Session 2. A Project perspective on Big Data architectural pipelines and benchmarks



Panelists



Arne Berre
Chief Scientist, SINTEF



Leonidas Kallipolitis *Aegis - I-BiDaaS Projects*



Brian ElvesæterResearch scientist, SINTEF
TheyBuyForYou Project



Athanasios Koumparos Senior Software Engineer, Vodafone Innovus Track&Know Project



Jon Ander Gómez Adrián Universitat Politecnica de Valencia DeepHealth Project

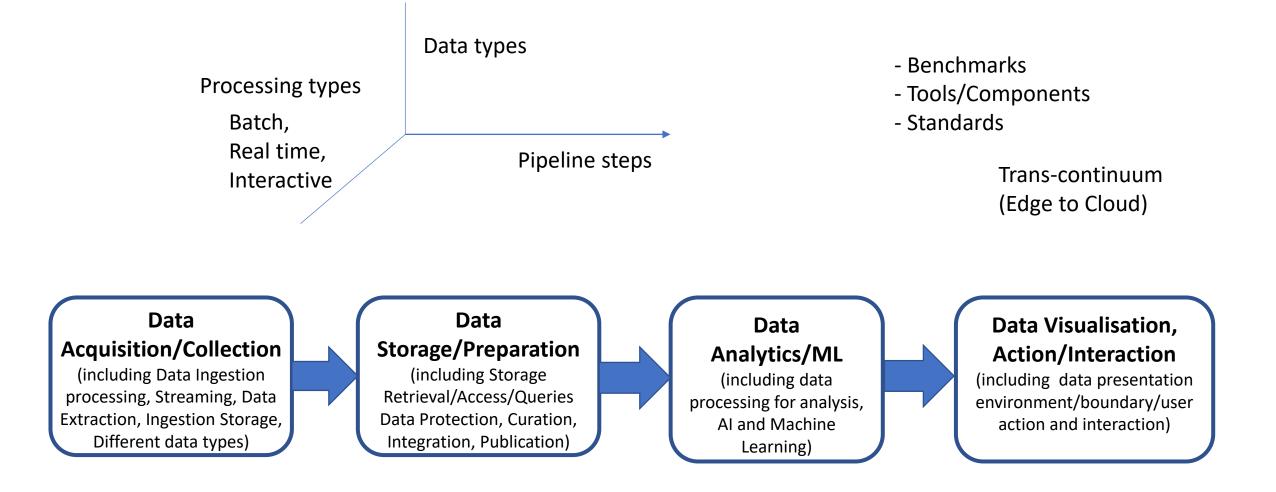


Caj SÖDERGÅRD
Professor, VTT Data-driven
Solutions
DataBio Project

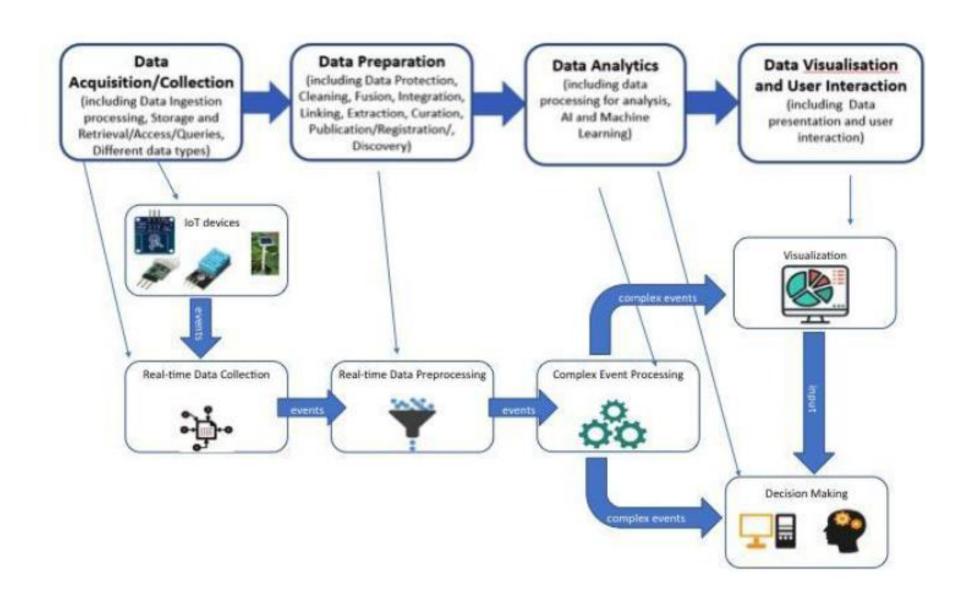


Introduction to Architectural pipelines

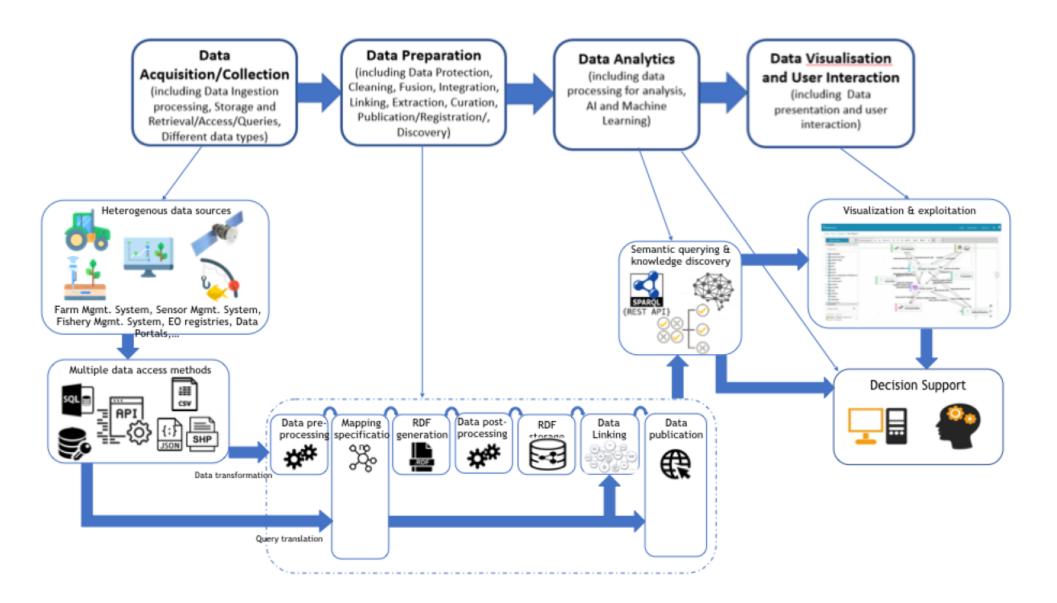
- I-BiDaaS
- TBFY
- Track&Know
- DataBio
- DeepHealth

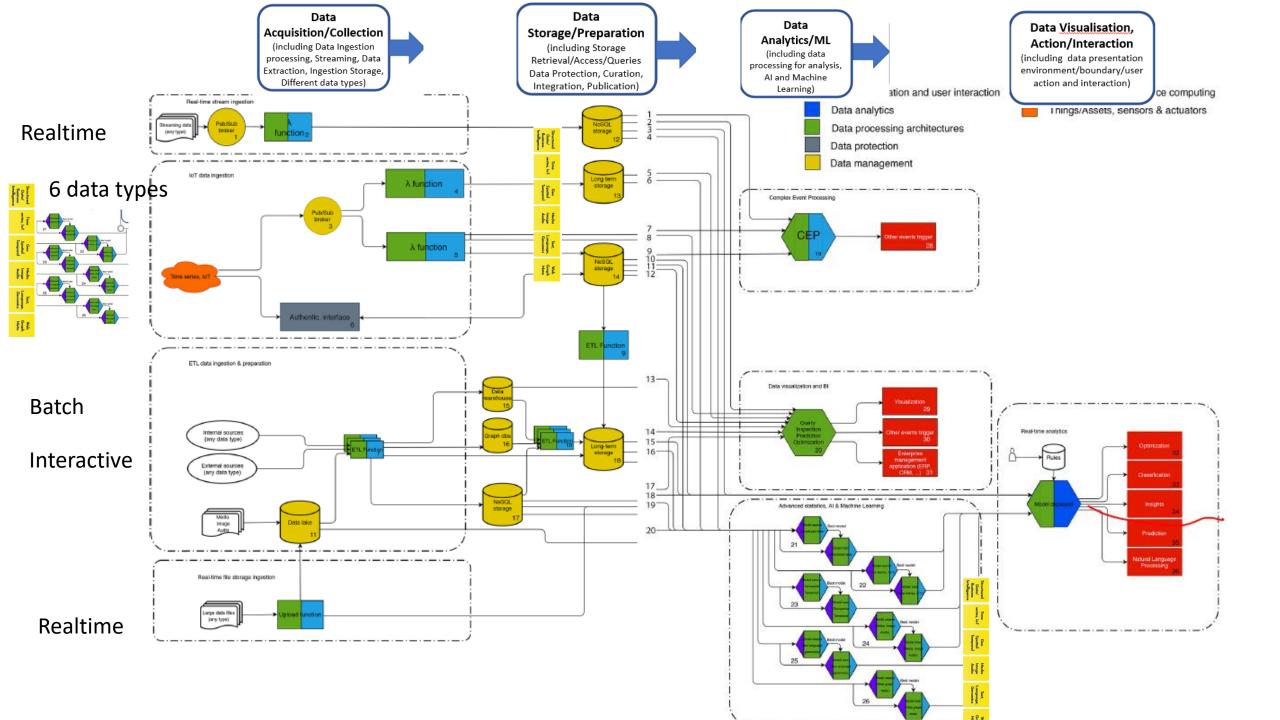


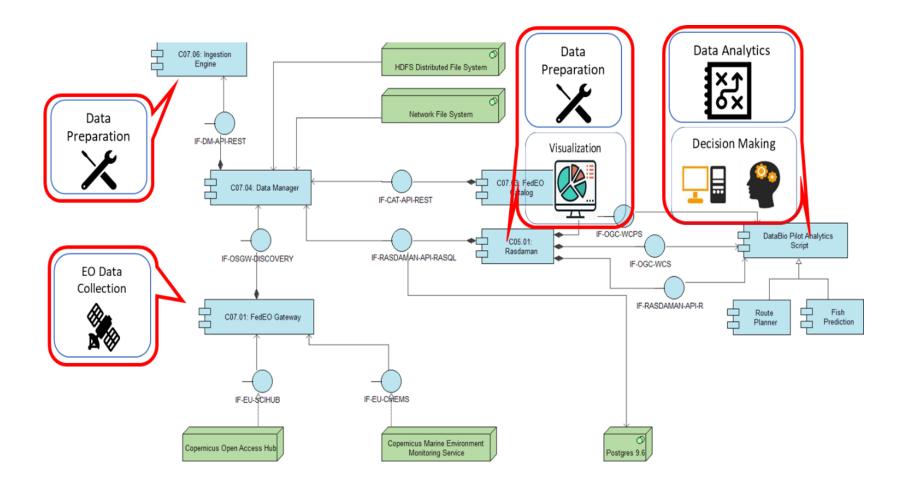
IoT – Real time Data Pipeline



Knowledge Graph/Ontology/Linked Data pipeline





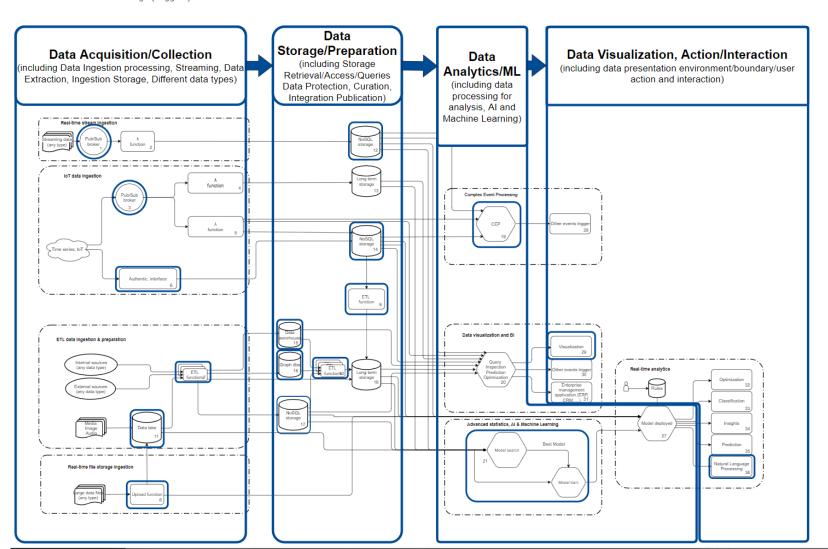


Search Search by Blueprint/Pipeline

Search by step of the Data Value Chain or for the specific components of the generic big data pipeline generated by DataBench

DataBench has devised a generic architectural blueprint mapped to a top level pipeline along the Data Vale Chain covering the steps of Data Acquisition/Collection (including data ingestion, processing, streaming, extraction and ingestion storage), Data Preparation/Storage (including storage retrieval/access/queries, data protection, curation, integration and publication), Data Analytics (including data processing for analysis, AI and Machine Learning) and Data Visualization/Interaction (including data presentation, environment/boundary/user action and interaction).

