motus.ml

Never Stop Learning at the Edge

www.motusml.com | Alessio Bernardo

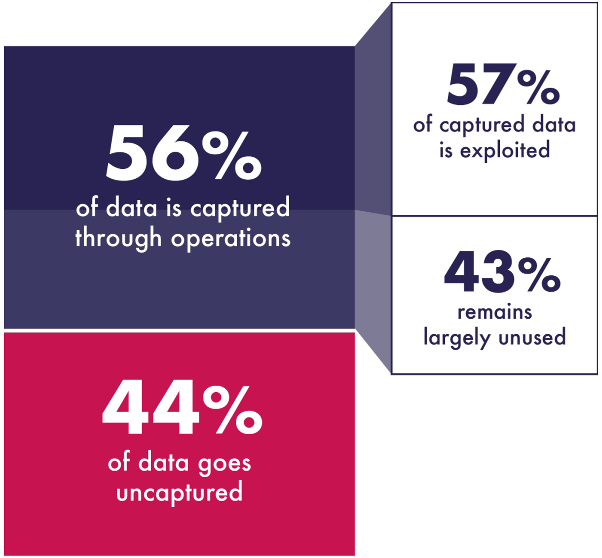
Big Data trend

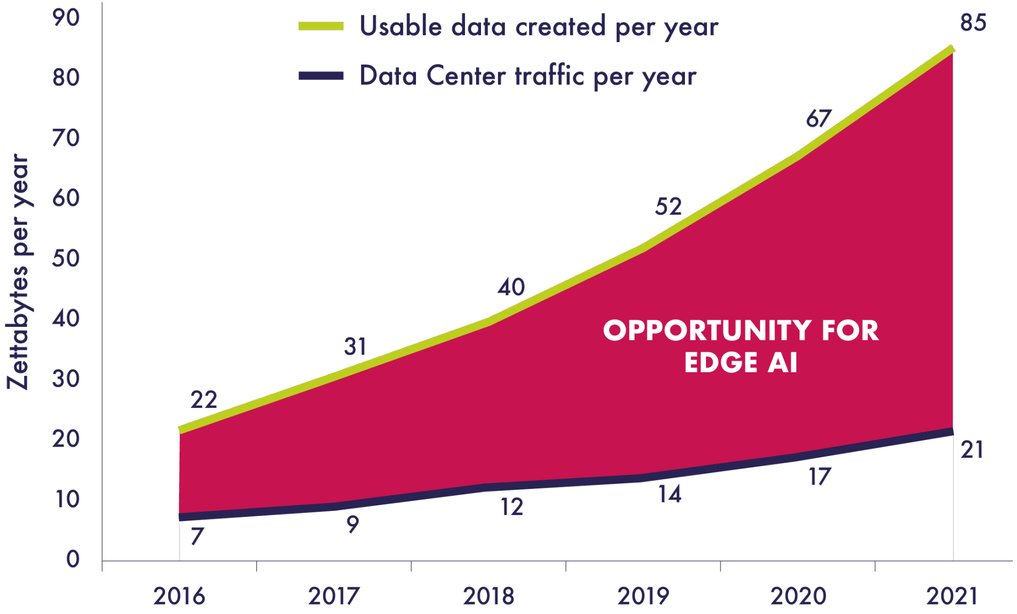
Data is growing, and the rate of growth is accelerating. The sum of data generated by **2025** is set to accelerate exponentially to **175 zettabytes**, an **order of magnitude bigger** than the **storage** production capability.

Innovation is not **driven by** trends, but by the need to create **more value under constraints**. This exponential inflation will thus require **analyzing** almost **30% of global data in real-time**.

