



BIG DATA & AI CONGRESS

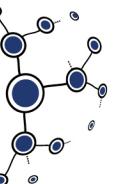
BARCELONA



5^a Edición | 17 OCT 2019
Auditorio AXA Barcelona

ORGANIZADO POR:

BIG DATA CoE
by eurecat



Síguenos en: @CoEBigData | #BIGDATAAI19

Patrocinadores Oro:



CaixaBank

Generalitat de Catalunya
Departament de Polítiques Digitals
i Administració Pública

sdg group

Analytics-Driven Decisions.

Patrocinadores Plata:



Patrocinadores Bronce:





CASOS DE ÉXITO II

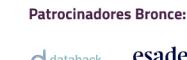
ORGANIZADO POR:



Patrocinadores Oro:



Patrocinadores Plata:





Jordi Navarro
CEO & co-founder
Cleverdata Solutions
cleverdata.io

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Patrocinadores Oro:



Patrocinadores Plata:



Michael Page

Excelencia Operacional con Natural Language Processing

El caso de éxito de Ricoh EU



cleverdata

5º BigData & AI
Congress

17 – OCT – 2019
Barcelona

RICOH
imagine. change.

3 retos que abordar en iniciativas de IA

1

Diseño

Cómo diseñar el Portfolio de Iniciativas

2

Ejecución

Cómo abordar la Gestión del Cambio

3

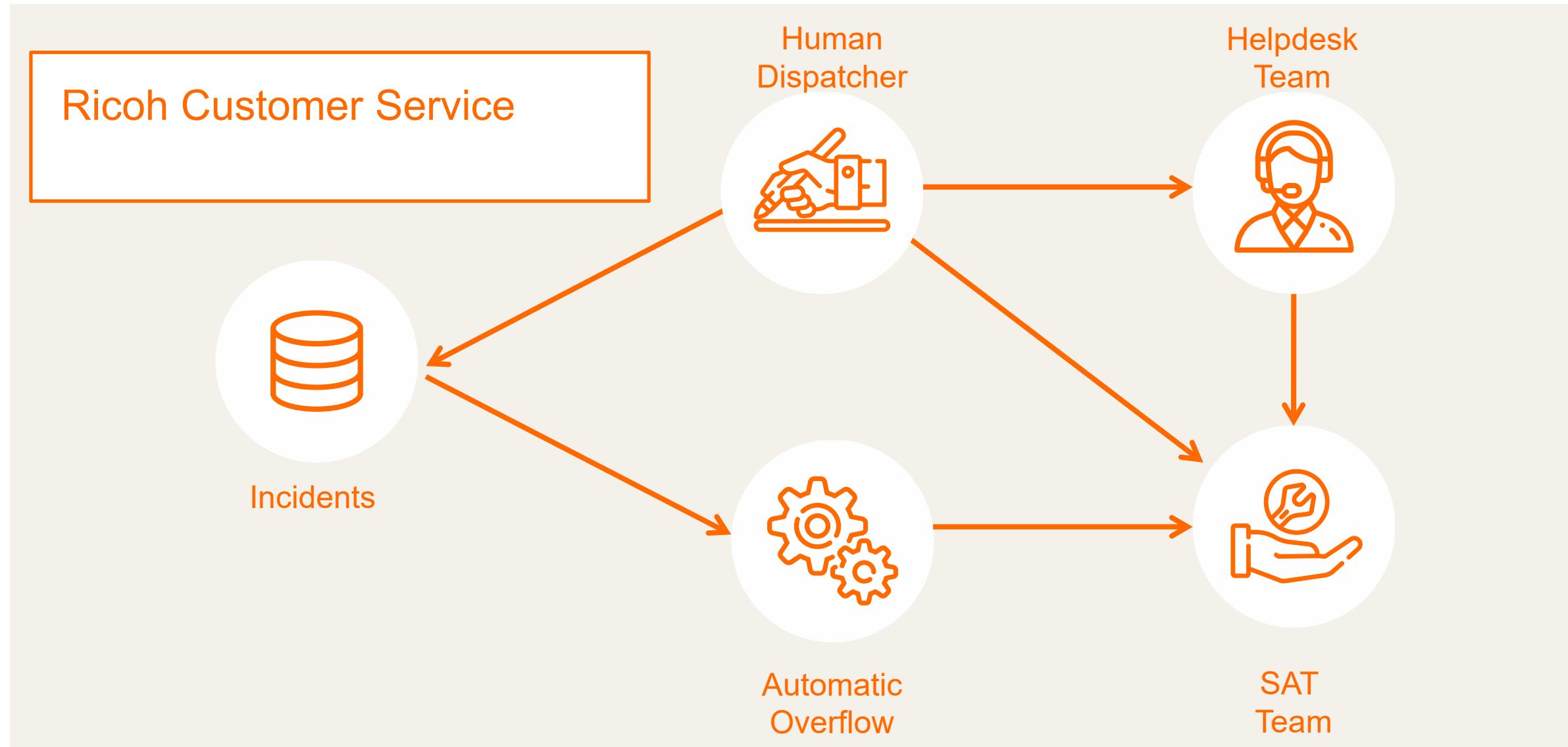
Evaluación

Cómo medir el Potencial y los Resultados

1. Diseño

El proceso original

El caso de éxito de Ricoh



1 Diseño

Cambio de mindset

Explorar los procesos con una nueva perspectiva



Mindset tradicional

Workforce

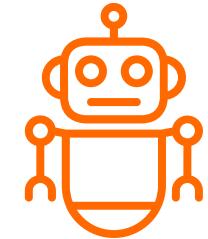
Transmisión de Conocimiento tradicional



Visión analítica

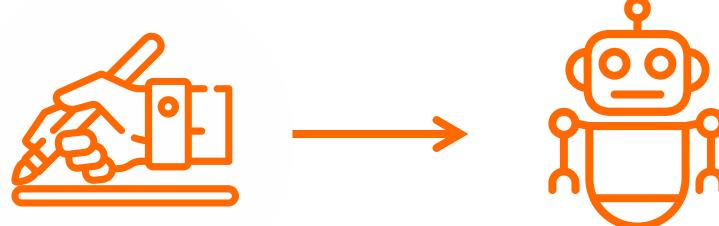
Machine Learning

Transmisión de Conocimiento desde los datos

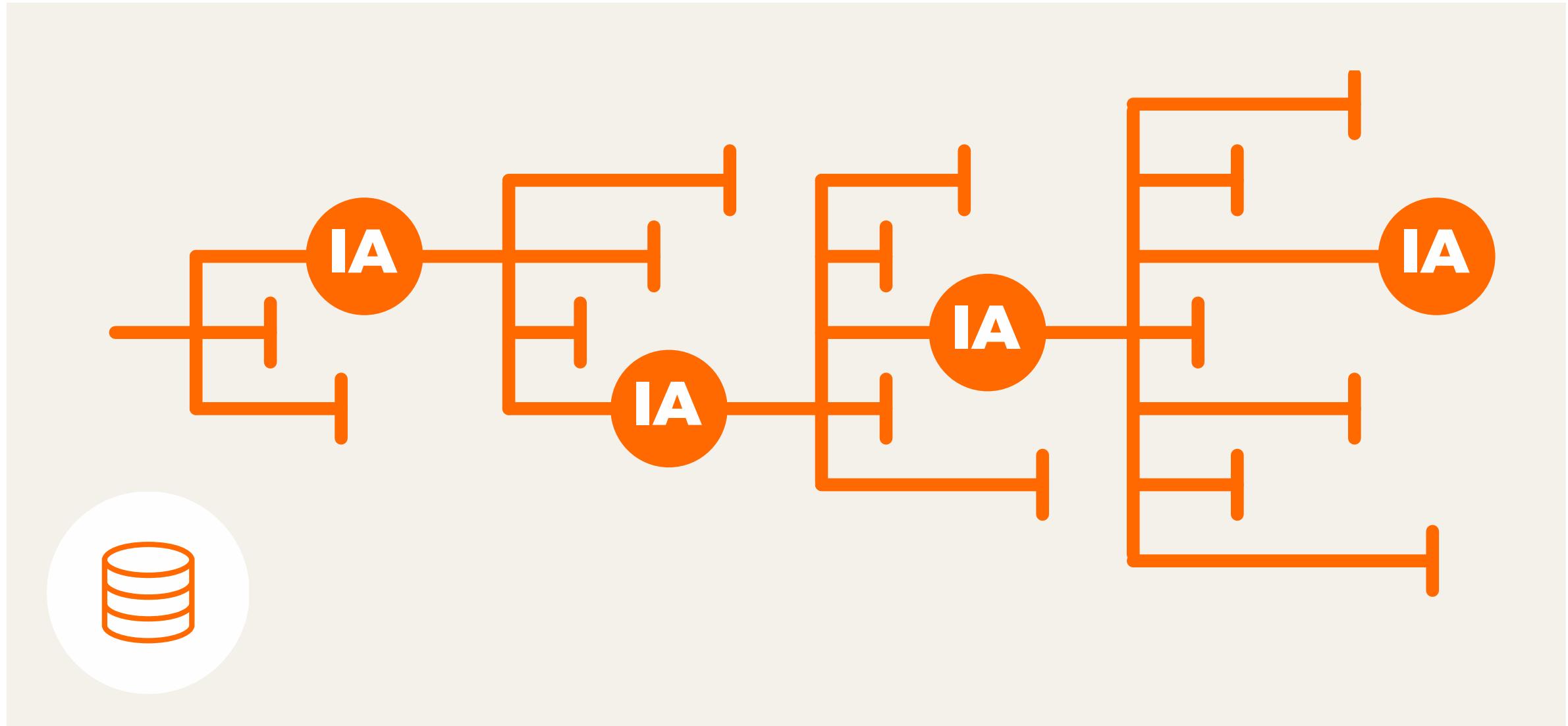


Decision Engineering:

Toma de decisiones inteligentes en un entorno Operacional Intensivo



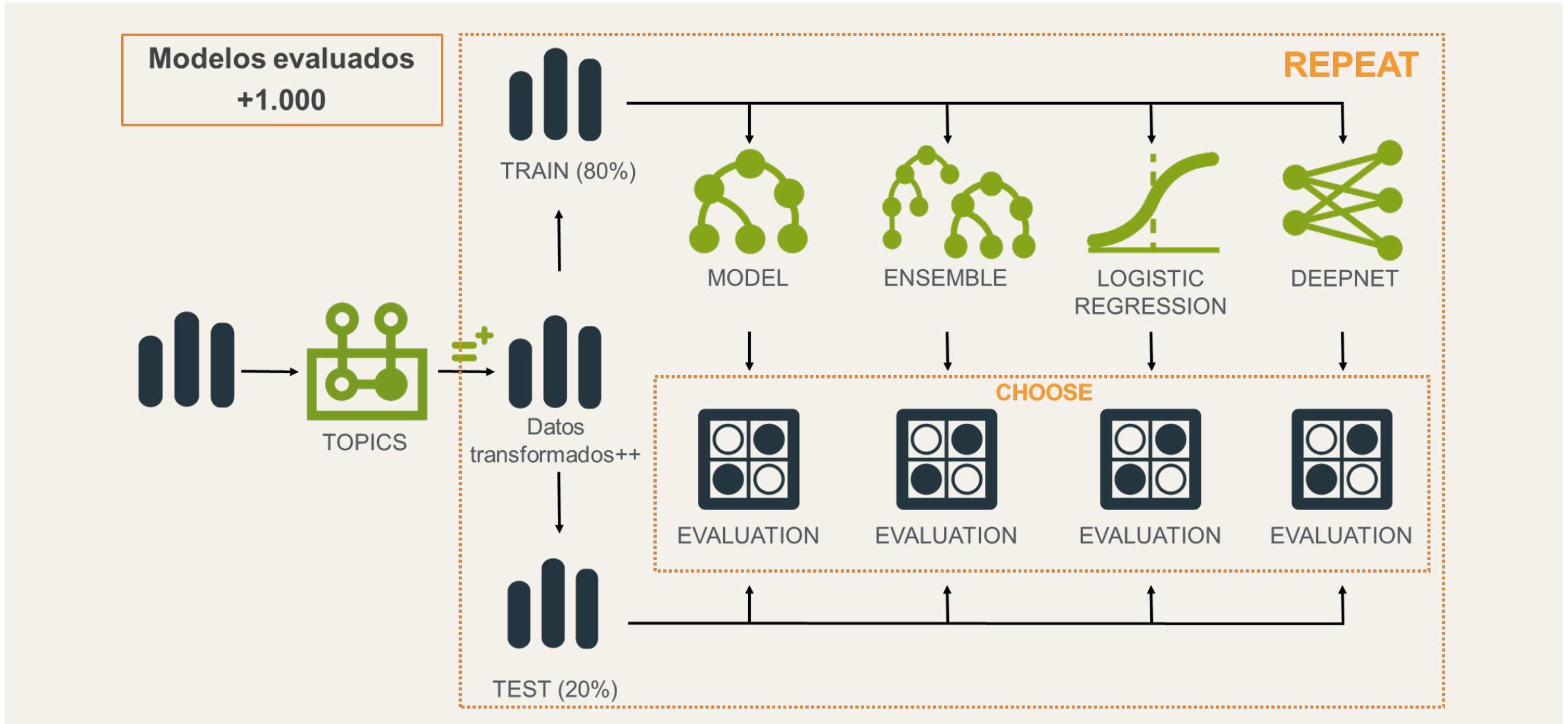
Los procesos: la fuente de las iniciativas de AI