By clicking on the image below on one of the four steps of the pipeline, or in one of the specific elements from the generic blueprint, this search interface will help you discovery benchmarks and associated knowledge (nuggets)



Conclusion on Pipelines and related benchmarks, Arne J. Berre, SINTEF

- I-BiDaaS
- TBFY
- Track&Know
- DataBio
- DeepHealth





Industrial-Driven Big Data as a SelfService Solution

Leonidas Kallipolitis, AEGIS





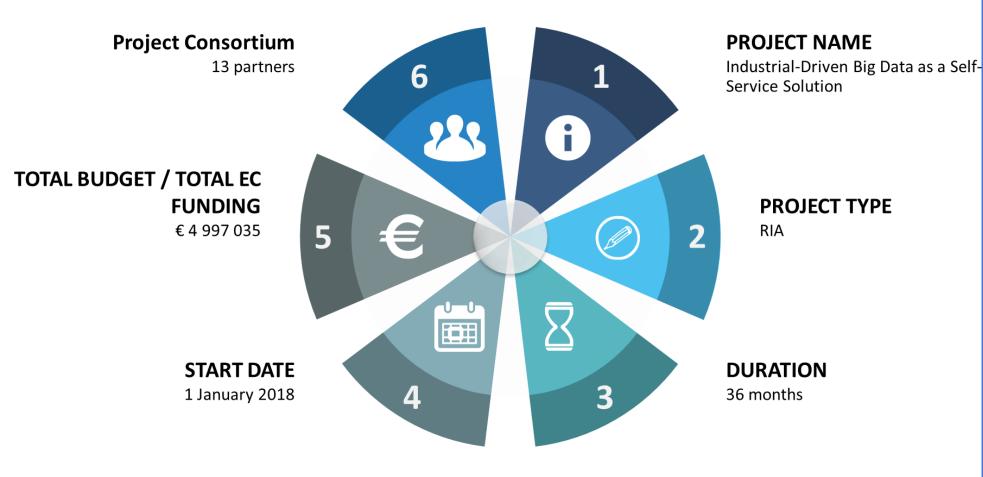












@Ibidaas

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https://www.linkedin.com/in/i-bidaas/



http://www.ibidaas.eu/

Consortium

- 1. FOUNDATION FOR RESEARCH AND TECHNOLOGY HELLAS (FORTH)
- 2. BARCELONA SUPERCOMPUTING CENTER CENTRO NACIONAL DE SUPERCOMPUTACION (BSC)
- 3. IBM ISRAEL SCIENCE AND TECHNOLOGY LTD (IBM)
- 4. CENTRO RICERCHE FIAT SCPA (CRF)
- 5. SOFTWARE AG (**SAG**)
- 6. CAIXABANK, S.A (CAIXA)
- 7. THE UNIVERSITY OF MANCHESTER (UNIMAN)
- 8. ECOLE NATIONALE DES PONTS ET CHAUSSEES (ENPC)
- 9. ATOS SPAIN SA (ATOS)
- 10. AEGIS IT RESEARCH LTD (AEGIS)
- 11. INFORMATION TECHNOLOGY FOR MARKET LEADERSHIP (ITML)
- 12. UNIVERSITY OF NOVI SAD FACULTY OF SCIENCES SERBIA (UNSPMF)
- 13. TELEFONICA INVESTIGACION Y DESARROLLO SA (**TID**)







Key messages



A **complete** and **safe environment** for methodological **big data experimentation**



Tool and services to **increase the quality** of data analytics



A Big Data as a **Self-Service solution** that helps in **breaking silos** and boosts EU's data-driven economy



Tools and services for **fast ingestion and consolidation** of both realistic and fabricated
data

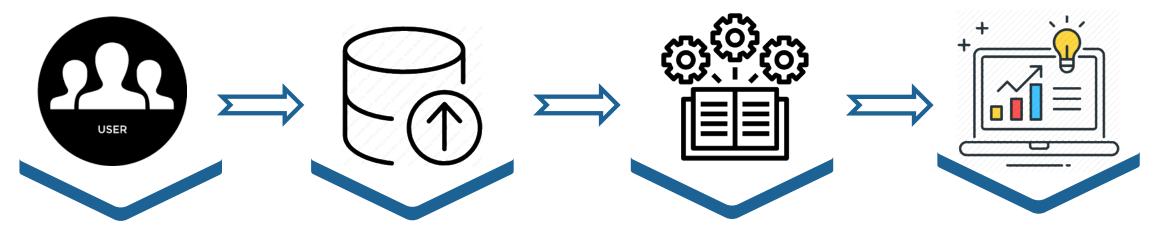


Increases impact in research community and contributes to industrial innovation capacity



Tools and services for the management of heterogeneous infrastructures





Users

- **Expert mode**
- Self-service mode
- Co-develop mode

Data

- Import your data
- Fabricate Data
- Tokenize data

Analyze your Data

- Stream & Batch Analytics
- Expert: Upload your code
- Self-service: Select an algorithm from the pool
- Co-develop: custom end-toend application

Results

- Visualize the results
- Share models

Benefits of using I-BiDaaS



Do it yourself In a flexible manner



Break data silos



Safe environment



Interact with Big Data technologies



Increase speed of data analysis

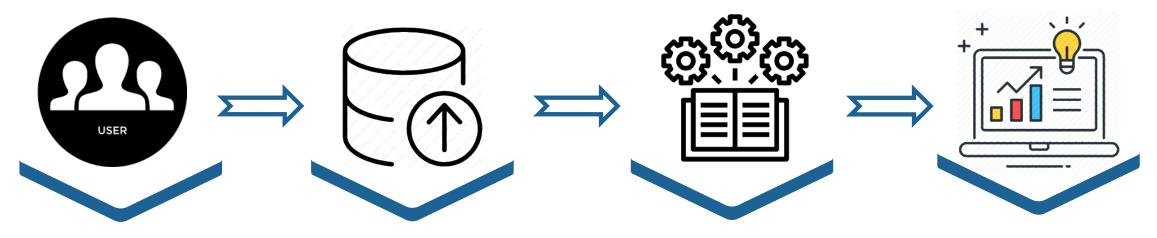


Intra- and interdomain data-flow



Cope with the rate of data asset growth





- **Expert mode**
- <u>Self-service mode</u>

Users

Co-develop mode

Benefits of using I-BiDaaS



Do it yourself In a flexible



Break data silos

Data

- Import your data

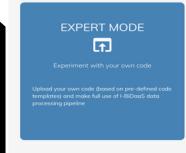
Analyze your Data

- **Stream & Batch Analytics**
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Flexible solution



SELF-SERVICE MODE

CO-DEVELOP MODE 眒



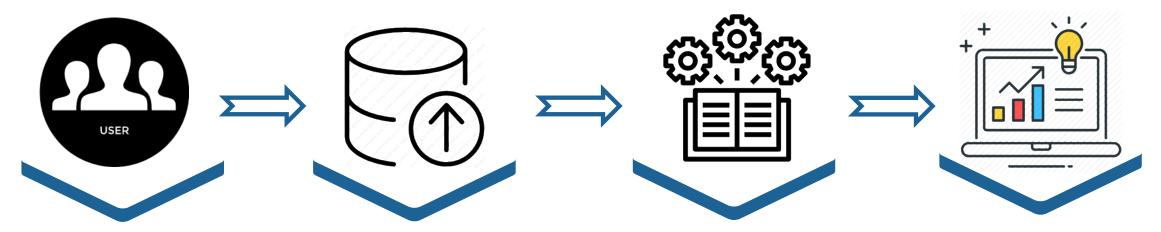
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Intra- and interdomain data-flow





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Do it yourself In a flexible manner



Break data silos

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 Data sharing lom end-lom end-lom
 & breaking silos on

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Interact with Big Data technologies



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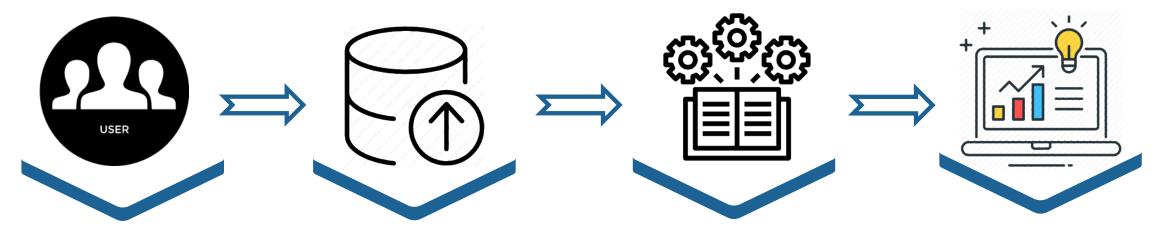


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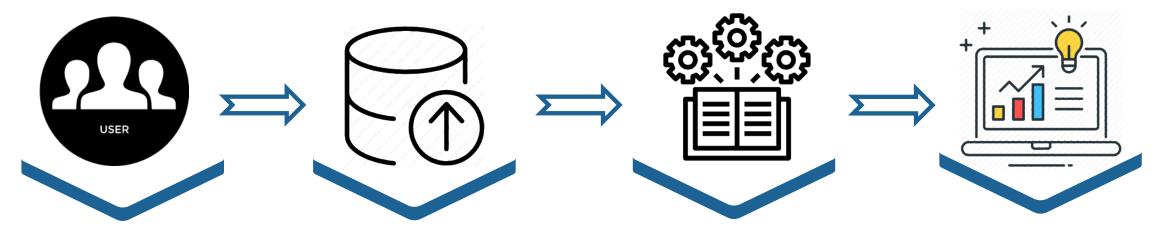


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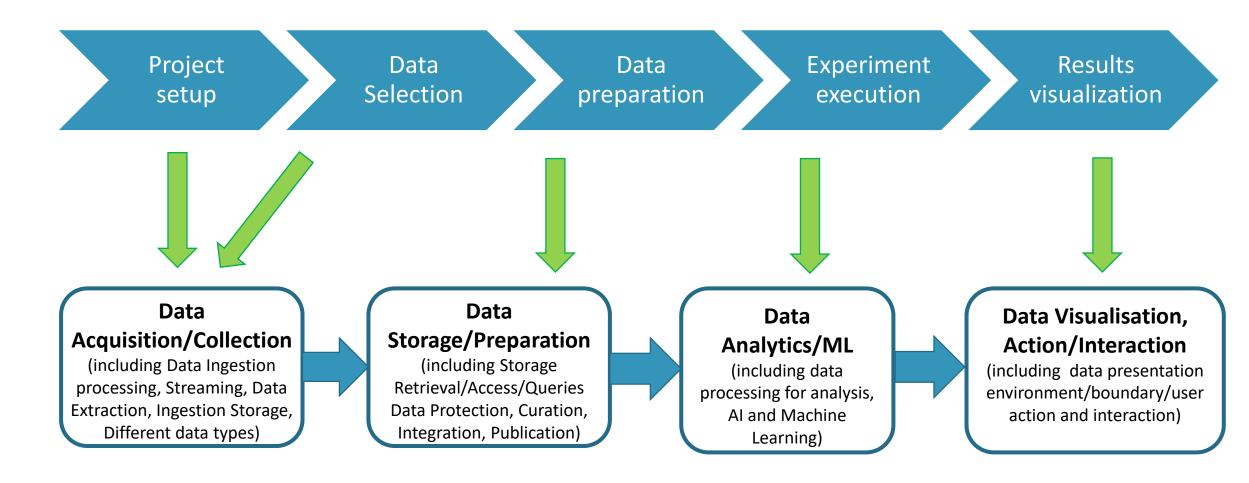
Intra- and interdomain data-flow



