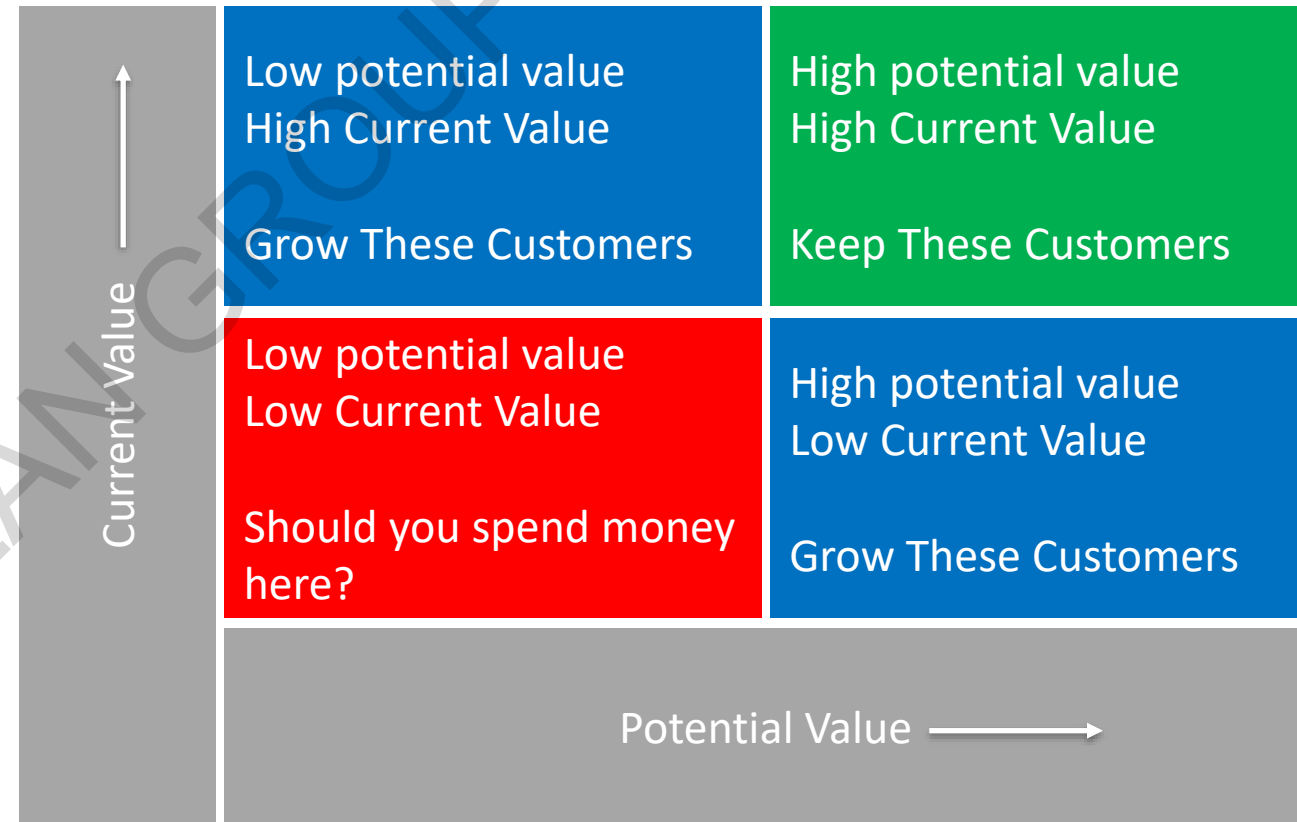
How Much is Your Future Business Worth?

Focus your marketing focuses on most valuable customers!

✓ Build a model that predict the customer group of a new customer

Data Set

➢ Demographics (e.g., Age, Gender, Income)
➢ Transactions

Ingestion, Cleaning, & Fusion

Noise Removal & Feature Engineering

Classification (e.g., Random Forest)

Regression

Customer	Customer Value Class
Nina	Silver
Sarah	Platinum
Tara	Silver
Katrin	Gold
Sam	Platinum

Customer	Customer Lifetime Value
Nina	$2,132
Sarah	S1,200
Tara	$3,750
Katrin	$10,000
Sam	$950

✓ 80% of your business comes from 20% of your customers
✓ It costs 10x less time to sell to an existing customer than finding a new customer
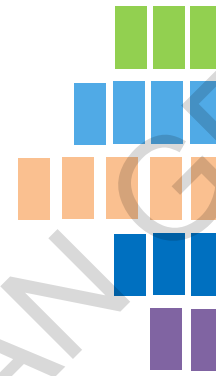
Are you Happy with me? (Churn Analysis)(I)

Find unsatisfied users and predict customer churn!