2. Ejecución

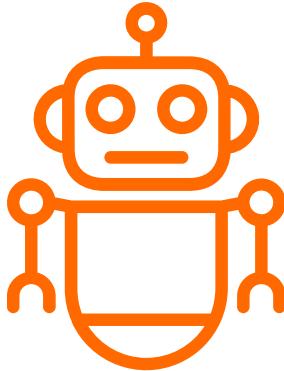
El caso de éxito de Ricoh

La cocina del algoritmo



3. Evaluación

El resultado



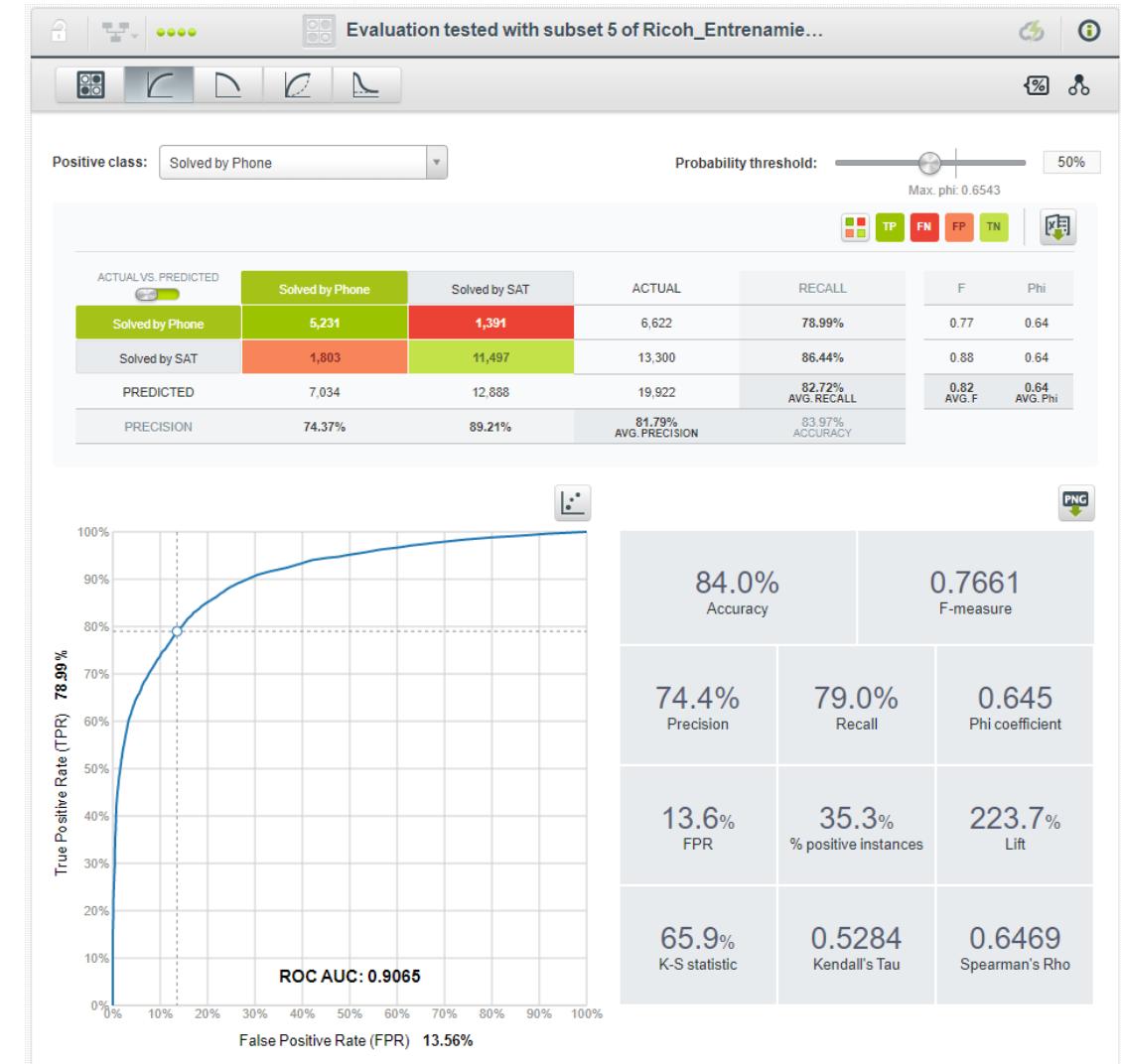
Decision Engineering:
Toma de decisiones
inteligentes en un entorno
intensivo en Operaciones

Características del Dispatching

Bot

- + Conocimiento encapsulado
- + Rápido (msecs)
- + Atributos (IoT)
- + Escalable (Cloud)
- + Disponible (DevOps)

El caso de éxito de Ricoh



2. Ejecución

El proceso actual

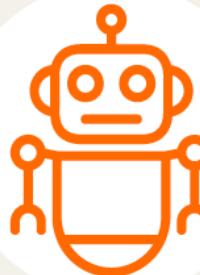
El caso de éxito de Ricoh

Ricoh Customer Service

Incidents



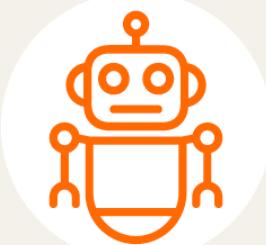
Dispatcher Bot



Helpdesk Team



SAT Team



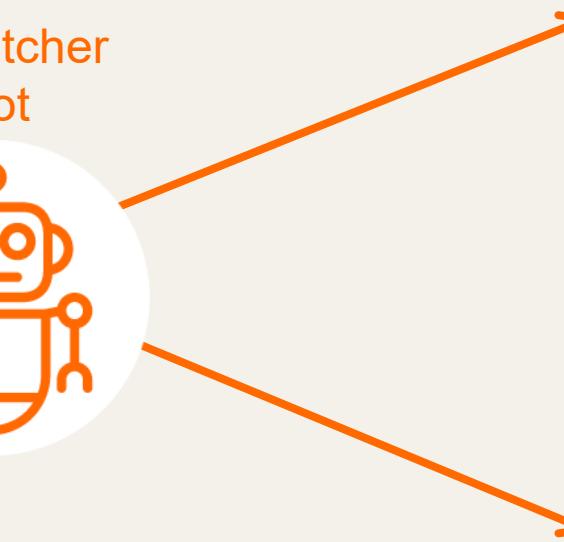
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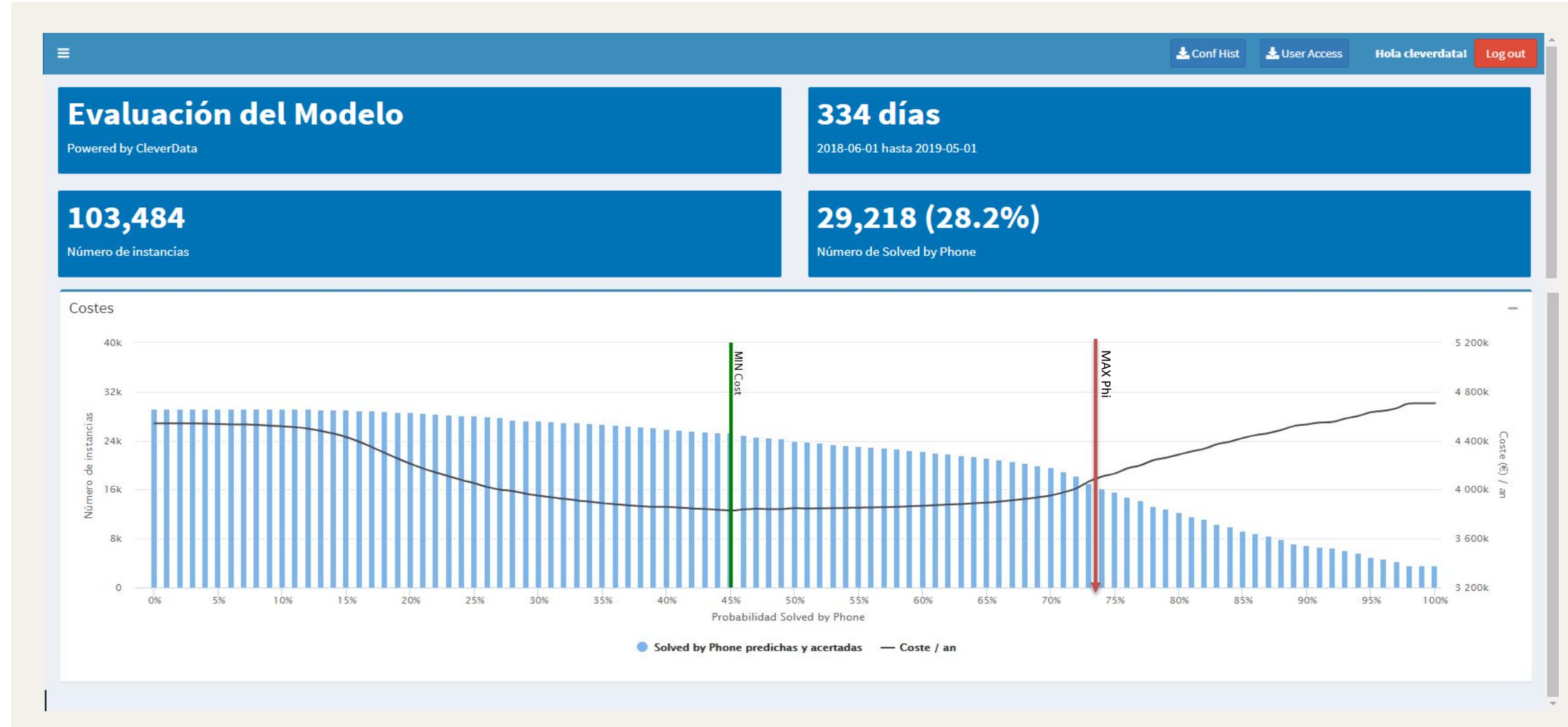
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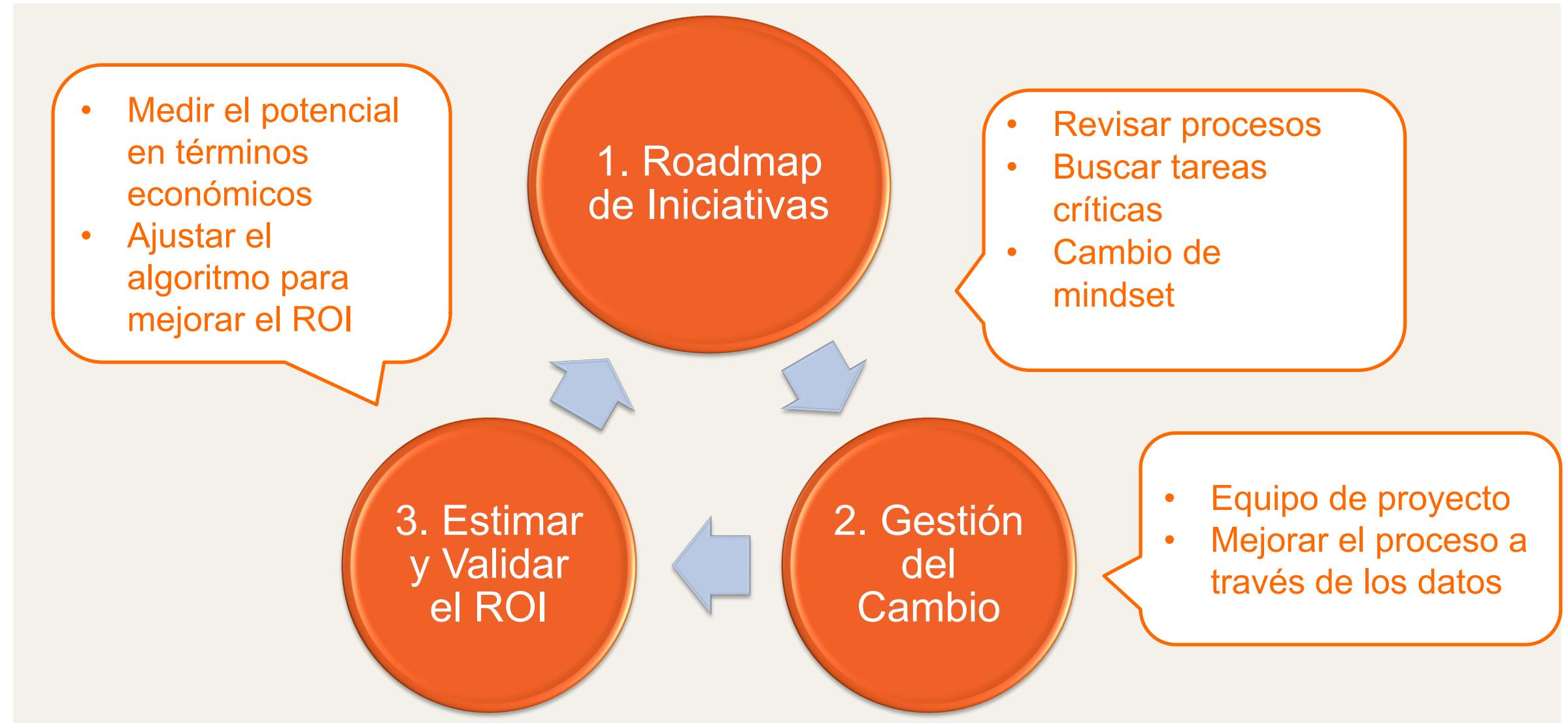
3. Evaluación

El caso de éxito de Ricoh

Como medir el Potencial y los Resultados



Como abordar los tres retos de la Inteligencia Artificial



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Javi Roca
Victoria Casaus
Jacobo Varela

RICOH
imagine. change.