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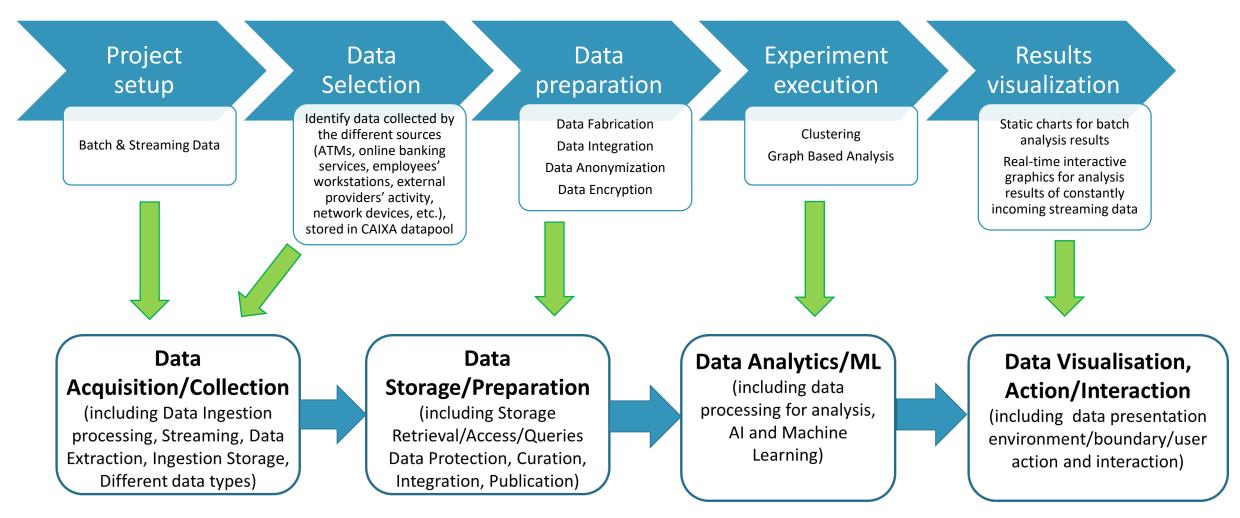
I-BiDaaS Experimental Workflow



DataBench Pipeline

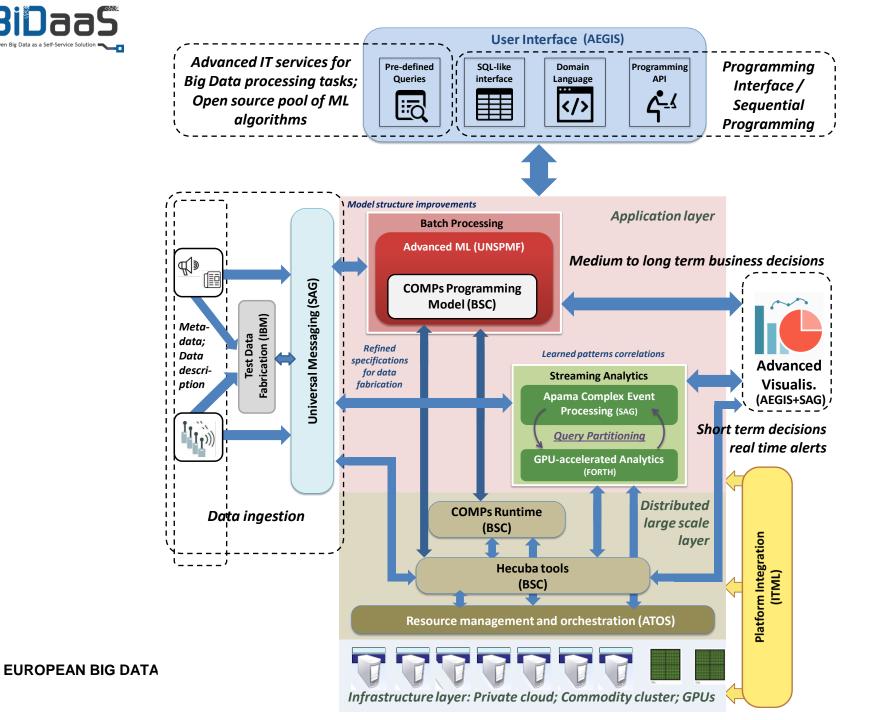


Example: Banking Experiments Workflow



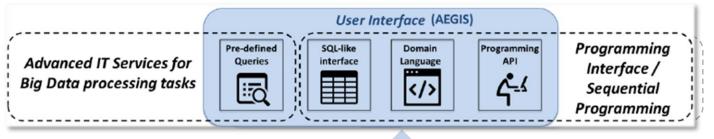
DataBench Pipeline

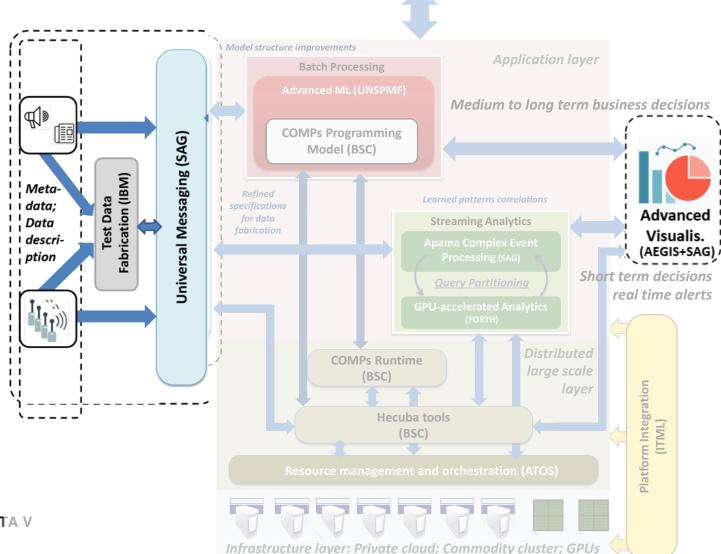




The I-**BiDaaS** solution: **Architecture** technologie







WP2
Data, user
interface,
visualization

Technologies:

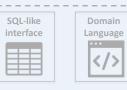
- IBM TDF
- · SAG UM
- AEGIS AVT

http://ibidaas.eu/tools



Advanced IT services for Big Data processing tasks; Open source pool of ML algorithms

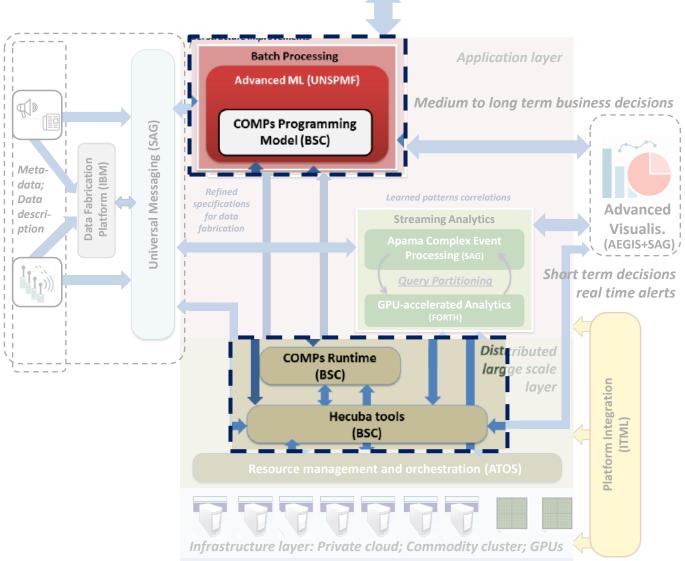




User Interface (AEGIS)



Programming
Interface /
Sequential
Programming



WP3 Batch Analytics

Technologies:

- BSC COMPSs
- BSC Hecuba
- BSC Qbeast
- Advanced ML (UNSPMF)

http://ibidaas.eu/tools

EUROPEAN BIG DATA V

| Benchmarking: Technology level | | | | ₽ <mark>-BiDa</mark> |
|--------------------------------|-----------------|---------------|-----------------------|----------------------|
| -BiDaaS | Technology name | Platform role | DataBench nineline | Current benchmarks |

Data pre-processing, Streaming Analytics

Sequential programming model for

distributed architectures

Data management framework with easy

interface

Multidimensional indexing and storage

Synthetic test data fabrication

Streaming Analytics

Message Broker

Visualization and interface

Batch analytics

Resource management

Step 3

Step 3

Step 2

Step 2

Step 1

Step 3

Step 1

Step 4

Step 3

Step 2

Custom benchmark (throughput, latency)

Applications (Own use cases)

Applications (Own use cases)

TPC-H

Several open source + commercial products (e.g., Grid tools of CA) / No known benchmarks yet

Custom benchmark (throughput)

Custom benchmark (throughput)

N/A

Respective MPI implementation;

Sklearn; HiBench

N/A

| benchinarking, recimology level | | | ري - | |
|---------------------------------|--|--|-----------|--|
| I-BiDaaS | | | DataBench | |

FORTH

BSC

BSC

BSC

IBM

SAG

SAG

AEGIS

UNSPMF

ATOS

GPU accelerator technology

COMPSs

Hecuba

Qbeast

Test Data Fabrication

Apama Streaming Analytics

Platform

Universal Messaging

Advanced visualization and

monitoring

Pool of ML algorithms in

COMPSs/Python

Resource management and

orchestration module



Benchmarking: Business, data & analytics

| | Business Objectives | Data Sets | Data Size | Processing Type | Type of Analysis |
|---------------|---|---|-----------|--|---|
| Telecoms | improve and optimize current operations | Anonymized mobility data (structured) Anonymized call center data (unstructured) | ТВ | - batch & streaming | predictive descriptive / diagnostic |
| Finance | improve decision making improve efficiency of Big Data solutions | Tokenized online banking control data (structured) Tokenized bank transfer data (structured) Tokenized IP address data (structured) | РВ | batch batch & streaming | - descriptive / diagnostic |
| Manufacturing | improve and optimise current operations improve the quality of the process and product | Anonymized SCADA/MES data (structured) Anonymized Aluminum Die- casting (structured) | GB | batch batch & streaming | predictivediagnostic |



Benchmarking: Business level

| I-BiDaaS | Use Case | Most relevant business KPIs | |
|----------|--|---|--|
| Partner | | | |
| TID | Accurate location prediction with high traffic and visibility | Acquisition of insights on the dynamics of cellular sectors Processing costs (cost reduction) Customer satisfaction | |
| TID | Optimization of placement of telecommunication equipment | | |
| TID | Quality of service in Call Centers | | |
| CAIXA | Enhanced control on online banking | - Cost reduction - Data accessibility | |
| CAIXA | Advanced analysis of bank transfer payment in financial terminal | - Time efficiency | |
| CAIXA | Analysis of relationships through IP addresses | - End-to-end execution time (from data request to data provision) | |
| CRF | Production process of aluminium die-casting | - 3 Product quality levels (High, Medium, Low) - Overall Equipment Effectiveness (OEE), | |
| CRF | Maintenance and monitoring of production assets | - Maintenance cost - Cost reduction | |



I-BiDaaS aims to empower IT and non-IT big data experts to easily utilize and interact with big data technologies.

Check out Website & Social

- www.ibidaas.eu
- twitter.com/ibidaas
- in linkedin.com/in/i-bidaas
- zenodo.org/communities/i-bidaas

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This project has received funding from the European Union's Horizon 2020 Research and Innovation program under grant agreement **No 780787**.



- Financial
- Telecommunications
- Manufacturing







5 Open Source 6 Proprietary

Thank you!
Questions?