We need to find unsatisfied users, or they go to our competitors

Preparation & Machine Learning (e.g., Regression)

Customer	SAT. Score
Nina	1.1
Sarah	2
Tara	4.3
Katrin	5
Sam	3.5

Data Set

➢ Demographic
➢ History
➢ Transaction
➢ Social medias
➢ Surveys

Only 10% of customers answer to surveys

Are you Happy with me? (II)

ML-driven incentives recommendation and loyalty program engine

Sam — Extended Warranty

Stefan — Free Software

Katrin — Coupon

1. Based on attrition and satisfaction score, we can detect which customer is willing to leave us!
2. Marketing and support team to reach customer with an offer that makes them stick with us!
3. We need to find an appropriate offer for each person, since different customers react differently to different offers (longer warranty, coupon)

➢ Machine Learning (Recommendation Engine) will find incentives for each user
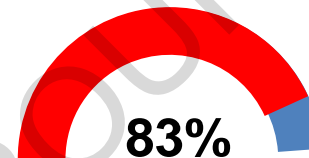
Sam

Sam
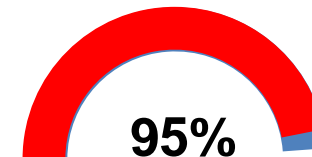
Male | 1983

Tehran

+98 21 12121333

Customer Satisfaction
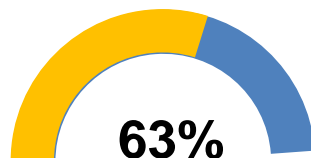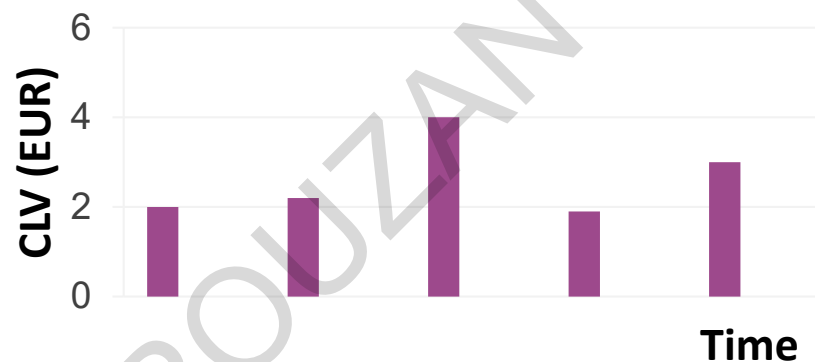
63%
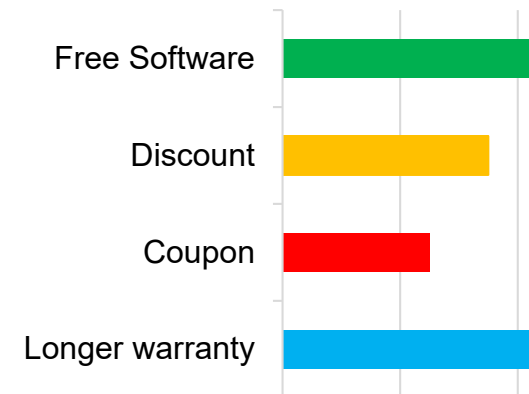
Probability to leave
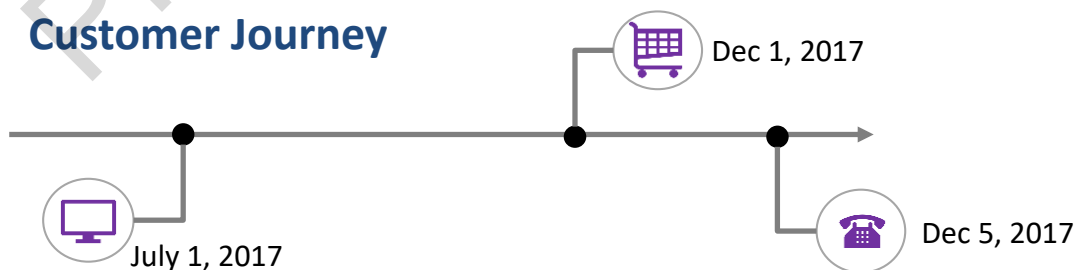
83%

Probability to Call

95%

Customer Lifetime Value (CLV)

CLV (EUR)

6

4

2

0

Time

Appropriate Incentives

Free Software

Discount

Coupon

Longer warranty

Customer Journey

Dec 1, 2017

July 1, 2017

Dec 5, 2017

Overall

Payment

Customer Service

- **Digital transformation**
- **Internet of Things, Big Data, Artificial Intelligence, Block-chain**
- **Different Industries**
  - Transportation, Banking, Healthcare, Hospitality, Insurance, ….
- **Use cases**
  - Artificial Intelligence Driven IoT Solutions for Logistics
  - Artificial Intelligence Driven Maintenance: From Device, Edge, To Cloud
  - Artificial Intelligence Driven Omni-channel Customer Journey: From Awareness, Purchase, Service, to Loyalty

Thank you

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