Gráinne Costigan

*Data Scientist. Large Format Printing
Hewlett-Packard Solutions*

hp.com

ORGANIZADO POR:



Patrocinadores Oro:



Patrocinadores Plata:



Patrocinadores Bronce:





Ignasi Puig de Dou

CEO

Datancia

datancia.com

ORGANIZADO POR:



Patrocinadores Oro:



Patrocinadores Plata:



Usage & Reliability Analysis for Large Format Print



Ignasi
Puig
CEO

Gráinne Costigan
Senior Data
Scientist



Agenda



- Introducción a HP Barcelona
- Nuestro negocio
- Service and Support
- Learnings from project



- ## Monitorización de equipos
- Objetivos
 - Segmentación
 - SPC multivariante
 - Monitorización de fallos

HP in Barcelona

+2300
employees

61
different nationalities

+30 years

Largest HP R&D
Lab outside the US

+700 R&D engineers

+150 patents per year

12
different businesses

WW HQ of the 3D Multi
Jet Fusion and Large Format
Printing Businesses

EMEA HQ
of the Graphic Solutions
Business



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WW HQ of the 3D Multi
Jet Fusion and Large Format
Printing Businesses

EMEA HQ
of the Graphic Solutions
Business

A global reference site
for value added activities

- Customer Support
- R&D
- Logistic Operations
- Finance/Credit &
Collections
- Sales Operations
- Sales
- Category & Marketing
- Demo & Training



HP Large Format Printers

Design

Production



Service & Support Transformation



Reactive Service to Proactive, Predictive and Prescriptive.



DATANCIA POC: Lessons Learnt

1. Not all data is useful.
2. Embed outcome in business process.
3. Flexible mindset to solve complex problems - failure an option.

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Data Products *Any deliverable whose primary objective uses data to facilitate an end goal.*

DATANCIA POC: Lessons Learnt

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Data Products *Any deliverable whose primary objective uses data to facilitate an end goal.*

- All projects within team developed and delivered as data products:
- A clear **definition** is key – must include objective, transformation of process, delivery methods and data sources.
 - Product developed **iteratively** – starting simple, validating and building upon.
 - Defined roles, **responsibilities** and deliveries for product owner, business and data team – closer collaboration.

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DATANCIA

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Objetivos

Desarrollo de un sistema de ayuda a la decisión para los ingenieros de soporte. El objetivo es identificar las impresoras industriales que precisan revisión en función de su desviación respecto a su funcionamiento habitual.

Esto incluye:

1. La segmentación de los equipos de impresión en función de su uso, patrones de errores o variables demográficas de los usuarios.
2. El desarrollo de un SPC multivariante (Statistical Process Control) para caracterizar el comportamiento “normal” de una impresora.
3. La implementación de un análisis de TTF (Time to Failuresk) para caracterizar la distribución de los tiempos hasta el fallo de cada máquina identificar aquellas que se desvíen de lo esperado.

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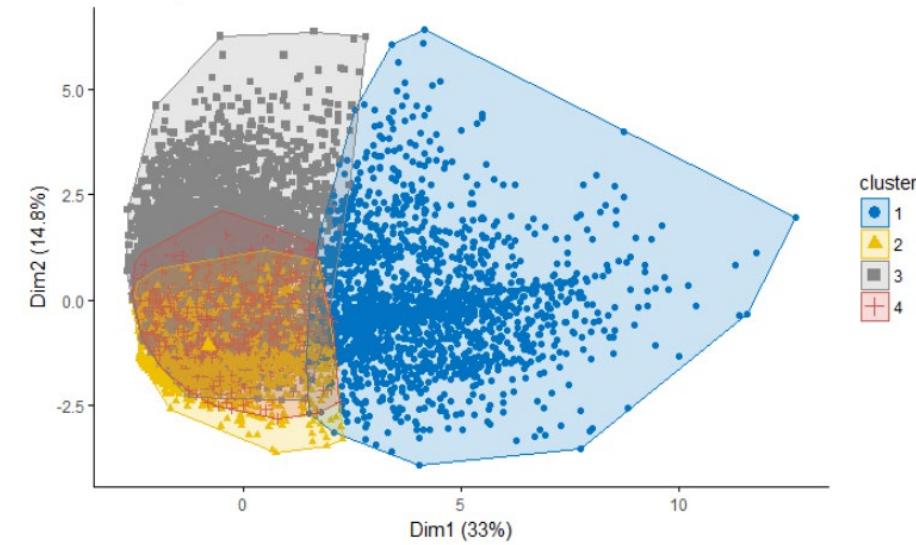
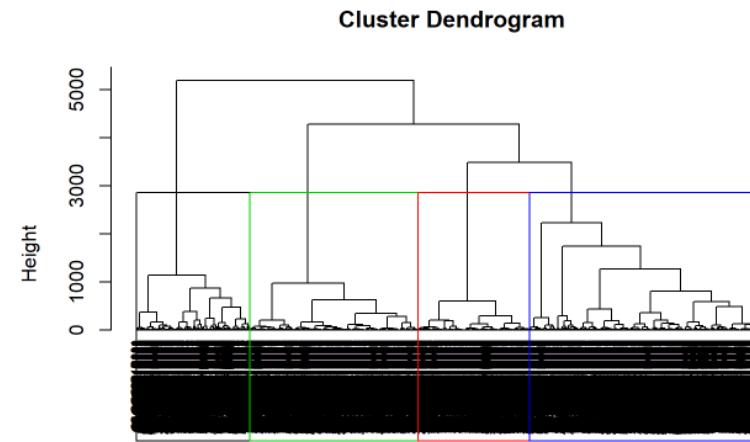
DATANCIA

- Monitorización de equipos
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Segmentación – Selección de datos relevantes

1. Consumo de tinta.
2. Consumo de media.
3. Características de los “jobs”.
4. Firmware.
5. Número de ciclos (“cuentaquilómetros”).
6. Availability y performance (OEE).
7. Tiempo de impresión.
8. Errores.
9.

Segmentación – Creación de clústeres



Segmentación – Creación de clústeres

size	36%	16%	22%	26%
usage	7	31	7	6
no. jobs	30	40	20	20
variability	0,31	0,07	0,09	0,06
failures	5	2	6	4

La segmentación permite la implementación de diferentes estrategias de seguimiento por clúster

Agenda



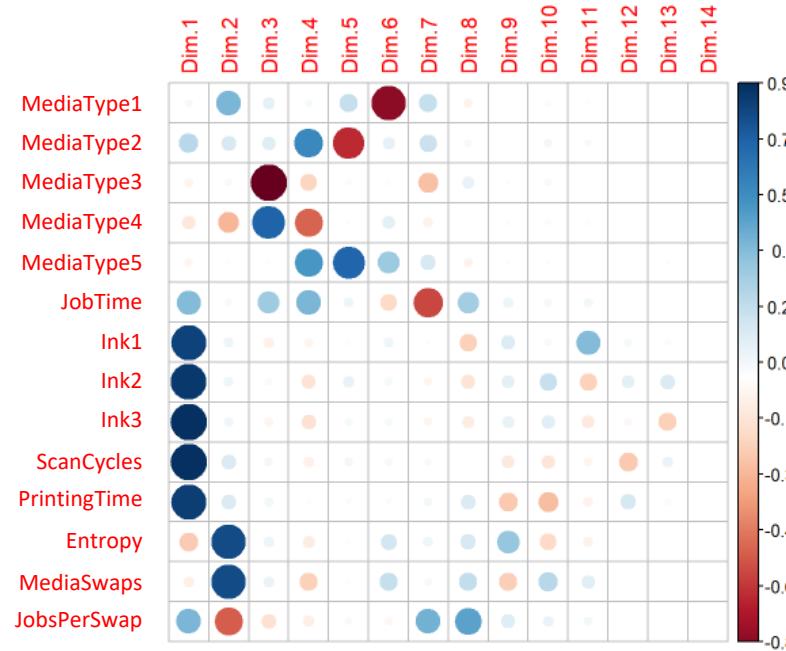
- Introducción a HP Barcelona
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DATANCIA

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SPC multivariante– Fase I (Definición)

Reducción de dimensiones

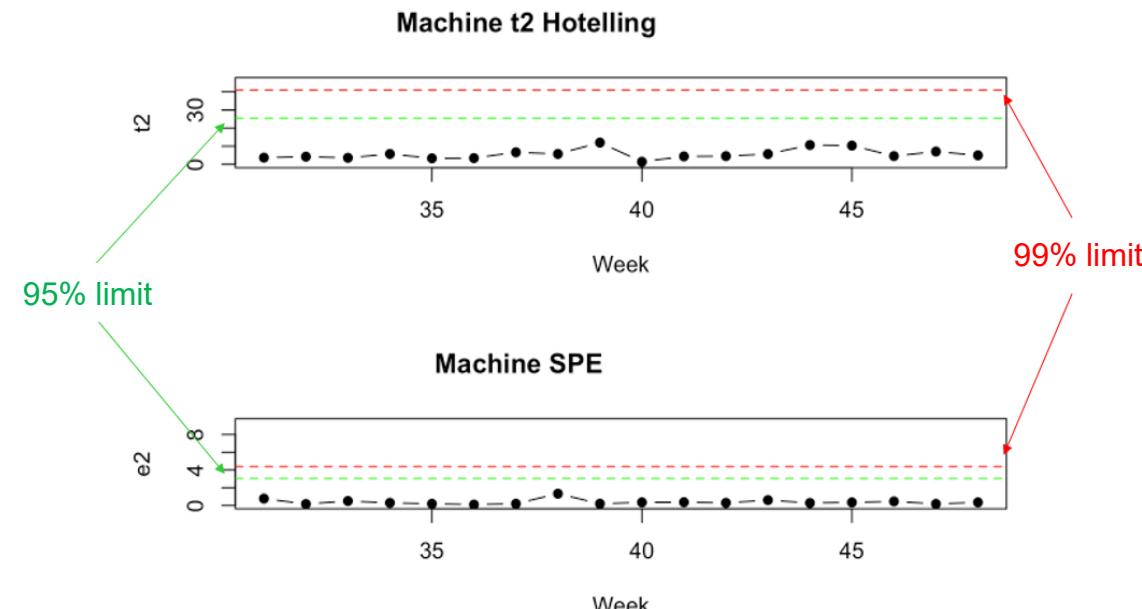


Las variables de uso de una máquina pueden resumirse en tres variables latentes:

1. **Volumen**
2. **Variabilidad** de los “jobs”
3. **Tipo de papel** usado

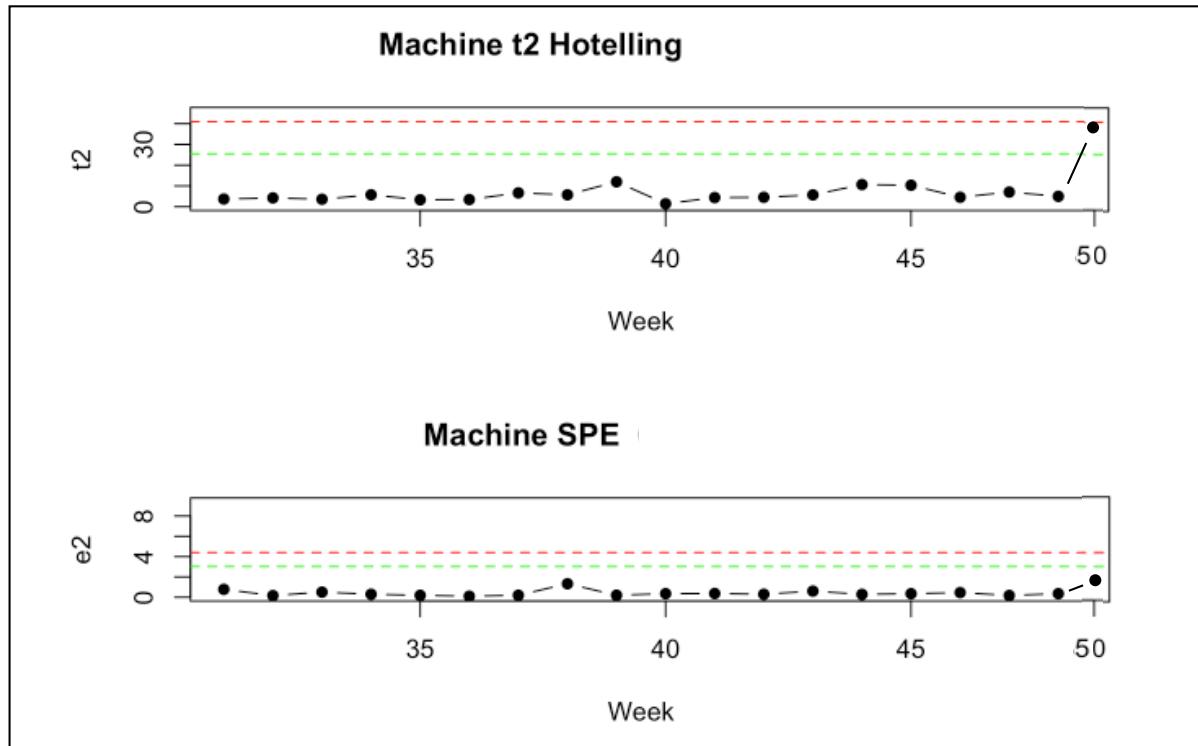
SPC multivariante– Fase I (Definición)

- Las variables de uso son “resumidas” vía un Análisis de Componentes Principales (PCA) y así identificar un número más reducido de variables latentes que reflejan el uso del equipo (t_1, t_2, \dots)
- Se calcula el estadístico T^2 Hotelling como resumen de todas la variables latentes y el SPE (Suma de Errores de Predicción) como monitorización del ajuste
- Se establecen límites de control para la T^2 y el SPE. Los primeros monitorizan el valor conjunto de las variables latentes, los segundos el mantenimiento de la estructura de correlaciones.



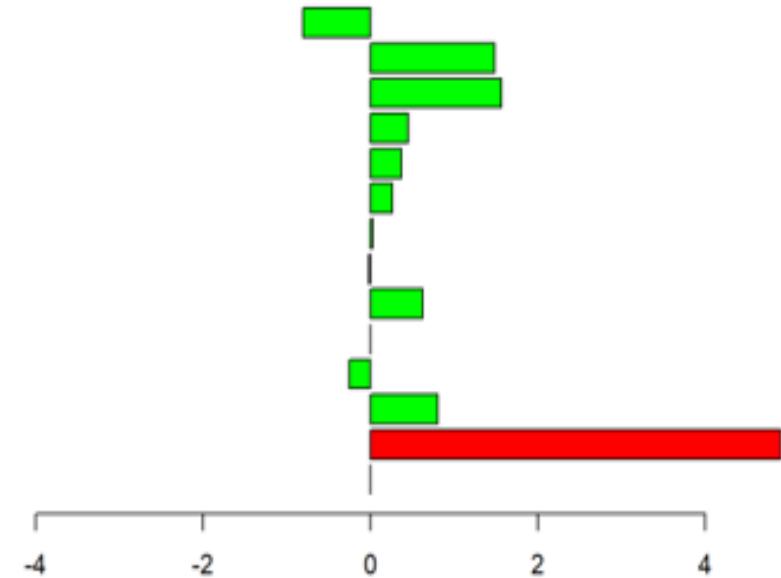
SPC multivariante– Fase II (Monitorización)

Variables anormalmente extremas



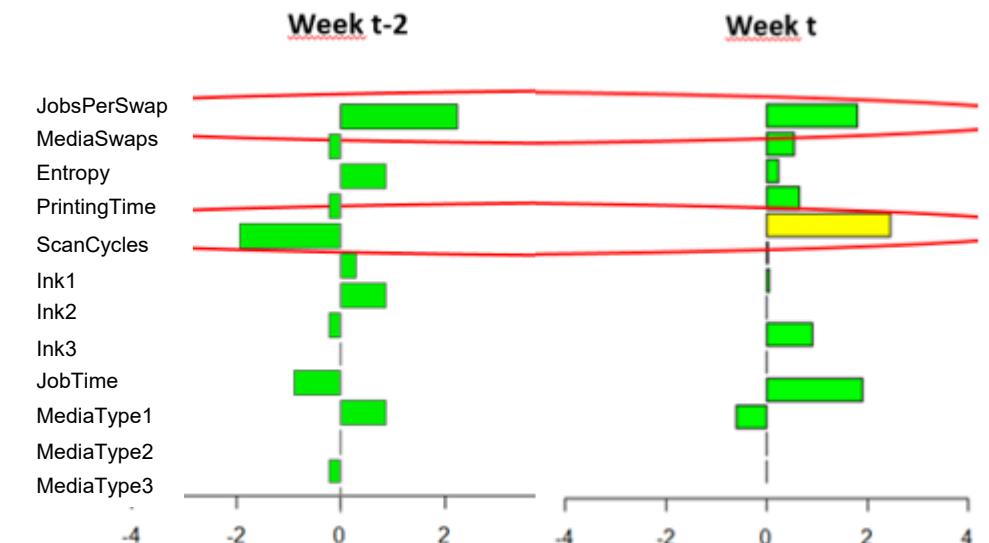
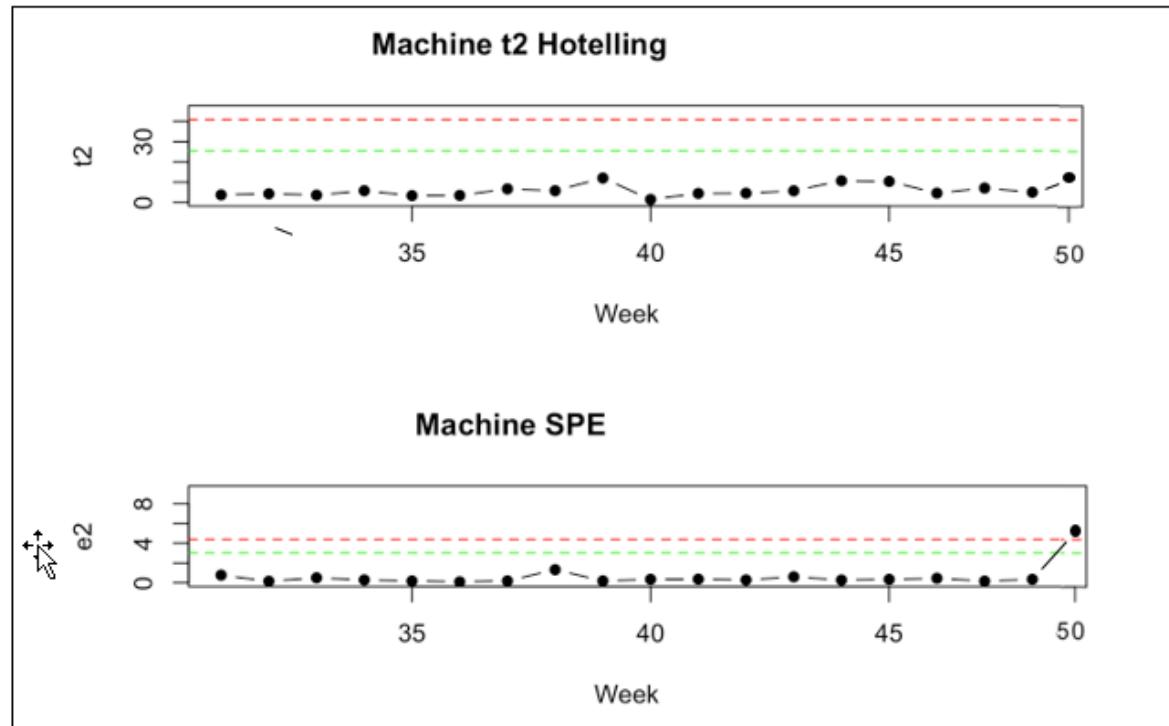
Valor de la variable estandarizado
(entre -2 y 2 son normales)

JobsPerSwap
MediaSwaps
Entropy
PrintingTime
ScanCycles
Ink1
Ink2
Ink3
JobTime
MediaType1
MediaType2
MediaType3
MediaType4
MediaType5



SPC multivariante– Fase II (Monitorización)

Rotura de la estructura de correlaciones



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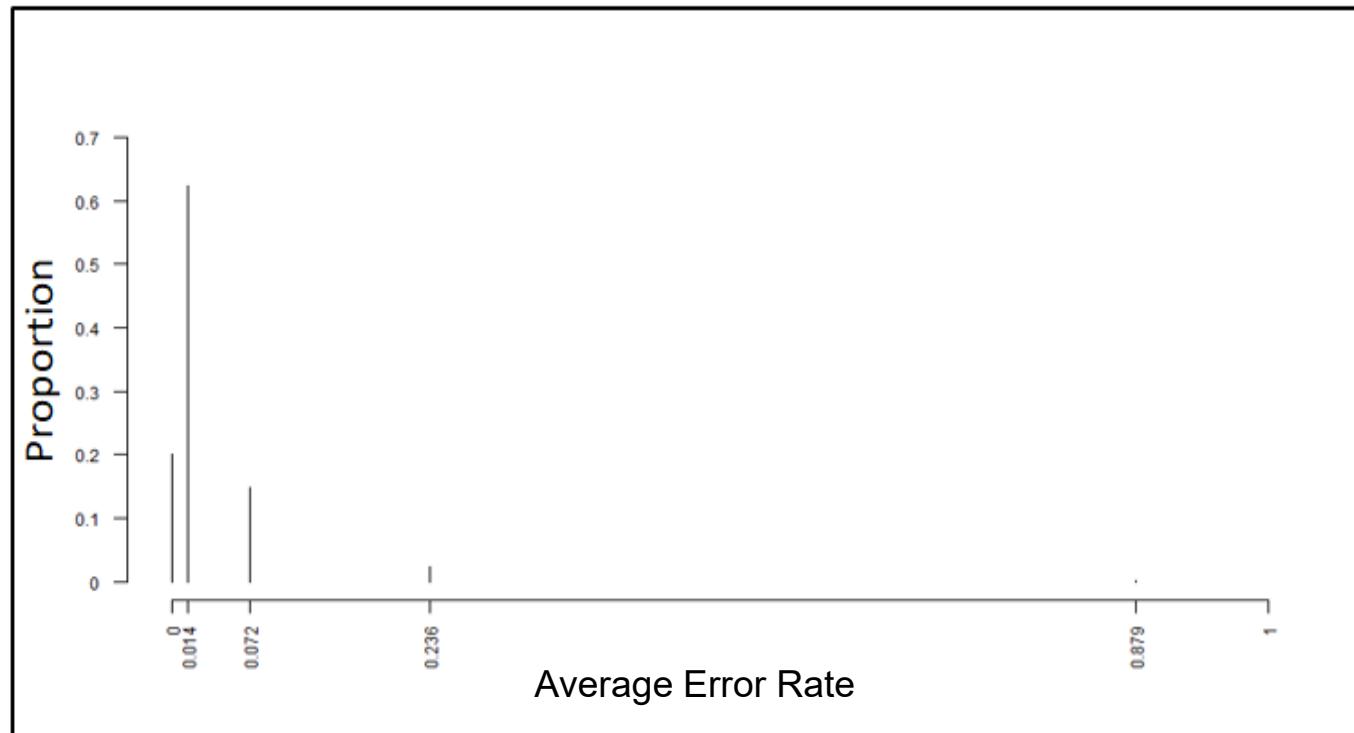
DATANCIA

- Monitorización de equipos
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 - **Monitorización de fallos**

Monitorización de la frecuencia de errores

Fase I (Definición)

Identificación de grupos de máquinas



Monitorización de la frecuencia de errores

Fase II (Monitorización)

Seguimiento de fallos

Asignación probabilística (método Bayesiano) de la impresora a un grupo de frecuencia de errores.

Ejemplo: La impresora ABC en la semana 48 ha tenido 1 error en las 10,007 horas que ha trabajado.