Enabling procurement data value chains for economic development, demand management, competitive markets and vendor intelligence

Brian Elvesæter, SINTEF

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https://theybuyforyou.eu

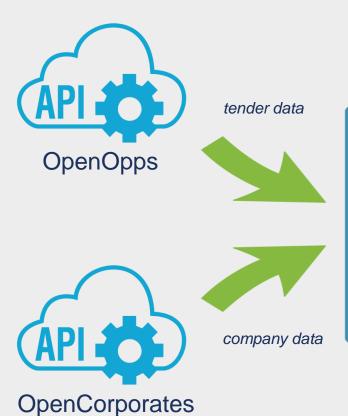
TheyBuyForYou (TBFY)

- Horizon 2020 Innovation Action
 - Grant agreement No 780247
- Duration: 36 months
 - Jan 2018 Dec 2020
- Overall budget
 - € 3 274 440
- Developing Big Data tools for Public Procurement
 - data access
 - data analytics
 - data interaction
 - data visualization
- 10 Partners from 5 countries

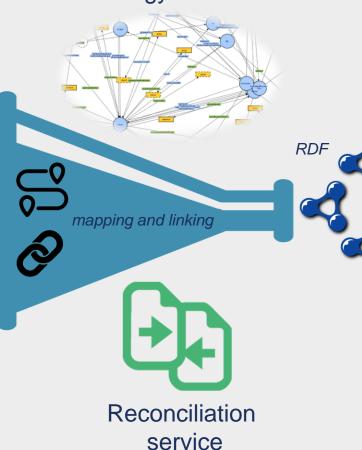
| Partner | Country | Organisation Type |
|---|---------|-------------------|
| SINTEF AS | NO | RTO |
| Municipality of Zaragoza | ES | Public sector |
| CERVED | IT | Private Company |
| OpenCorporates | UK | Private Company |
| Josef Stefan Institute | SI | RTO |
| Ministry of Public Sector Innovation | SI | Public Sector |
| OESÍA Networks | ES | Private Company |
| OpenOpps | UK | Private Company |
| Universidad Politécnica de Madrid | ES | University |
| King's College London | UK | University |



TBFY Knowledge Graph



Ontology network



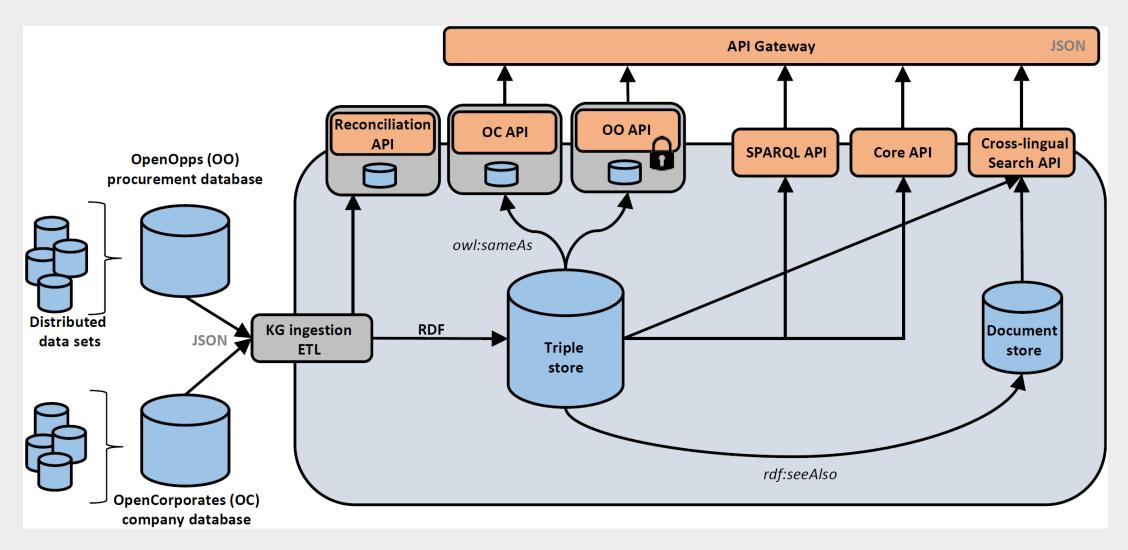
129 million triples

- more than 1.35 million tenders
- more than 1.58 million awards
- around 100 thousand companies

http://data.tbfy.eu

Triple store

TBFY Platform

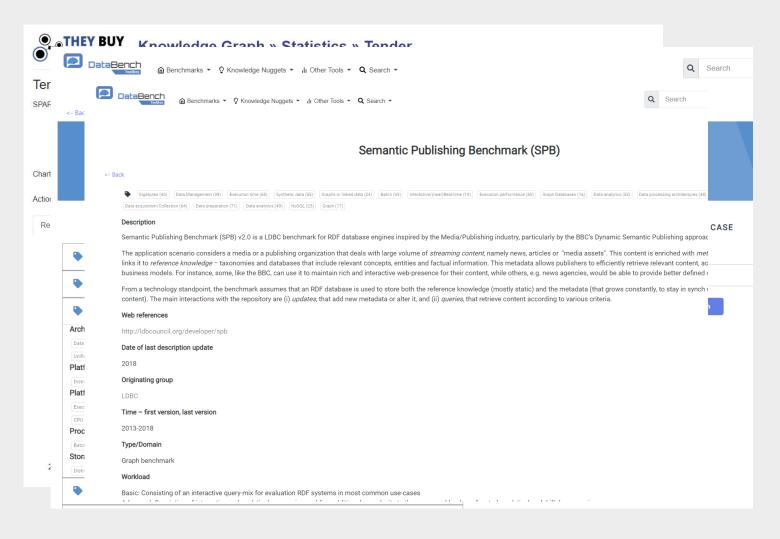


Benchmark case #2:

Query/visualization



- SPARQL Query Performance
 - KG API (RESTful API wrapping predefined SPARQL queries)
 - Visualization
- Benchmark questions?
 - Which triple store (RDF) database to choose?
 - Which cloud computing (resource) plan to choose?
 - https://aws.amazon.com/pricing/
 - Database stability issues
 - JVM heap size
- DataBench ToolBox
 - LDBC Semantic Publishing Benchmark (SPB) to benchmark RDF triple stores
 - GraphDB
 - Apache Jena Fuseki & TDB
 - ...





Questions?

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https://theybuyforyou.eu



Getting to know Vodafone Innovus



Who we are

a 100% Vodafone company located in Athens, Greece, est. 2004

Operating in 7 Vodafone OpCos



What we do

We design and implement innovative IoT solutions based on VF Group strategy & customer needs



What we deliver

We have built Vodafone **Group products** as well as the **Global Device Management** solution



Our advantages

- ✓ World class Platform
- Global & local expertise
- Operations experience
- Agile way of working

World class capabilities build a world class eco-system



Enterprise Fleet | Overview

Logistics Vertical Soho / SME / Corporate segments

Developed by VF Innovus

Refreshed platform, GDSP connected

A well-established solution, applicable to customers with advanced needs for location tracking, sensor monitoring & in-depth reports / analytics!

Markets deployed

VF Greece & VF Albania

>13k active assets >6k assets in cold chain logistics 11 years of experience

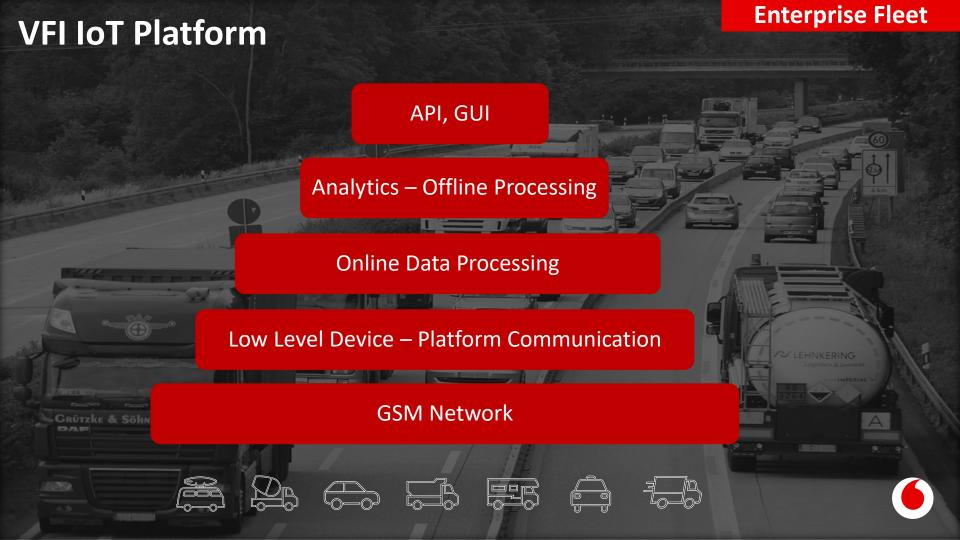
providing an excellent solution since 2009

A fresh, award winning approach

new platform with re-designed UI, advanced Driver Safety & enhanced capabilities MOBILITY

Innovation

We participate in EU programs
(Track & Know, Trustonomy) and
collaborate with the Hellenic
Organization of Intelligent Transport
Systems to enhance the solution
capabilities



Devices on vehicles



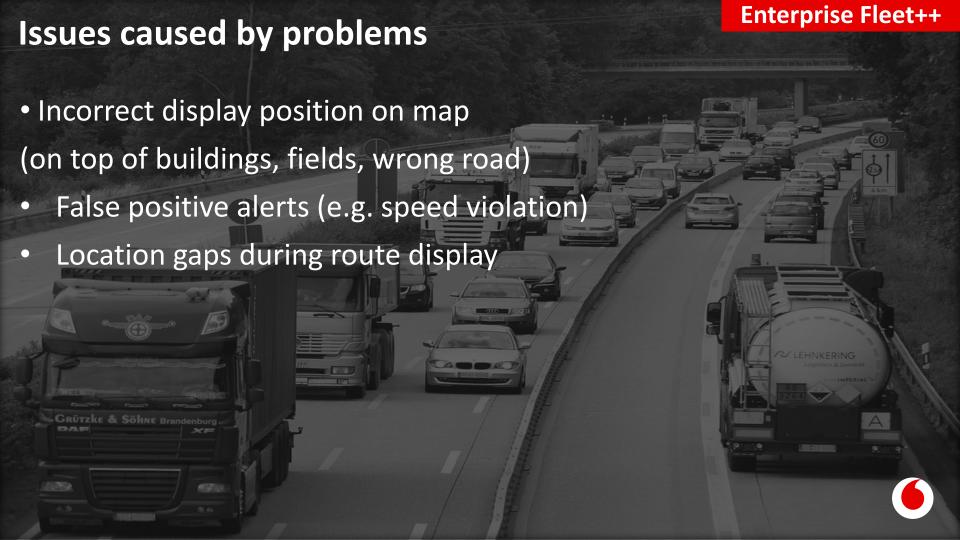
Device in vehicles

- Devices are installed under the hood (or bonnet)
- Vehicles vary in type, age and electronics

Data

- More than 3M data packets received daily by the platform
- GPS data (coordinates, angle, speed, date)

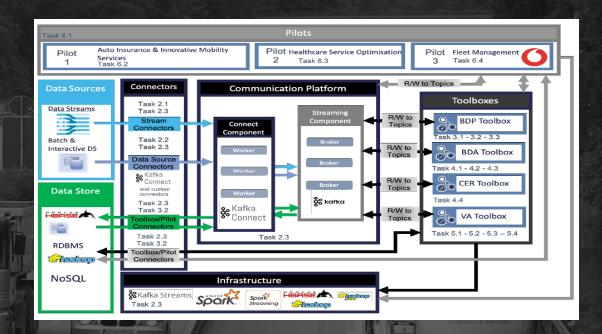




Enterprise Fleet++

Track & Know

- Big Data Analytics
- ML based components
- Scalable
- Online Processing
- Offline Processing
- Versatile
- Easy to integrate (Kafka Topics)



Data Collection / Collection

Live data streaming from devices (GPS/Sensors)

Data Storage / Preparation

Cleansing, enrichment, storage in NoSQL stores

Data Analytics / ML

Pattern recognition Location forecasting Clustering Mobility networks

Data Visualization Action / Interaction

Visual analytics End user GUI



Integration VFI IoT Platform to Track & Know

Online Processing Flows:

- Data cleansing
- · Data enrichment
- · Data pattern recognition
- Future location prediction
- Driver behavior analysis

Offline Processing Flows

- Individual mobility networks, predict next service period
- Hot spot analysis
- Trajectory matching
- Visualization

API, GUI

Analytics – Offline Processing



Online Processing



Low Level Device – Platform Communication

GSM Network









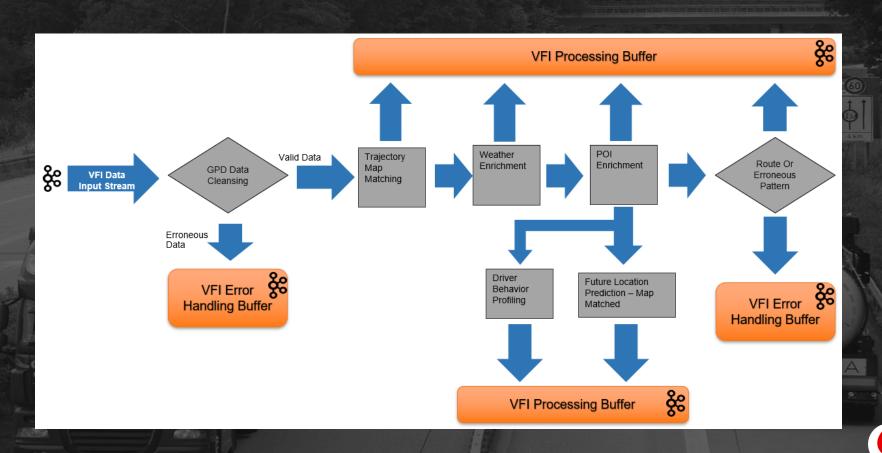




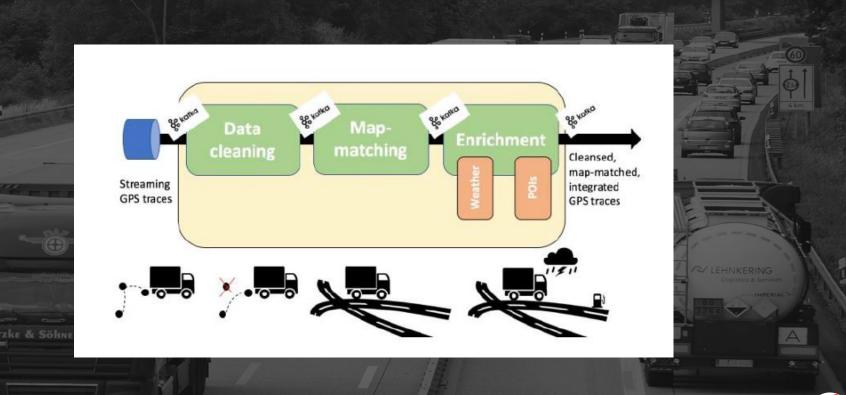




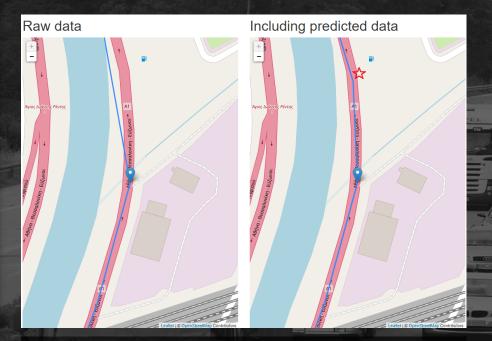
Data Flows T&K Platform



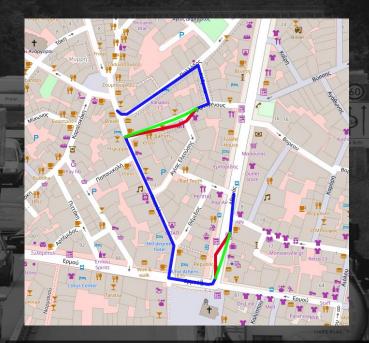
Data cleansing tool - Map matching tool



GPS post enhancements

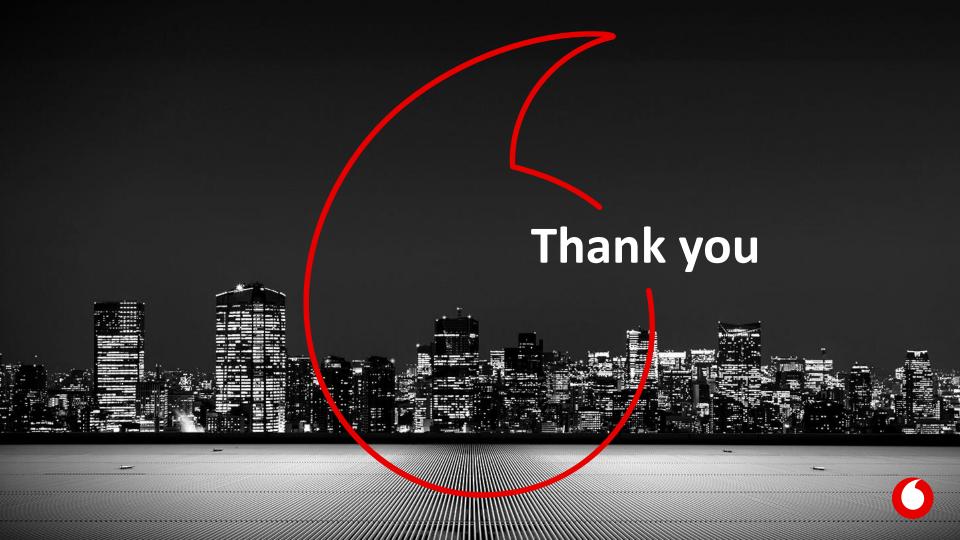


- Vehicle moving on a highway
- Sampling rate at 30 seconds



- Vehicle moving in dense urban area
- GPS reception not always good









This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 732064



This project is part of BDV PPP



Prof. Dr. Caj Södergård,Technical Manager of DataBio



VTT Technical Research Centre of Finland

European Big Data Forum 2020 DataBench session 4.11.2020





Data-driven Bioeconomy - DataBio

DataBio aim: Develop big data tools for enhancing production of raw materials for food, energy and biomaterials industries

- A EU-funded project with 48 partners
- 27 bioeconomy pilots in 17 countries
- Duration 2017-2020



Responsible and sustainable production of food, energy and biomaterials



Better raw material utilisation from agriculture, forestry and fishery sources



New business
opportunities
through market-ready
big data technologies



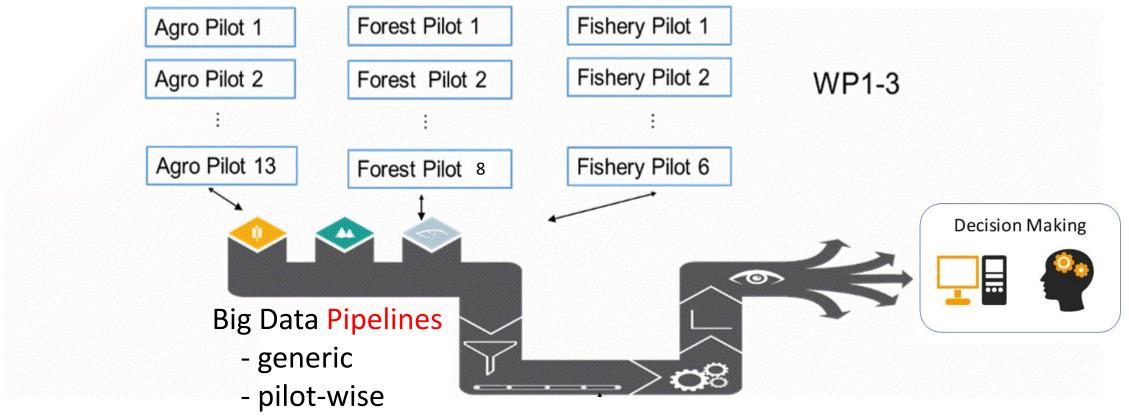
Motivation

Population growth and urbanisation are increasing the demand for natural resources, which is putting a strain on the Earth's carrying capacity.

We aim to develop new sustainable ways to use forest, farm and fishery resources and to communicate real-time information to decision-makers and producers.

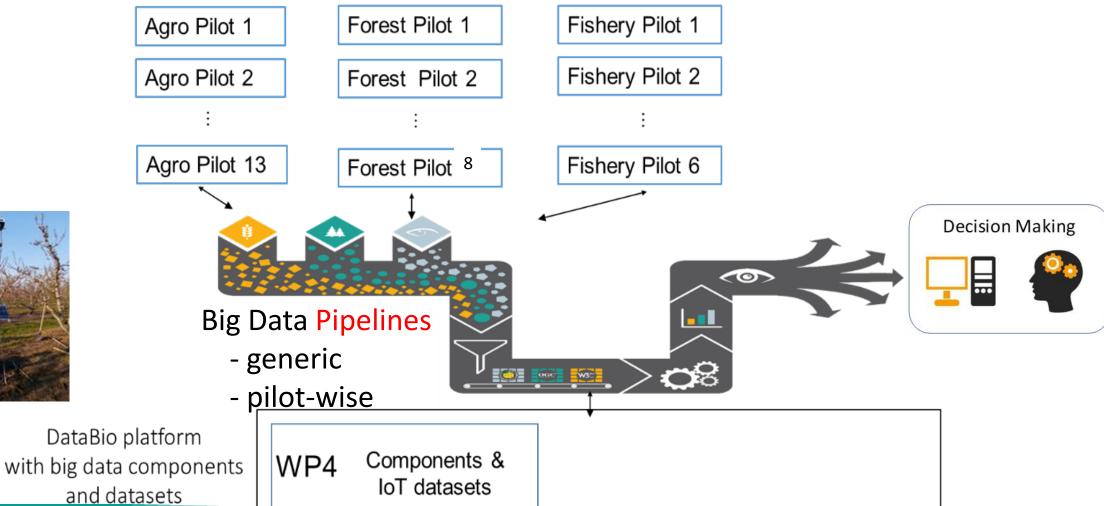
DataBio platform serves the 27 pilots





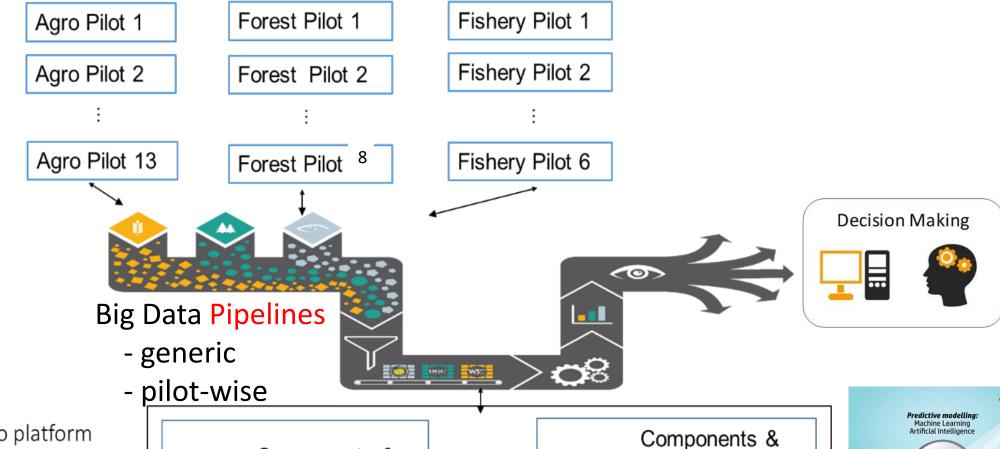
DataBio platform serves the 27 pilots





DataBio platform serves the 27 pilots





DataBio platform with big data components and datasets

WP4 Components & IoT datasets

WP5 Earth Observation datasets





Pipelines vs. Services

Pipeline

- A chain of real-time processing components:
 - Acqusition/Collection,
 - Preparation
 - Analytics
 - Visualisation, User interaction
- Clear interfaces between components and to outside
- A "white box" showing internal wiring for developers

Service

- Provides usability to end users
- No display of internal wirings of components
- Accessed through API:s (web services, remote calls)
- Activated remotely through database queries ("end points") and executed in the cloud.
- Represents a "black box".