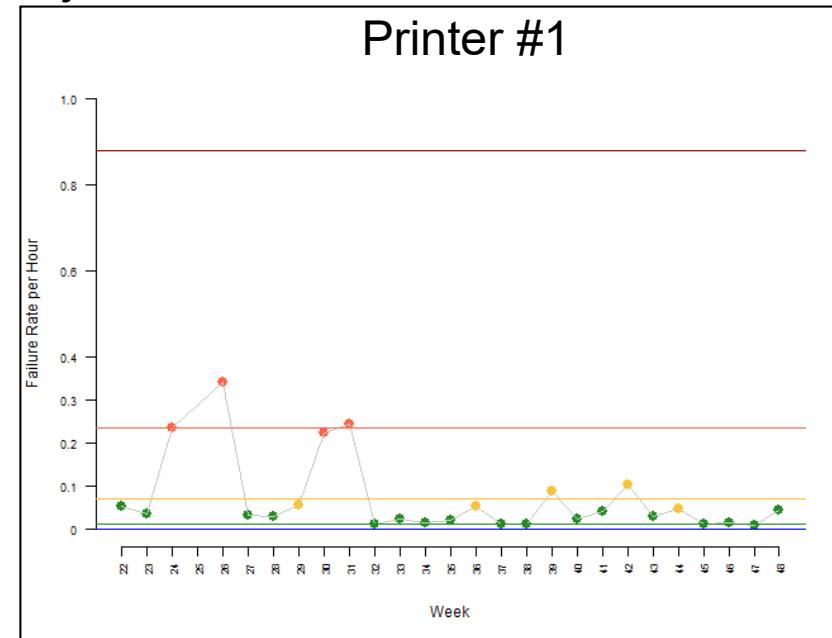
Cluster	Average error rate	Proportion	Probability
j	$\hat{\phi}_j$	\hat{p}_j	$\frac{\hat{p}_j g(O_{it} \theta_{it} = \hat{\phi}_j)}{\sum_{j=1}^k \hat{p}_j g(O_{it} \theta_{it} = \hat{\phi}_j)}$
1	0.000	0.202	0.000
2	0.014	0.623	0.574
3	0.072	0.150	0.387
4	0.236	0.024	0.039
5	0.880	0.002	0.000

Monitorización de la frecuencia de errores

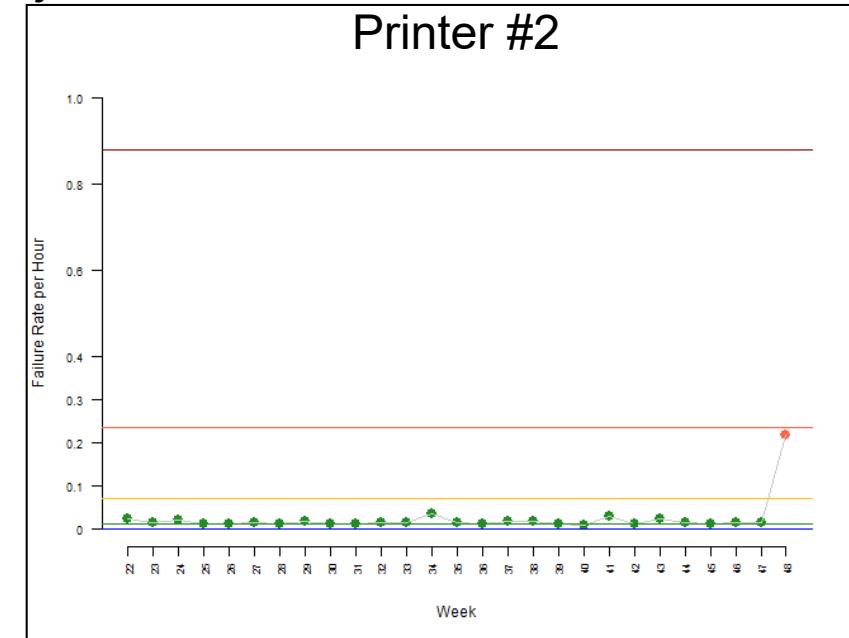
Fase II (Monitorización)

Seguimiento de fallos

Ejemplo: La impresora 1 en la semana 48 ha tenido 1 error en las 10,007 horas que ha trabajado.



Ejemplo: La impresora 2 en la semana 48 ha tenido 9 errores en las 95 horas que ha trabajado.



Gracias!



**Ignasi
Puig**
CEO

Gráinne Costigan
Senior Data
Scientist





Asier Rodríguez
Lead Data Scientist
Olocip
olocip.com

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Patrocinadores Plata:



Patrocinadores Bronce:





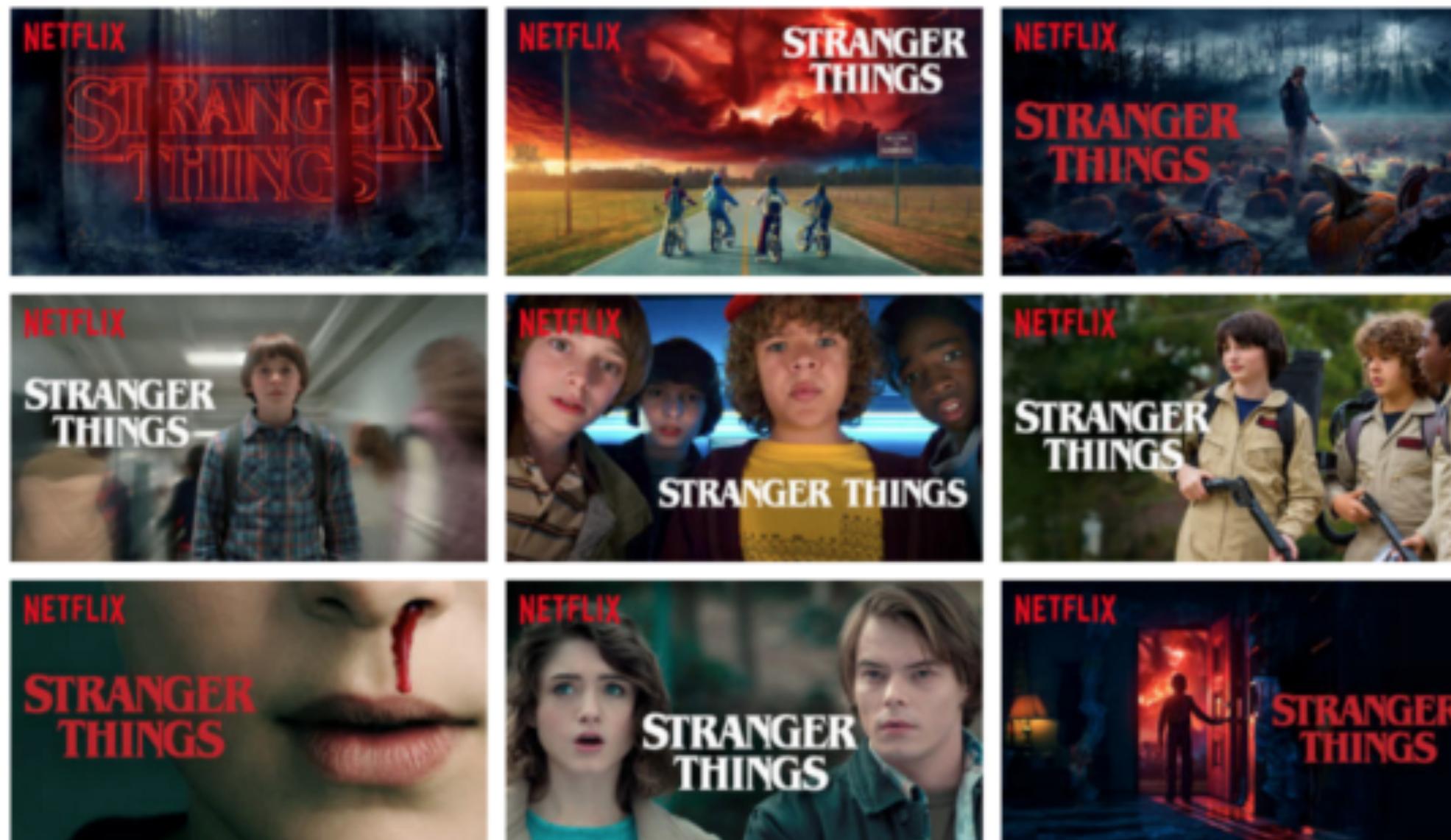
olocip

Artificial Intelligence in professional football

Asier Rodriguez
Lead Data Science at Olocip

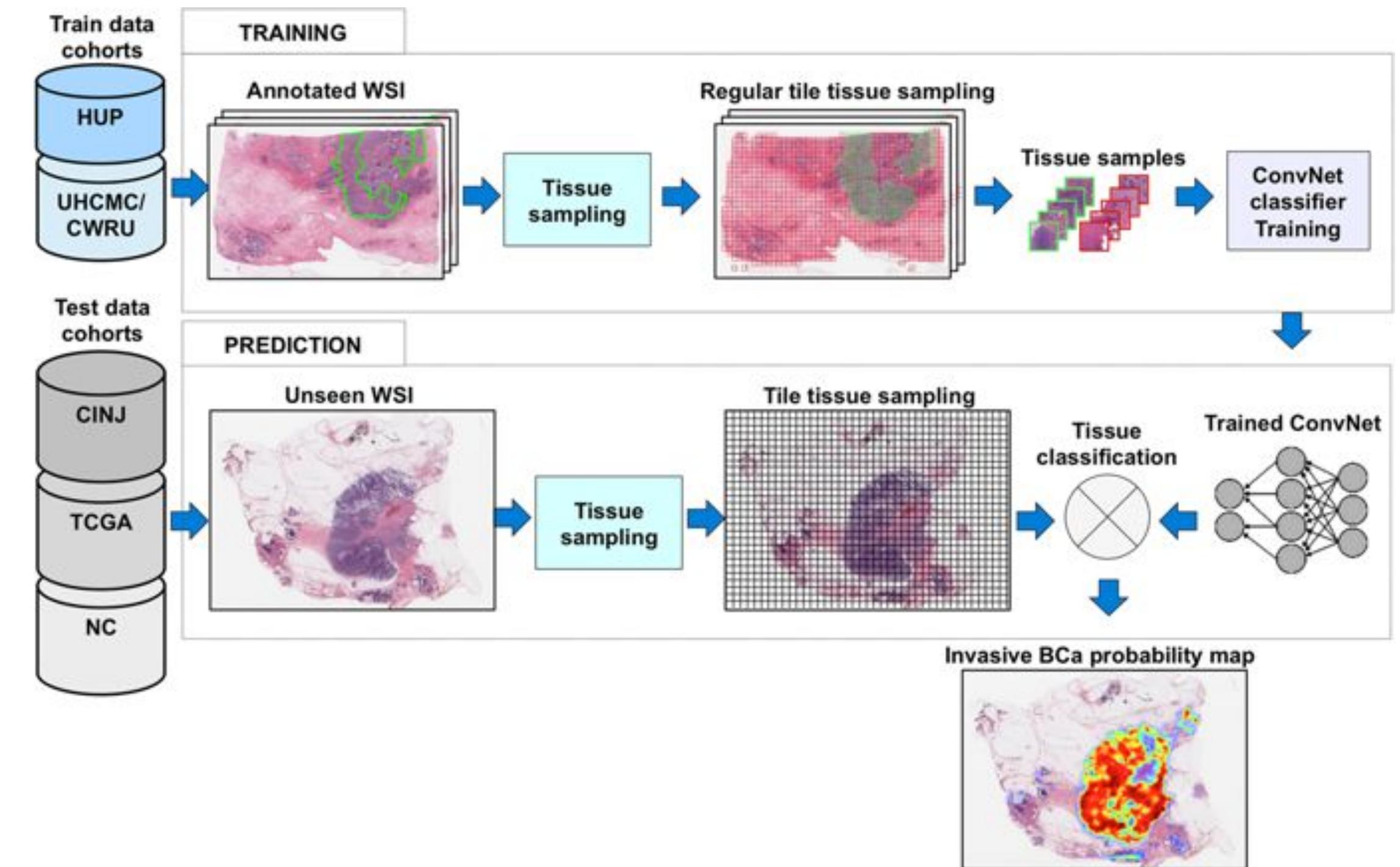
AI THE NEW ELECTRICITY

NETFLIX



Netflix uses machine learning to generate many variations of high-probability click-thru image thumbnails that it relentlessly and continuously A/B tests throughout its user base—for each user and each movie—all to increase the probability that you will click and watch.

nature
International journal of science

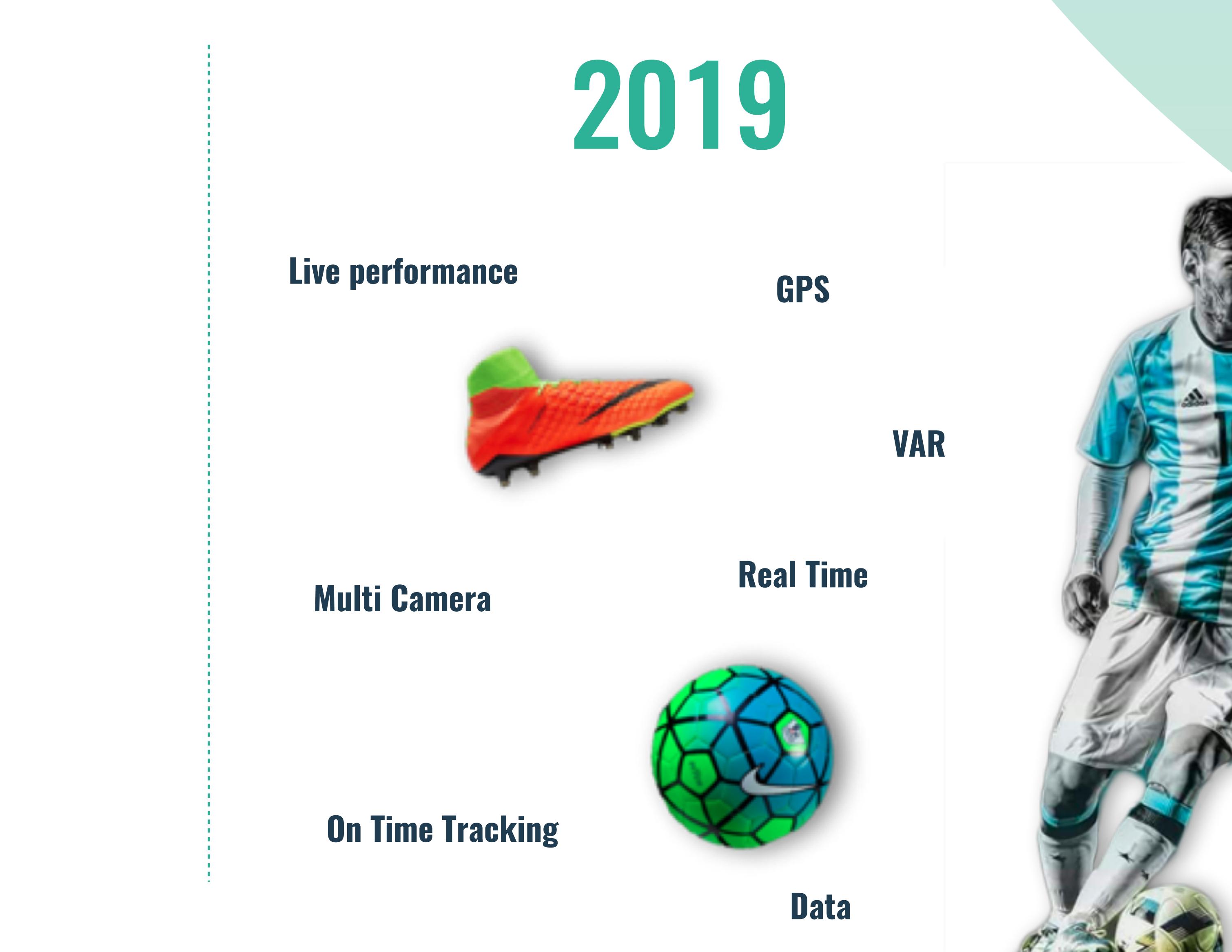


TECHNOLOGY IN SPORTS

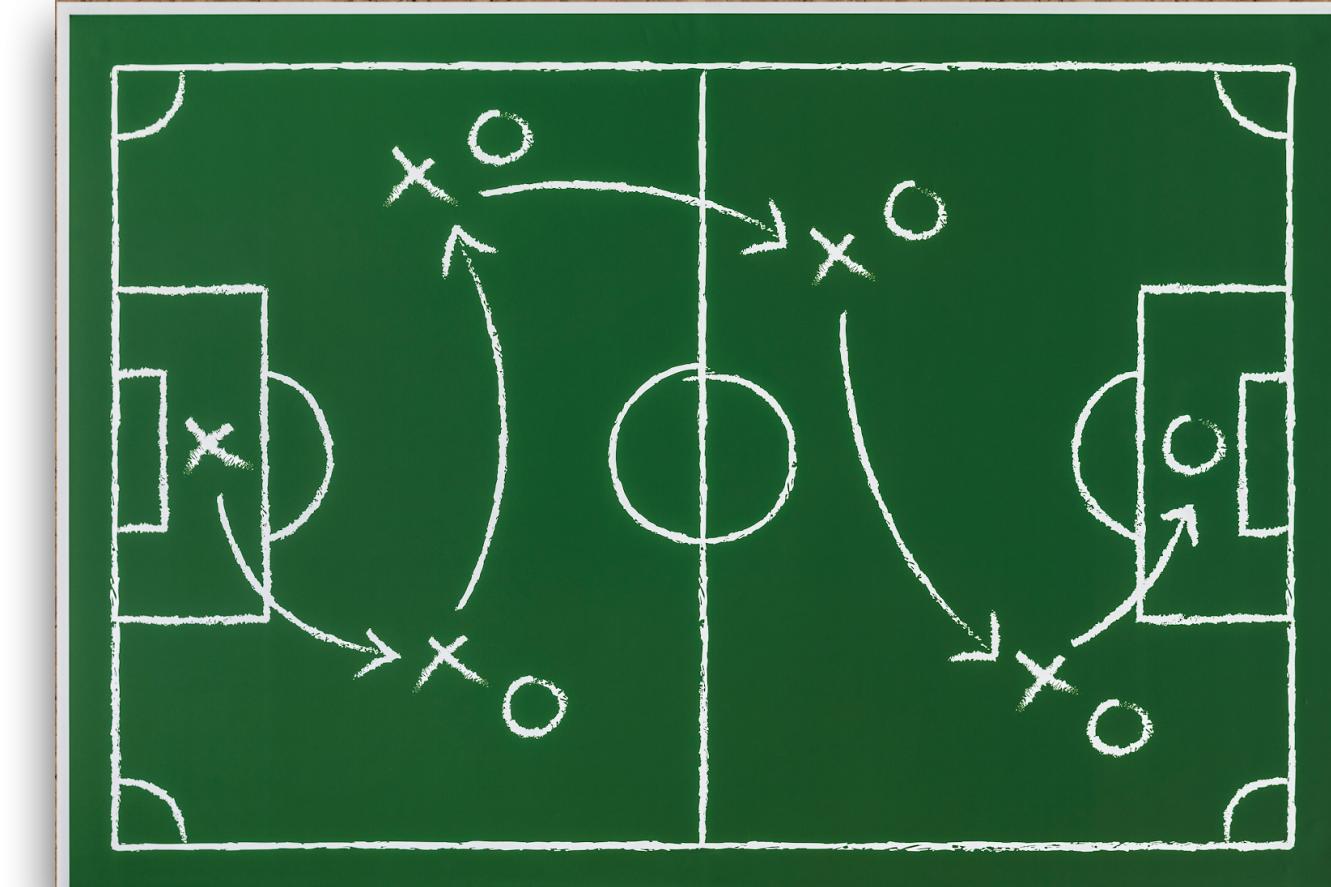
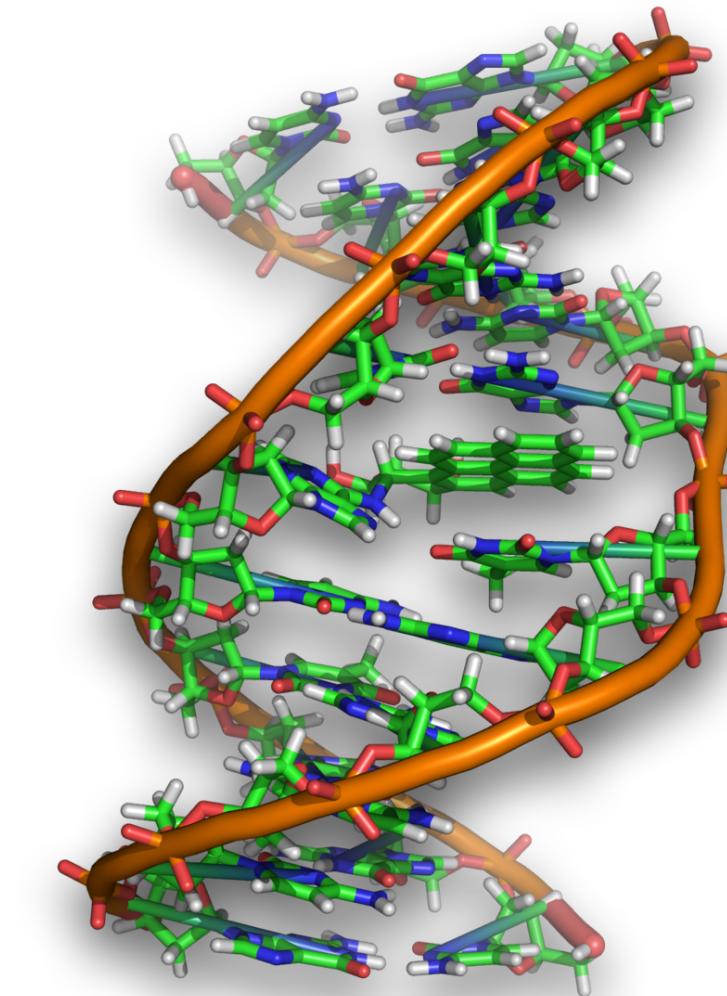
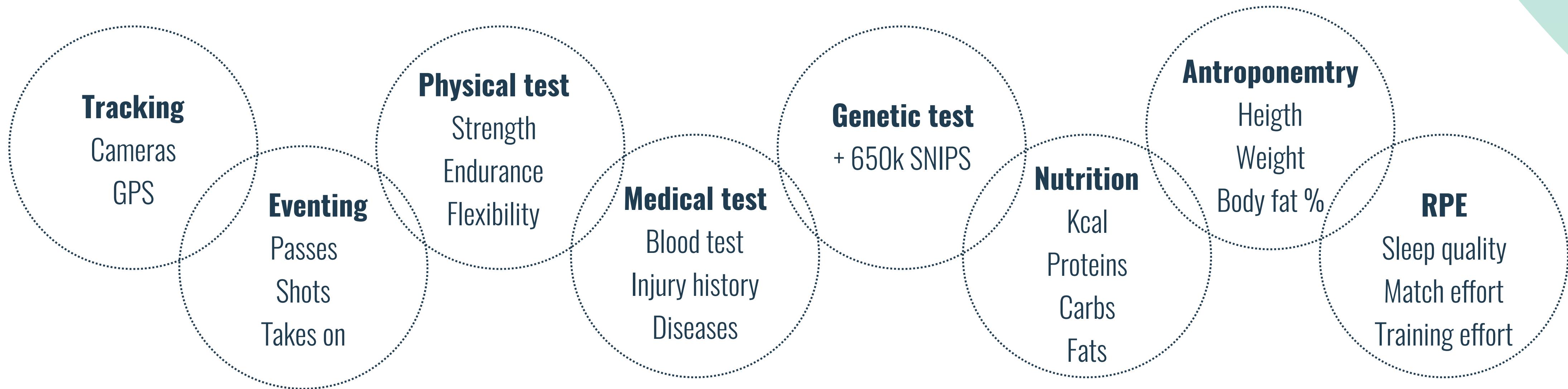
1950