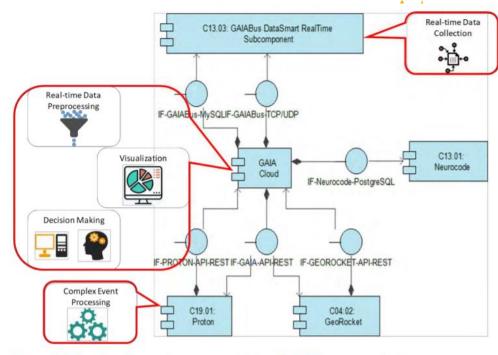
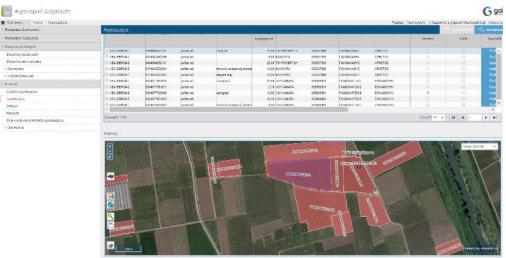
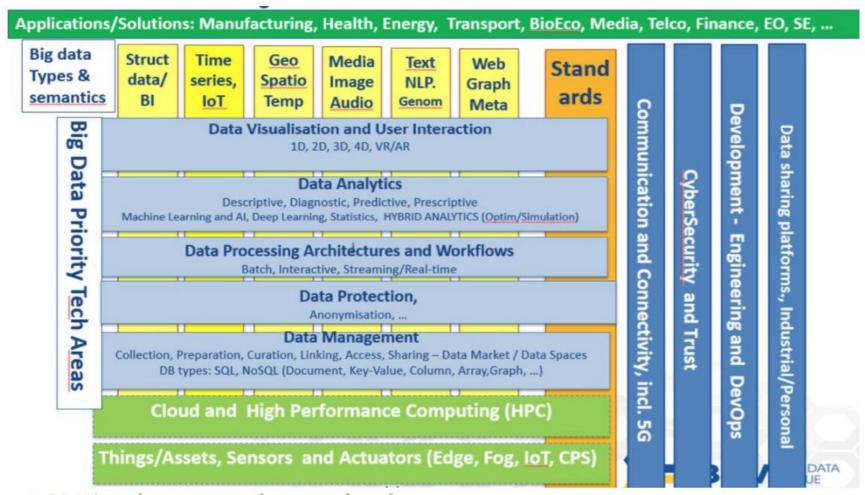


Figure 17: Mapping of generic components into pilot A1.1 component view



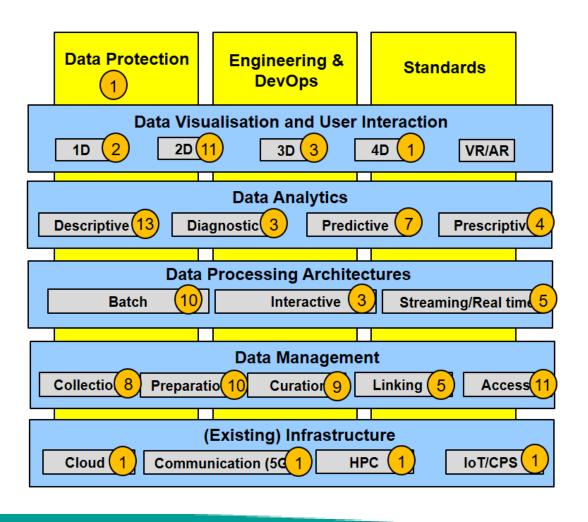
We used the BDVA Reference Model





Platform development in DataBio in numbers



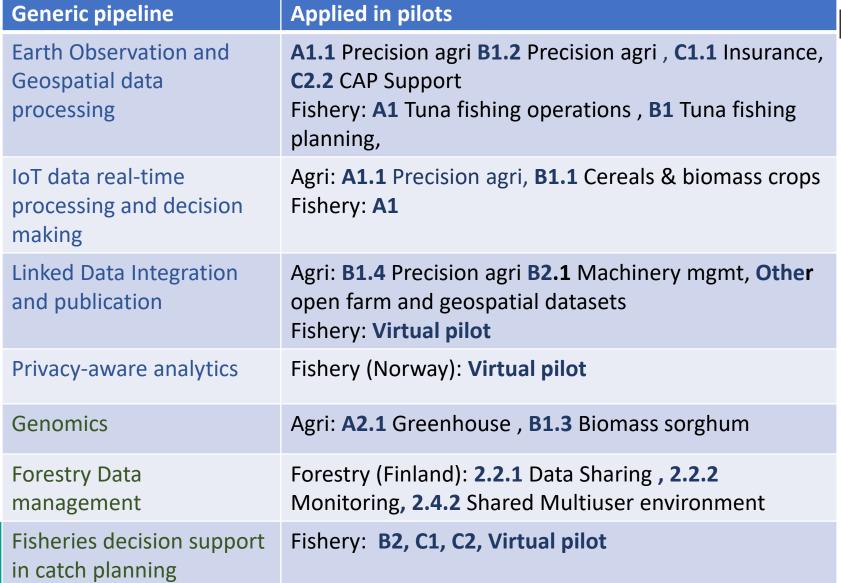


- 62 components from 28 partners in two trial rounds
- 1-6 components per pilot (average 2)

- 14 new user interfaces
- 59 new **APIs**
- +2,7 in Technology Readiness Level (1-9)



Generic pipelines in DataBio





DATABio

Search the hub

Explore

Q

loT data real-time processing and decision making

♦ 0.0.1 | □ Release | ② Updated tunti sitten

The "Generic pipeline for IoT data real-time processing and decision making" is an example of a pipeline pattern that fits the two aspects of generalization. It has been applied to three pilots in the project from the agriculture and fishery domain, and it can also be applied to other domains as discussed in the summary section. The main characteristic of this generic pipeline is the collection of real-time data coming from IoT devices to generate insights for operational decision making by applying real-time data analytics on the collected data.

GenericPipeline A1.1 C1.1 C2.2 A1 B1 Pipeline

Linked data integration and publication

● 0.0.1 | □ Release | ② Updated tunti sitten

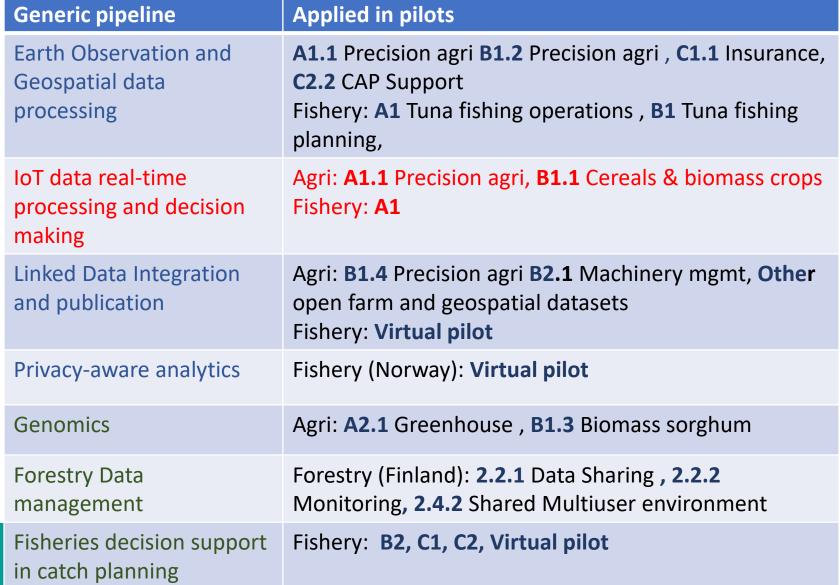
In DataBio project and some other agri-food projects Linked Data has been extensively used as a federated layer to support large scale harmonization and integration of a large variety of data collected from various heterogeneous sources and to provide an integrated view on them. The triplestore populated with Linked Data during the course of DataBio project (and few other related projects) resulted in creating a repository of over 1 billion triples, being one of the largest semantic repositories related to agriculture, as recognized by the EC innovation radar naming it the "Arable Farming Data Integrator for Smart Farming". Additionally, projects like DataBio have also helped in deploying different endpoints providing access to the dynamic data sources in their native format as Linked Data by providing a virtual semantic layer on top of them. This action has been realised in DataBio project through the implementation of the instantiations of a 'Generic Pipeline for the Publication and Integration of Linked Data", which have been applied in different uses cases related to the bioeconomy sectors. The main goal of these pipelines instances is to define and deploy (semi-) automatic processes to carry out the necessary steps to transform and publish different input datasets for various heterogeneous sources as Linked Data. Hence, they connect different data processing components to carry out the transformation of data into RDF [REF-27] format or the translation of queries to/from SPARQL [REF-28] and the native data access interface, plus their linking, and including also the mapping specifications to process the input datasets.

GenericPipeline B1.4 B2.1 Pipeline

9



Generic pipelines in DataBio





DATABio

Search the hub

Explore

C

loT data real-time processing and decision making

● 0.0.1 | □ Release | ② Updated tunti sitten

The "Generic pipeline for IoT data real-time processing and decision making" is an example of a pipeline pattern that fits the two aspects of generalization. It has been applied to three pilots in the project from the agriculture and fishery domain, and it can also be applied to other domains as discussed in the summary section. The main characteristic of this generic pipeline is the collection of real-time data coming from IoT devices to generate insights for operational decision making by applying real-time data analytics on the collected data.

GenericPipeline A1.1 C1.1 C2.2 A1 B1 Pipeline

Linked data integration and publication

No.0.1 | ☐ Release | ② Updated tunti sitten

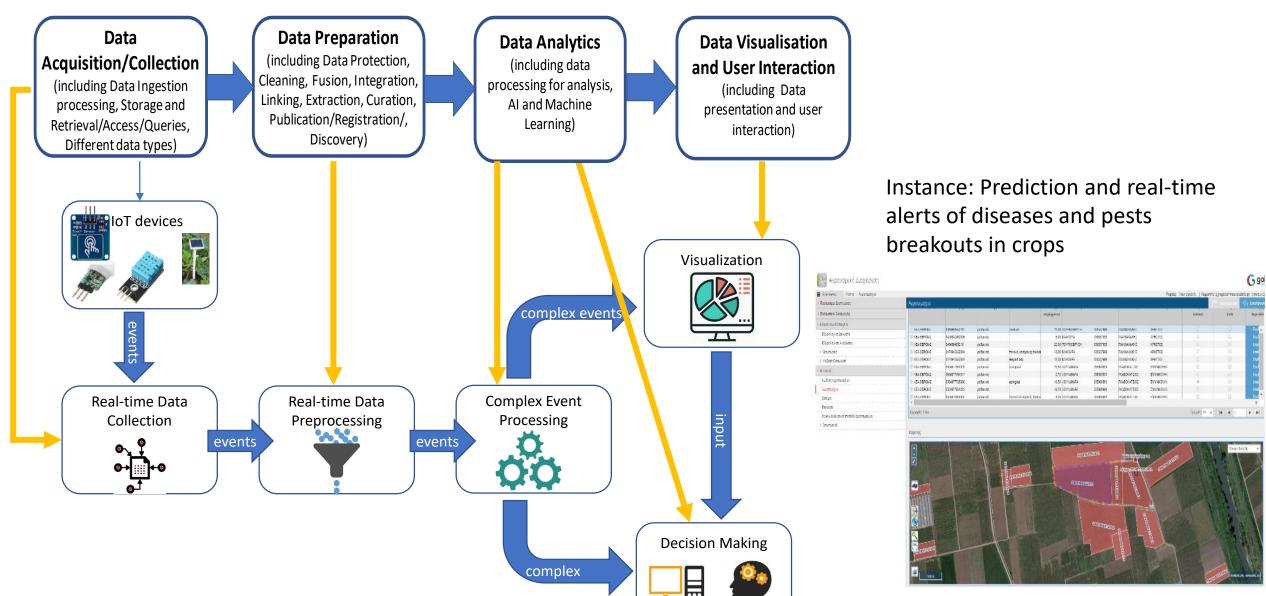
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GenericPipeline B1.4 B2.1 Pipeline

10

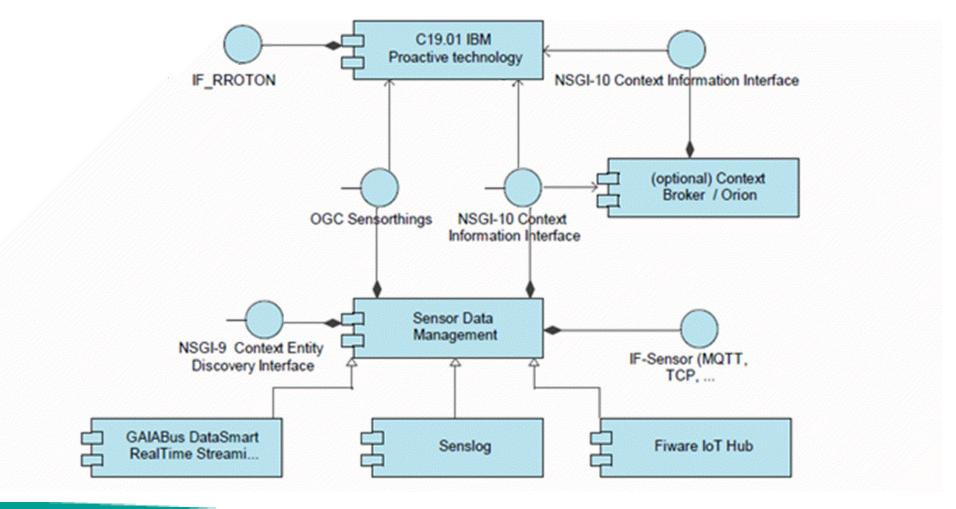
Source: Deliverable D4.4 Service documentation