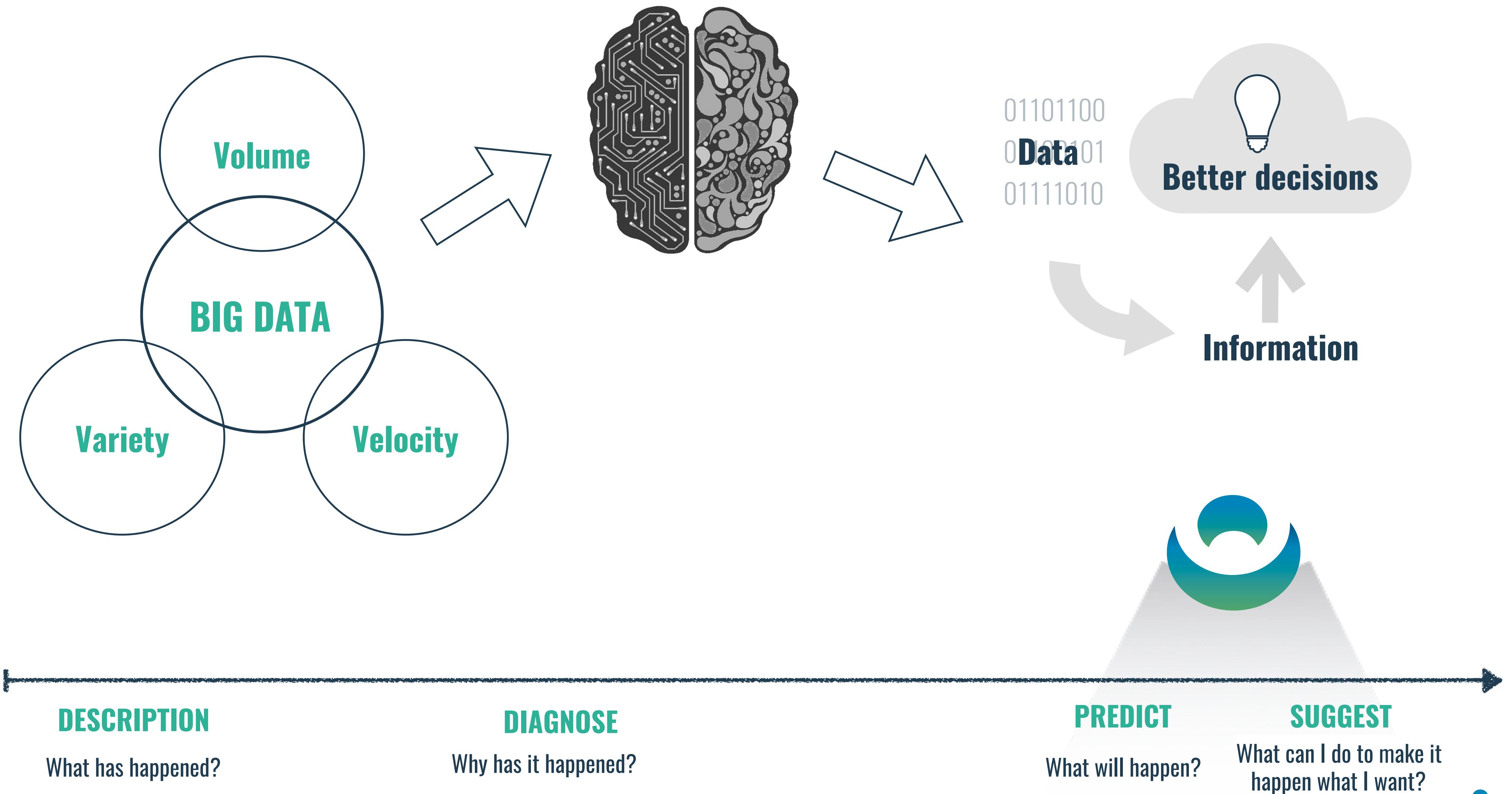
2019



BIG DATA IN SPORTS



FROM BIG DATA TO AI



Olocip Managing Team

Esteban Granero
CEO & FOUNDER

Professional football Player



"Unlike the current descriptive analysis techniques that are being carried out, the use of AI allows Olocip to satisfy predictive and prescriptive dimensions"

Gaizka San Vicente
CTO & CO-FOUNDER

PhD in Industrial Engineering



"Artificial intelligence enhances human capabilities"

Concha Bielza
TECHNOLOGICAL PARTNER

AI Dept Professor



"We are able to investigate the science of the game and use the information to analyze, predict and take better decisions"

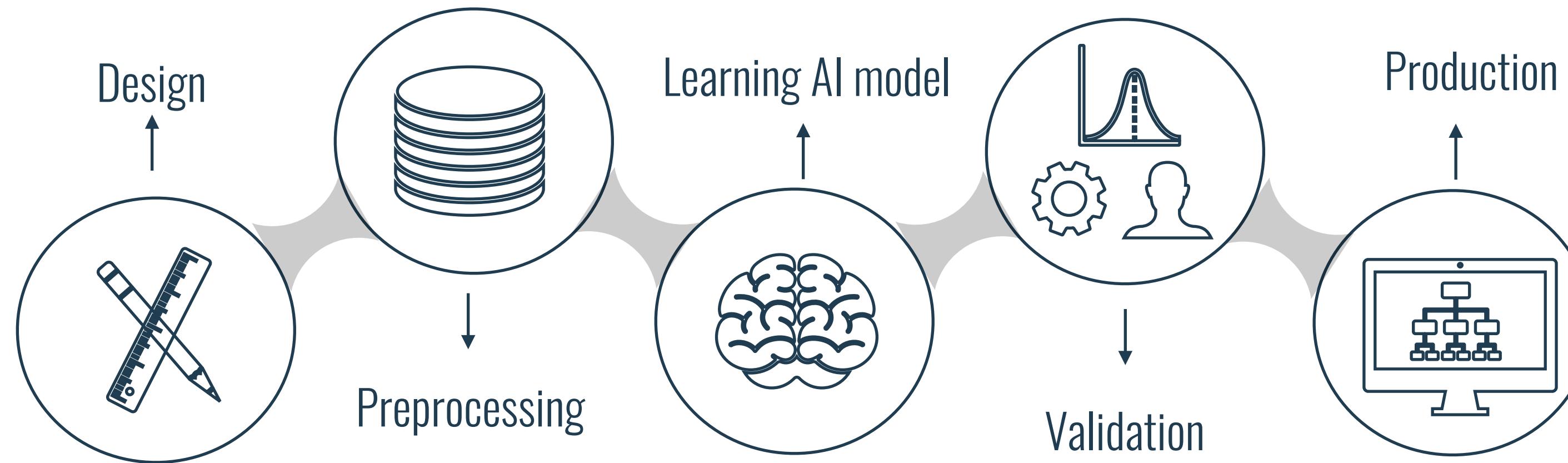
Pedro Larrañaga
TECHNOLOGICAL PARTNER

Computer Sci. & AI Professor



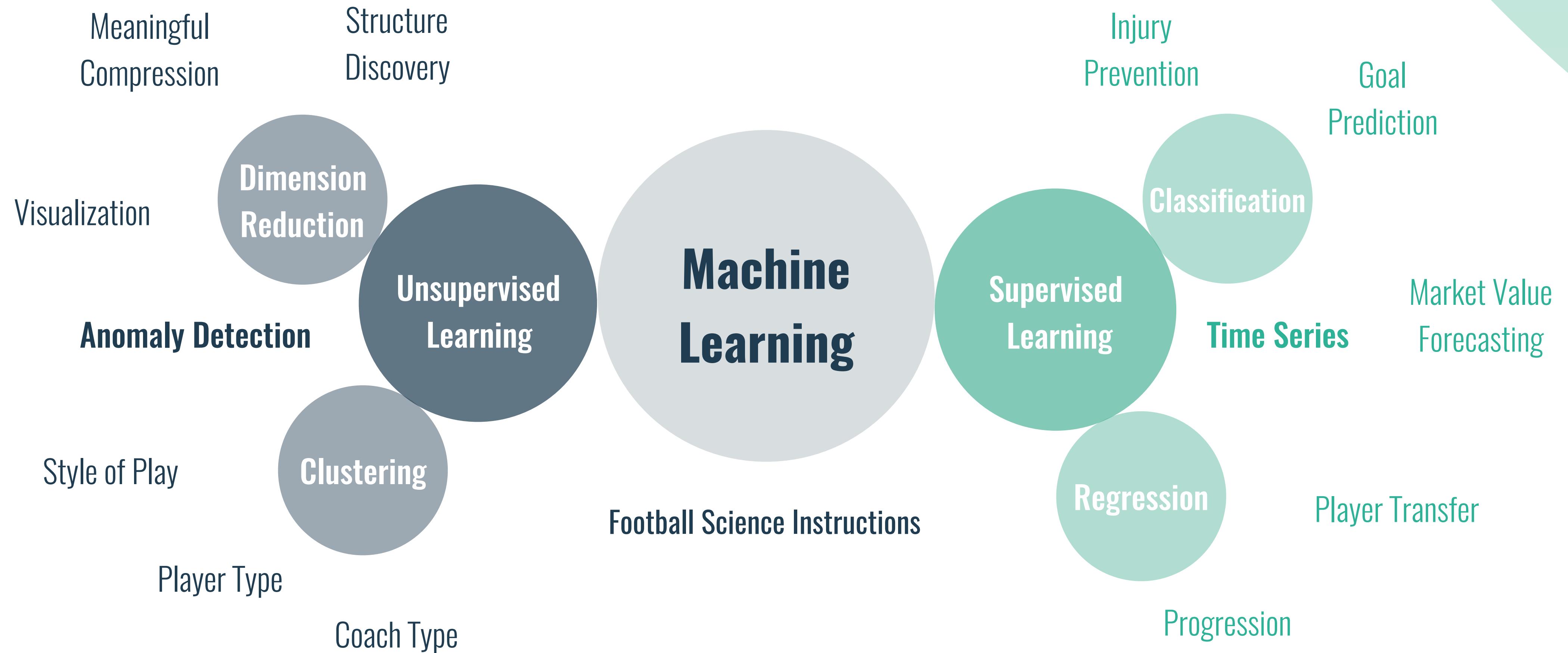
"We transform spatio-temporal data into understandable predictive models, which provide useful knowledge in a future context"

OLOCIP APPROACH



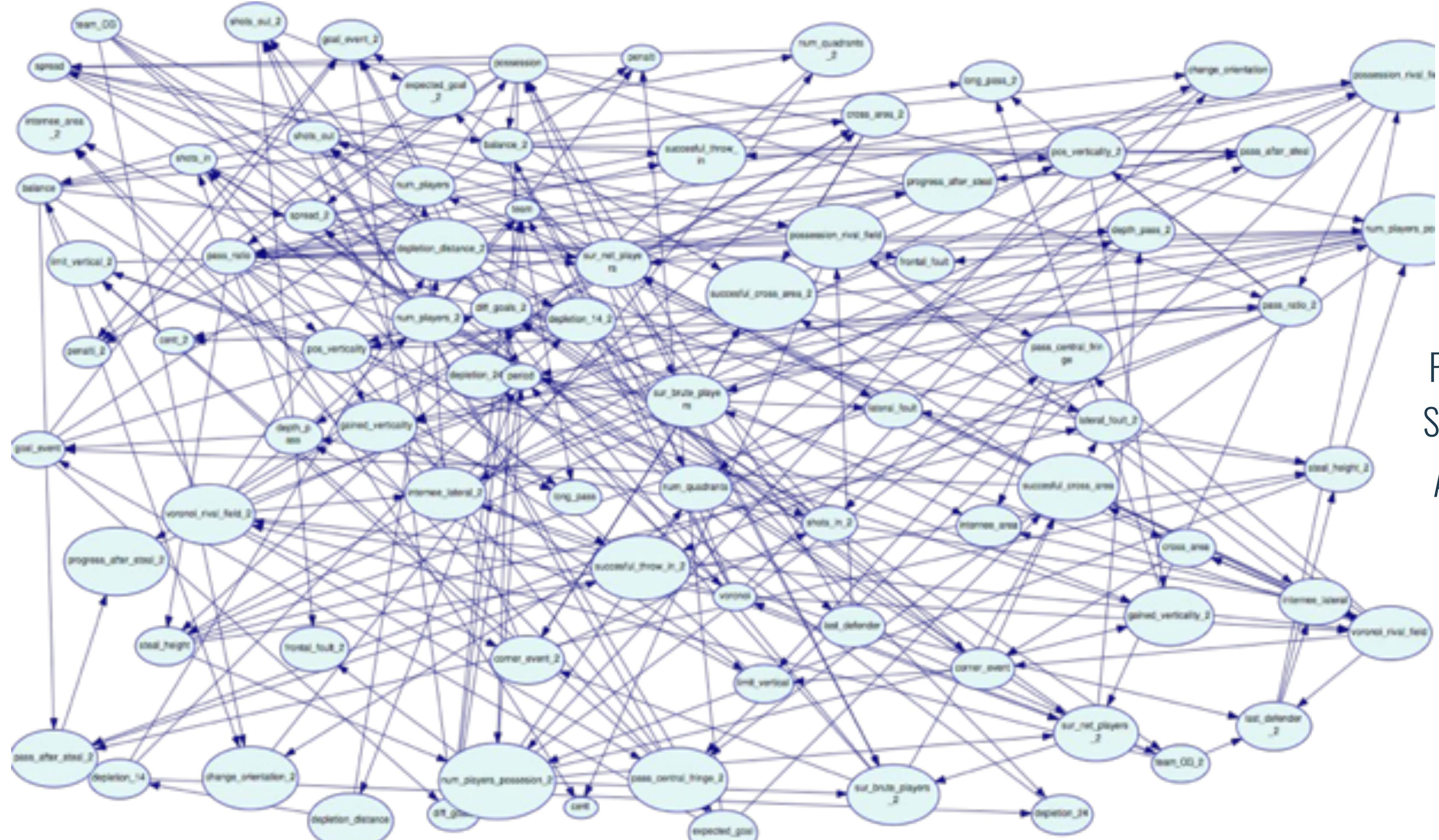
- **Ethics**
- **Interpretability, transparency (The 23 Asilomar Principles on Beneficial AI, Dec. 2017)**
- **Human-in-the-loop**

ML IN SPORTS ANALYTICS



AI MODEL

MEMORY
SPEED
OBJETIVITY
FLEXIBLE
TAILOR MADE



PREDICTIONS

SUGGESTIONS

ALERTS

RESULTS: Descriptive Vs Predictive

Descriptive analysis → **0,177 goals**

Predictive analysis → **0.357 goals**

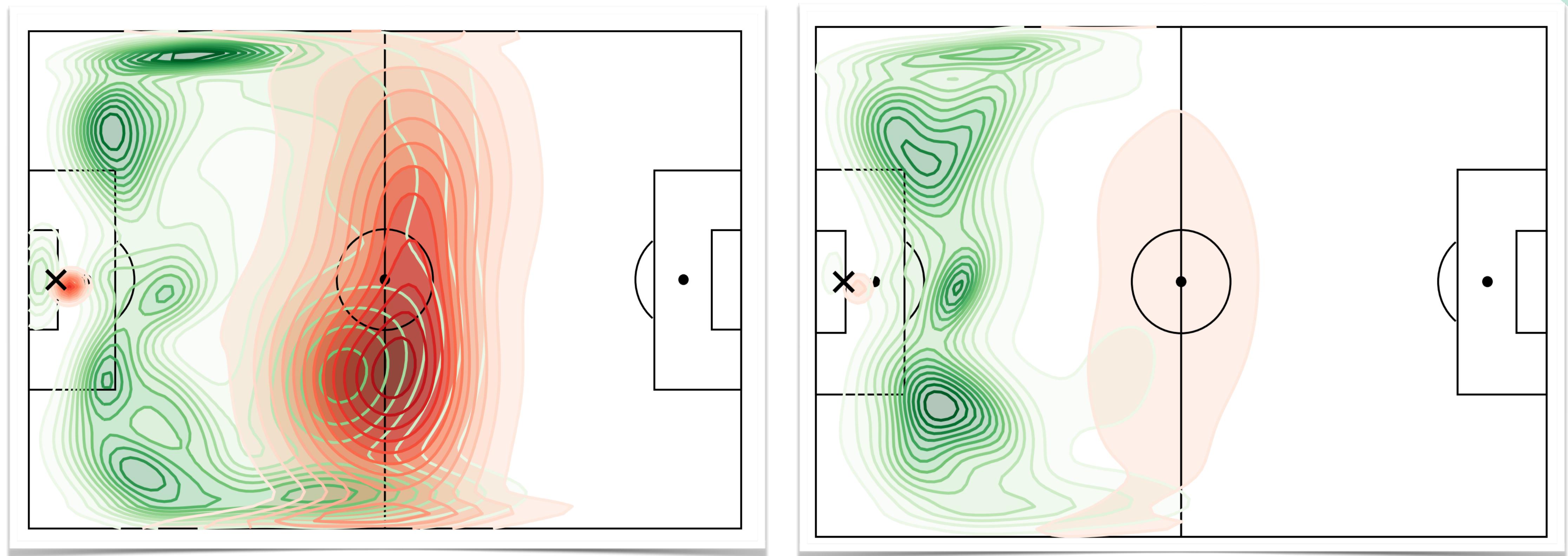
2018/2019 season → **0.361 goals**

46% improvements in goals prediction

48% improvements in assist prediction



RESULTS



Goal kick prediction (Pre match)

OLOCIP SPORT SERVICES

AI DEPARTMENT

Inhouse development



SOLUTIONS

Systems installation and training

KNOWLEDGE

Tailor made

TCT DOC



TCT COACH



TCT - coach
olocip

TCT - coach **olocip**

Hello, Global Administrator Olocip

Match

Choose match file: MANCI-JUVEN-150915 **Load Match**

Player

Choose objective

Objectives: Maximise the chance of scoring

Team: Local **Execute**

Video: P1 00:02:52 P2 00:48:21

From 68:55 To 70:58

Instructions

- Maximise the chance of scoring (Local)

Instruction	Configuration	Improvement
Team's permeability	High	+2.2211%
Block rival pass lines	Low	+0.3532%
Long passes ratio	High	+0.1483%
Team width	High	+0.1481%

Goal probability

Manchester City: 27%

Juventus: 19%

Match Events

Timeline: 0' to 90'. Ball possession percentages for both teams fluctuate throughout the match.

Juventus

TCT SCOUT

Similar Player

My Player Progression Player Transfer Scouting **Search Similar** Descriptive Library

Hello, Global Administrator Olocip

Player of reference

Season: 2018 League: Spanish La Liga Team: Atlético de Madrid Player: Antoine Griezmann

League filter: Argentina Superliga, Belgian Jupiler Pro League, Brazilian Serie A, Chinese Super League, Dutch Eredivisie, English Football League - Championship, English Premier League, French Ligue 1, French Ligue 2, German Bundesliga, German Bundesliga Zwei, Indian Super League, Italian Serie A, Italian Serie B, Portuguese Primeira Liga, Spanish La Liga, Spanish Segunda Division

Statistics: Aerials lost, Aerials won, Assists, Back passes, Ball recoveries, Blocked passes, Build Up Play, Challenges, Clearances, Crosses, Dispossessed, Errors, Expected assists, Expected goals, Fouls won, Front passes, Goals, Interceptions, Launches, Lay off passes, Long passes, Pull backs, Shots, Successfull passes, Switches of play, Tackles lost, Tackles won, Takes on lost, Takes on won, Turnovers, Unsuccessfull passes

Similar players

League: -- Team: -- Position: -- Player: Search player

Age: 17 years Value min (€): 0 Value max (€): 50.000.000 Min. Played: 353 mins Max. Played: 4 331 mins

Marco Reus (93% similarity): German Bundesliga, Borussia Dortmund, Winger, 29, 2425, 46.922.000 €. Add to Scouting, View in Descriptive.

Andrej Kramaric (93% similarity): German Bundesliga, TSG 1899 Hoffenheim, Striker, 27, 2468, 35.529.000 €. Add to Scouting, View in Descriptive.

Xherdan Shaqiri (92% similarity): English Premier League, Liverpool, Winger, 27, 1130, 24.909.000 €. Add to Scouting, View in Descriptive.

Daniel Sturridge (91% similarity): English Premier League, Liverpool, Striker, 29, 1130, 13.077.000 €. Add to Scouting, View in Descriptive.

Kevin Volland (91% similarity): German Bundesliga, Bayer 04 Leverkusen, Second Striker, 26, 571, 13.077.000 €. Add to Scouting, View in Descriptive.

Florian Thauvin (91% similarity): French Ligue 1, Marseille, Attacking Midfielder, 25, 2716, 32.455.000 €. Add to Scouting, View in Descriptive.

Raúl Jiménez (91% similarity): English Premier League, Wolverhampton Wanderers, Striker, 27, 3207, 45.356.000 €. Add to Scouting, View in Descriptive.

Divock Origi (91% similarity): English Premier League, Liverpool, Striker, 23, 407, 35.404.000 €. Add to Scouting, View in Descriptive.

Malcom (91% similarity): Spanish La Liga, Barcelona, Winger, 21, 655, 21.497.000 €. Add to Scouting, View in Descriptive.

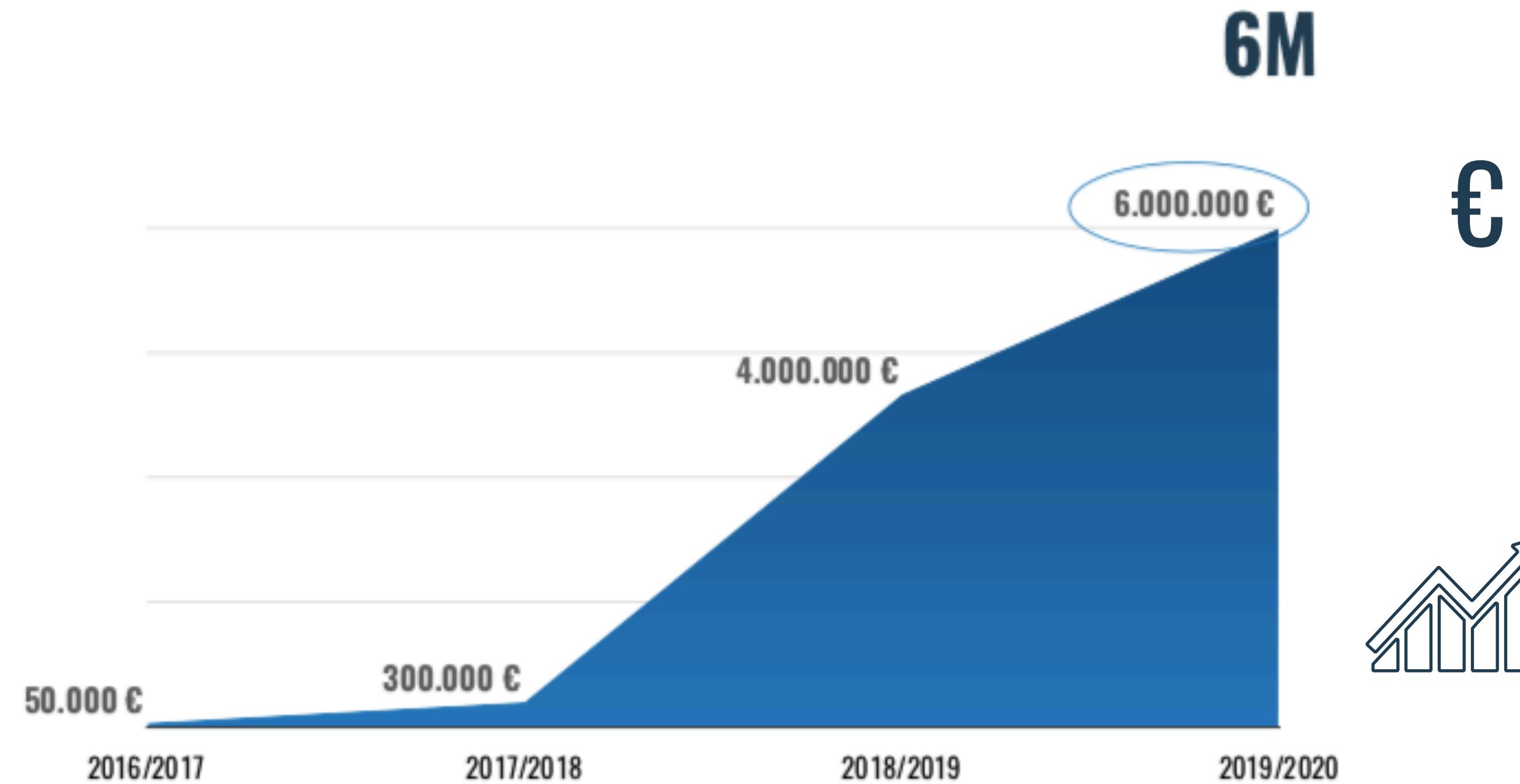
Samuel Chukwueze (91% similarity): Spanish La Liga, Villarreal, Winger, 19, 1762, 40.425.000 €. Add to Scouting, View in Descriptive.

Marc Arnal (90% similarity): Spanish La Liga, Valencia, Striker, 28, 1000, 29.284.000 €. Add to Scouting, View in Descriptive.

View in Descriptive

TCT SCOUT

Market Value Prediction



*Player's market value evolution over his career

Player's value increases ·
5M€ increase estimated

Revaluation of the player still
increases in the club, reaching
70M€ of market value estimation.

MEDIA

europapress

europapress

FÚTBOL

Cristiano Ronaldo marcó menos goles y dio más asistencias en la Juve como predijo la IA

f  t  w  e 



The screenshot shows two cards for Cristiano Ronaldo. The left card is for Real Madrid, showing stats: GOLES: 1.82, ASISTENCIAS: 0.79, TIR: 4.40, AEG: 1.30, PÉR: 1.00. The right card is for Juventus, showing a comparison between 'REALIDAD' and 'PREDICIÓN': GOLES: 0.71 vs 0.76, ASISTENCIAS: 0.27 vs 0.26, TIR: 1.46 vs 1.42, AEG: 1.30 vs 1.30, PÉR: 1.21 vs 1.31. The report is dated SEPTEMBER DE 2018 VS REALIDAD.

as Fútbol Motor Baloncesto Tenis Ciclismo Más deporte asTV asO



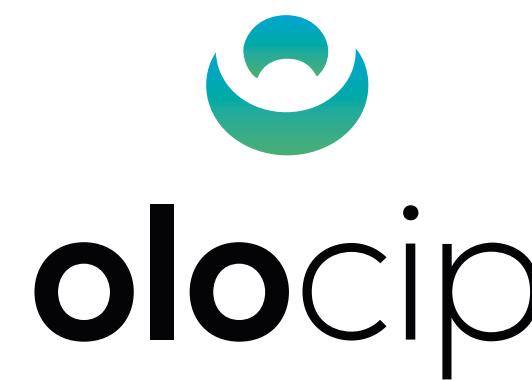
asTV

Una empresa de IA ya predijo el brote goleador de Benzema

El estudio de la compañía artificial Olocip clavó los registros del francés teniendo en cuenta diversas variables, entre ellas la marcha de Cristiano.

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Q&A





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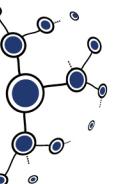
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