Generic Pipeline – IoT data realtime processing



Crop monitoring using "IoT Generic Pipeline





VTT

Generic pipelines in DataBio

| Generic pipeline | Applied in pilots |
|---|---|
| Earth Observation and Geospatial data processing | A1.1 Precision agri B1.2 Precision agri, C1.1 Insurance, C2.2 CAP Support Fishery: A1 Tuna fishing operations, B1 Tuna fishing planning, |
| IoT data real-time processing and decision making | Agri: A1.1 Precision agri, B1.1 Cereals & biomass crops Fishery: A1 |
| Linked Data Integration and publication | Agri: B1.4 Precision agri B2.1 Machinery mgmt, Other open farm and geospatial datasets Fishery: Virtual pilot |
| Privacy-aware analytics | Fishery (Norway): Virtual pilot |
| Genomics | Agri: A2.1 Greenhouse, B1.3 Biomass sorghum |
| Forestry Data management | Forestry (Finland): 2.2.1 Data Sharing , 2.2.2 Monitoring, 2.4.2 Shared Multiuser environment |
| Fisheries decision support in catch planning | Fishery: B2, C1, C2, Virtual pilot |



DATABio

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loT data real-time processing and decision making

♦ 0.0.1 | ☐ Release | ② Updated tunti sitten

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GenericPipeline A1.1 C1.1 C2.2 A1 B1 Pipeline

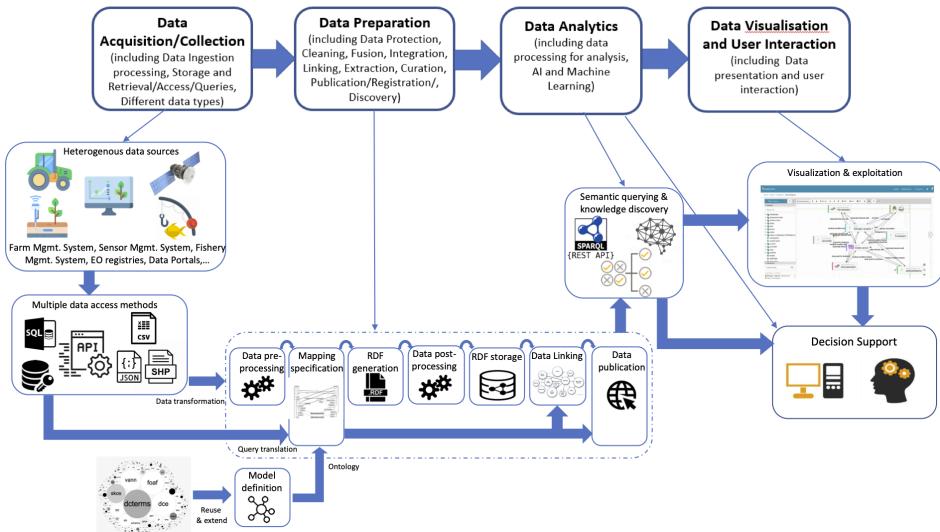
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GenericPipeline B1.4 B2.1 Pipeline

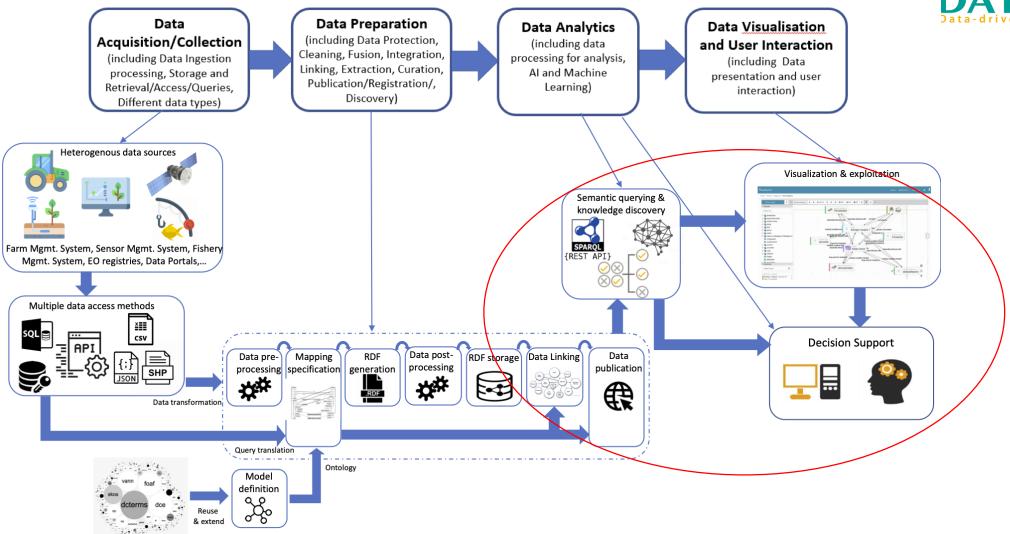
Linked Data Integration and Publication Pipeline





Case: Link discovery from knowledge graphs





Case: Link discovery from knowledge graphs



We applied discovery of RDF spatial links based on topology (Geo-L):

- Identifying fields from Czech LPIS data with specific soil type, from Czech open data
- Identifying all fields in a specific region which grow the same type of crops like the one grown in a specific field over a given period of time
- Identifying "risky" plots from *Czech LPIS* data which intersect with *buffer zones* around water bodies.

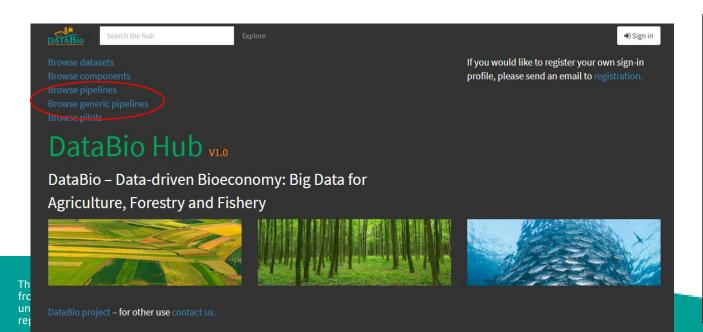


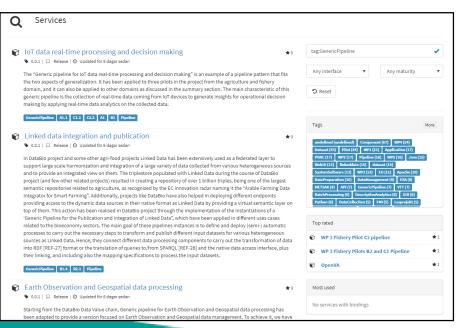
Figure: Risky overlap area between a crop field and a buffer zone of a water

Managing project assets: components, pipelines, datasets and reports



- DataBio Hub (DataBioHub.eu) is central in the development platform
 - Provides a catalogue of public (and private) digital assets of DataBio
 - Links resources together (project reports, models, docker modules etc)
 - Describes currently 101 components, 65 datasets, 25 pipelines (7 generic), 27 pilots
- Provides links to Deliverables, Interfaces (SPARQL endpoints, REST...)







Conclusions



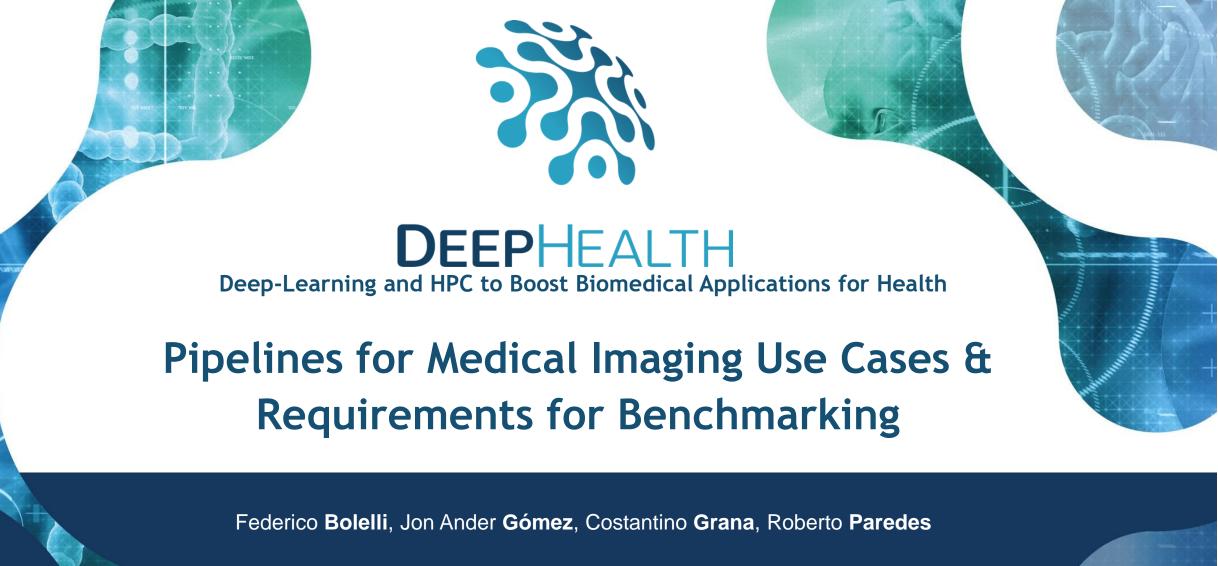
- DataBio designed a *common* development platform for 27 pilots in agriculture, forestry and fishery
- Big Data pipelines were central in this platform as a tool for developers
- We showed that a few generic pipelines can be applied in numereous diverse applications
- Instantations of the generic pipelines were used in the pilots
- All Dtabio results are available in the searchable and cross-linked DataBio Hub.





Thank you for your attention!





Evaluation schemes for Big data and AI Performance of high Business impact

EBDVF 2020, November 3-5, 2020





About DeepHealth



- Put HPC computing power at the service of biomedical applications with DL needs and apply DL techniques on large and complex image biomedical datasets to support new and more efficient ways of diagnosis, monitoring and treatment of diseases.
- Facilitate the daily work and increase the productivity of medical personnel and IT professionals in terms of image processing and the use and training of predictive models without the need of combining numerous tools.
- Offer a unified framework adapted to exploit underlying heterogeneous HPC and Cloud architectures supporting state-of-the-art and next-generation Deep Learning (AI) and Computer Vision algorithms to enhance European-based medical software platforms.

Key facts





Budget EU funding 12.774.824 €

14.642.366 €



22 partners from 9 countries:

Research centers, Health organizations, large industries and SMEs

Research Organisations















Large Industries





SMEs













Stockholms läns landsting

Health Organisations





Developments & Expected Results



The DeepHealth toolkit

- Free and open-source software: 2 libraries + front-end.
 - EDDLL: The European Distributed Deep Learning Library
 - ECVL: the European Computer Vision Library

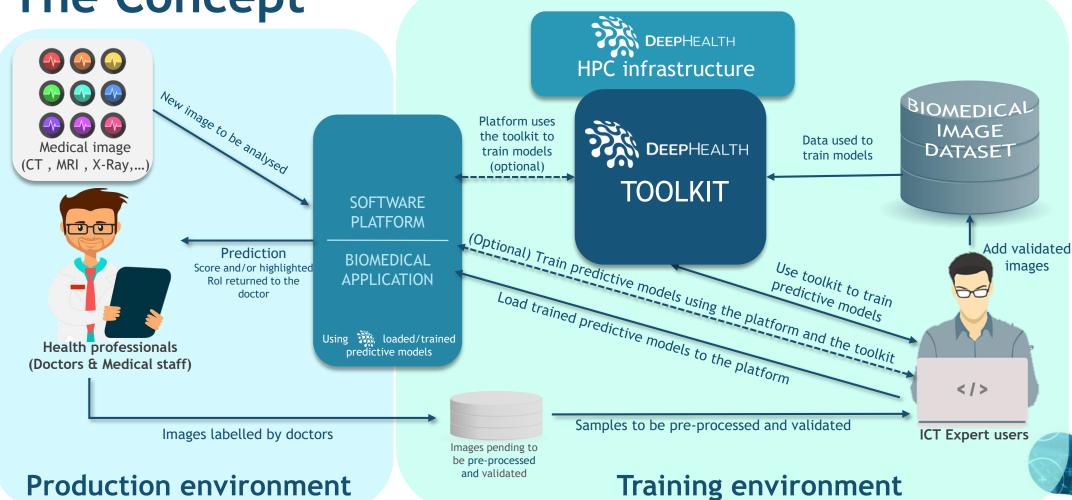


- Ready to run algorithms on Hybrid HPC + Cloud architectures with heterogeneous hardware (Distributed versions of the training algorithms)
- Ready to be integrated into end-user software platforms or applications
- **HPC infrastructure** for an efficient execution of the training algorithms which are computationally intensive by making use of heterogeneous hardware in a transparent way
- Seven enhanced biomedical and Al software platforms provided by EVERIS, PHILIPS, THALES, UNITO, WINGS, CRS4 and CEA that integrate the DeepHealth libraries to improve their potential
- Proposal for a structure for anonymised and pseudonymised data lakes
- Validation in 14 use cases (neurological diseases, tumor detection and early cancer prediction, digital
 pathology and automated image annotation).





The Concept

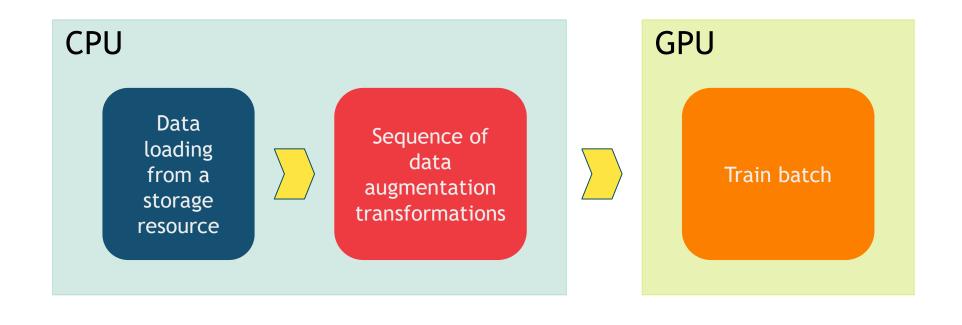


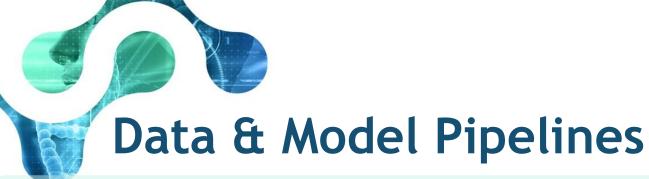






A pipeline is a set of operations sequentially applied to a data block (subset of samples)







| Data Pipeline | | | | | | | | |
|-------------------|---------------------|------------------|-------------------------------|----------------------|----------------------|-------------------------------|---------------------------------|------------------------|
| | | | AI/ML/DL Model Pipeline | | | | | |
| | | | | Training Pipelii | ne | | | |
| Dataset design | Data Acquisition | Data Curation | Persistent Data Storage | Data Partitioning | Data Augmentation | AI/ML/DL Model training | AI/ML/DL Model evaluation | Solution Deployment |

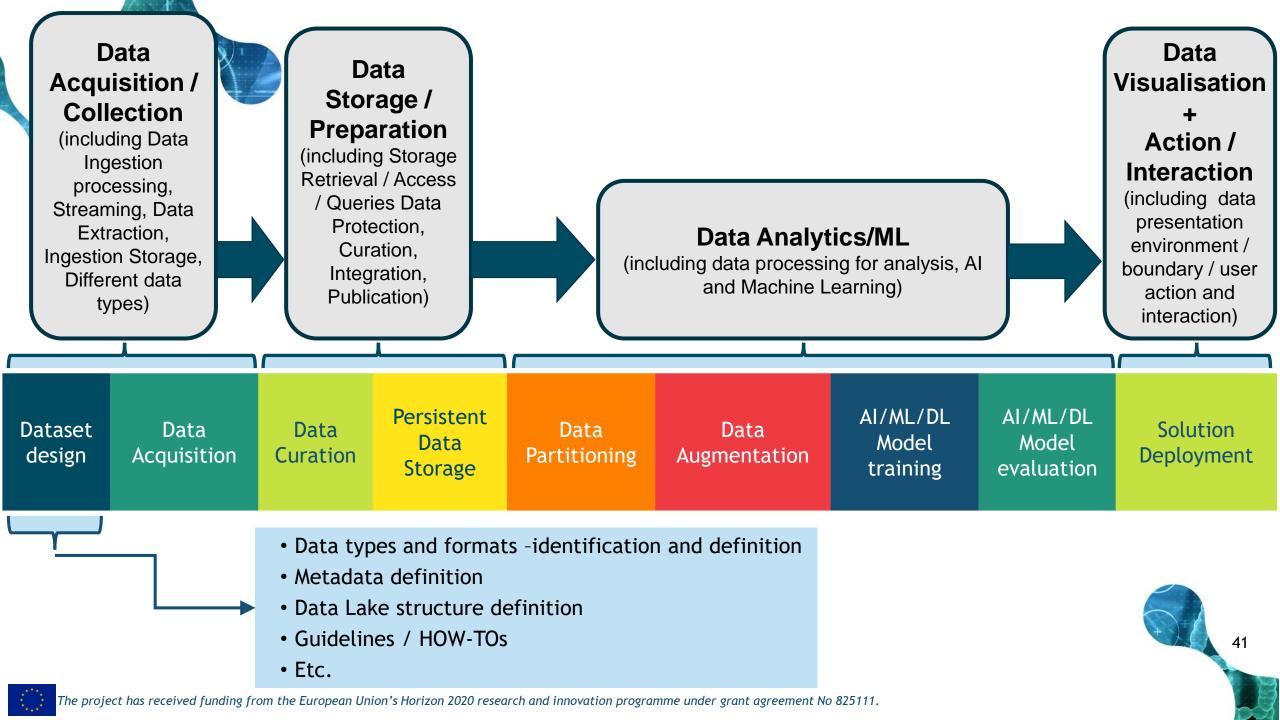
Training Pipeline is at the core of the **Model Pipeline** which in turn is considered part of the **Data Pipeline**

Both pipelines are suitable for business and research applications

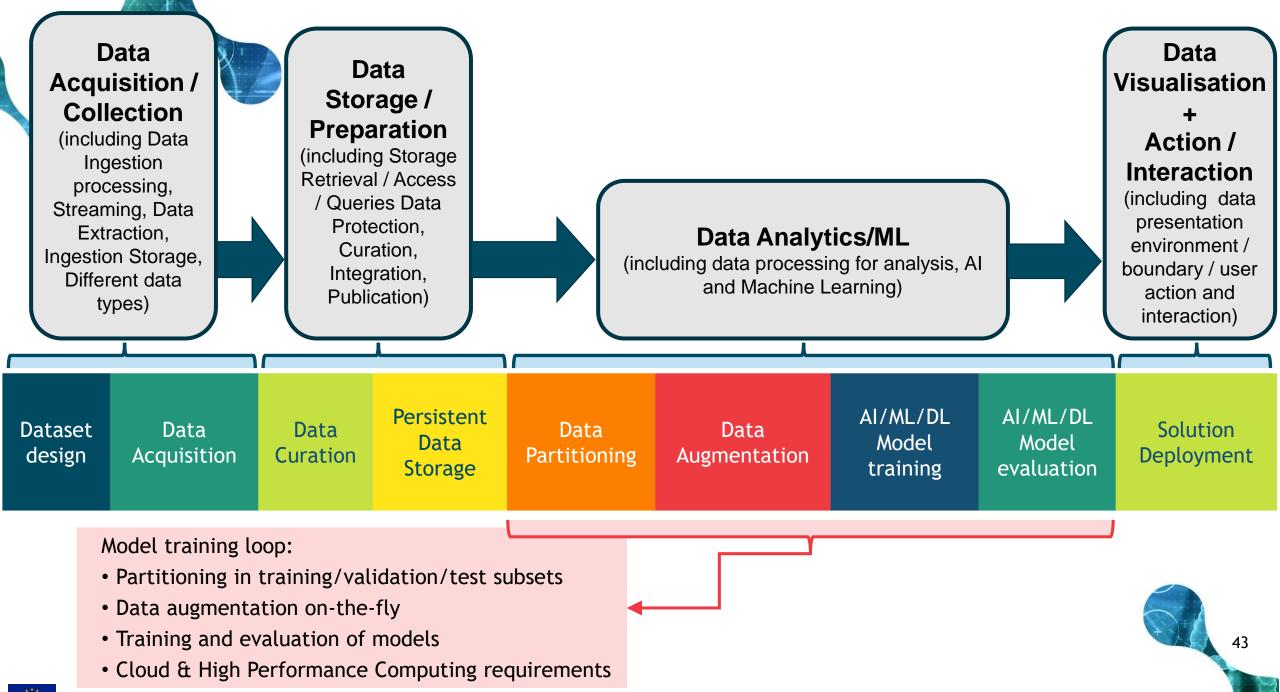
The whole *Data Pipeline* is applicable to any sector. Our project is focused on the Health sector



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Data Data Data **Visualisation** Acquisition / Storage / Collection **Preparation** (including Data Action / (including Storage Ingestion Interaction Retrieval / Access processing, (including data / Queries Data Streaming, Data presentation Protection, Extraction. Data Analytics/ML environment / Curation. Ingestion Storage, (including data processing for analysis, Al boundary / user Integration, Different data and Machine Learning) action and Publication) types) interaction) Persistent AI/ML/DL AI/ML/DL Dataset Data Data Data Data Solution Model Model Data design Acquisition Curation **Partitioning** Deployment Augmentation Storage training evaluation Data acquisition continuum Data cleansing/cleaning/wrangling/crunching Aggregated data/values computation Implementation of the data-lake definition Creation of users and permissions or make data public



Skin Lesion Detection and Classification



- Use case no 12 of the DeepHealth project is based on the International Skin Imaging Collaboration dataset
- Aims: identification (segmentation) and diagnosis (classification) of skin lesion images among different classes



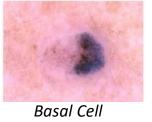
Data Acquisition

Data Curation Persistent

Data Storage

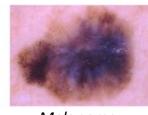












Actinic Keratosis

Benian Keratoses

Carcinoma

Nevus

Dermatofibroma

Melanoma

- Retrospective acquisition
- 23.906 annotated images
- Publicly available on the ISIC archive website
- jpeg data format

Data Partitioning

Data Augmentation

Model training

Model evaluation

- **Training 19.000**
- Validation 906
- Test 4.000







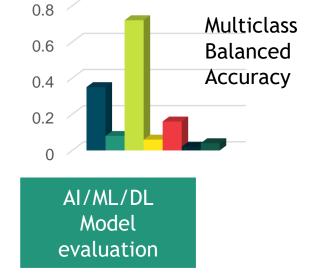
Skin Lesion Detection and Classification



Performed using the DeepHealth toolkit. Models are already available in the front-end.

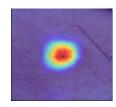


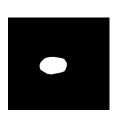
Data Augmentation AI/ML/DL Model training



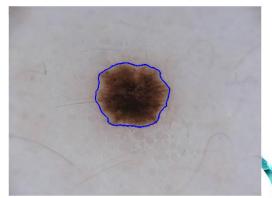
Explainability plays a fundamental role in this context. Ensuring Confidence Calibration and providing a Visual Explanation of the models is essential to support clinicians.







Jaccard Index (Intersection over Union)

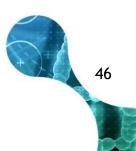


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Evaluate datasets in terms of

- 1. Findability where should a data scientist search for the dataset?
- 2. Availability how long does a data scientist need to start the initial exploratory data analysis?
- 3. Interoperability how long does a data scientist need to start training AI/ML/DL models with a dataset?
- **4. Reusability** are previously obtained results with a dataset public and available to other researchers / data scientists?
- 5. **Privacy / Anonymisation** can the dataset be made public without compromising the identity of individuals?
- **6. Quality** is the dataset biased or unbalanced? What procedure has been followed to validate annotations?







Evaluate Deep Learning libraries in terms of

- 1. Speed-up is distributed learning really efficient?
- 2. Convergence does the distributed learning reach the same model accuracy in less time?
- **3. Usability** how long does a developer need to use the libraries effectively?
- **4. Integrability** how difficult is it to integrate the libraries as part of solutions to deploy?
- **5. KPIs:** time-of-training-models (**totm**), performance/power/accuracy trade-off, etc.
- **6.** Others can you help us to evaluate other aspects?



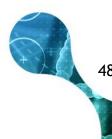




Needs & Requirements

Evaluate Software Platforms in terms of

- 1. **Usability** how long does a domain application expert need to manage the software tool effectively?
- 2. Completeness does the application platform provide all the algorithms/procedures/functions to allow domain application experts to easily define the sequences of steps to implement the data and/or model pipelines?
- 3. Compatibility how many data formats does the platform admits to import/export data and models from/to other frameworks?
- **4. KPIs:** time-to-model-in-production (**ttmip**), time-of-pre-processing-images (**toppi**), etc.
- 5. Others can you help us to evaluate other aspects?







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BIGDATA VALUE FORUM

EUROPEAN

This project has received funding from the European Horizon 2020 Programme for research, technological development and demonstration under grant agreement n° 780966