Dave Mosley,
CEO of Seagate Technology

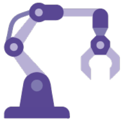
Data at the Edge: A Missed Opportunity

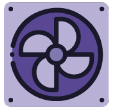




src: Statista

Data, data everywhere





Pressure

VOCs

Ultrasonic

Chemical properties oil

Temperature

Vibration

Acoustic

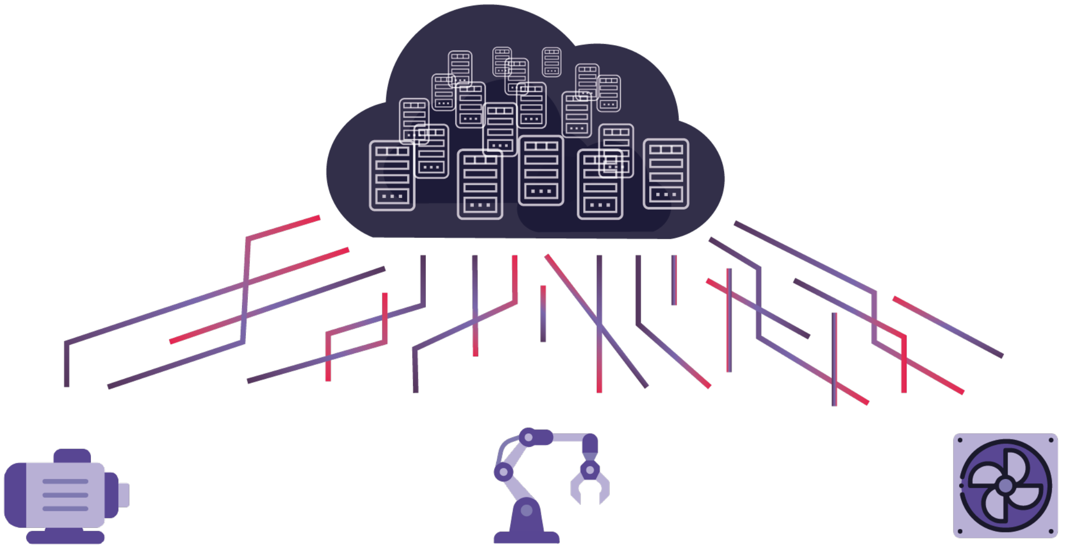
Thermal images

Rotation speed

Power consumption

Current

Data, data everywhere



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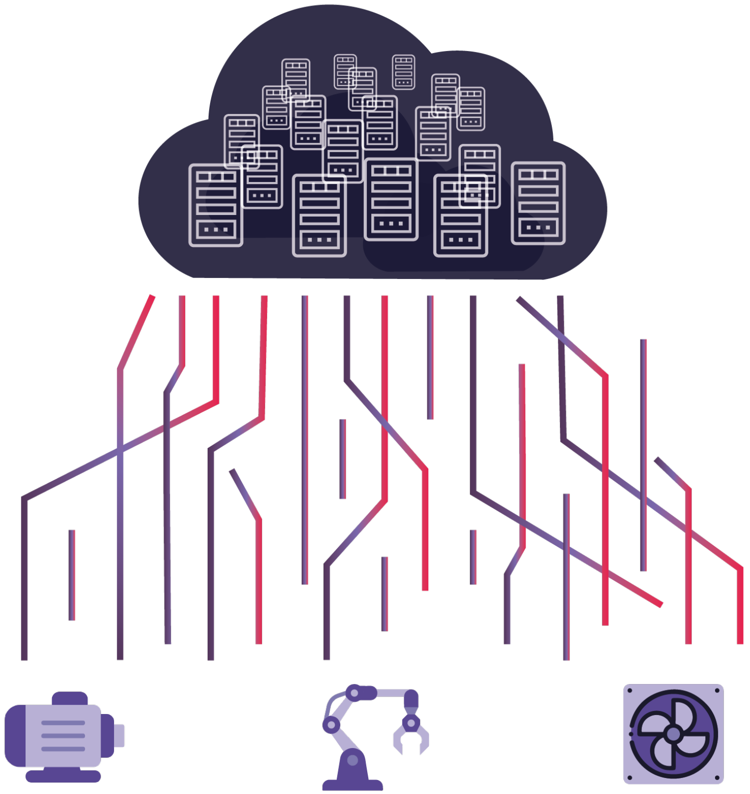
Cloud-centric analytics



Slow

High latency and network traffic load

Expensive

High implementation and data transmission costs

Insecure

Sending sensitive data on external service providers

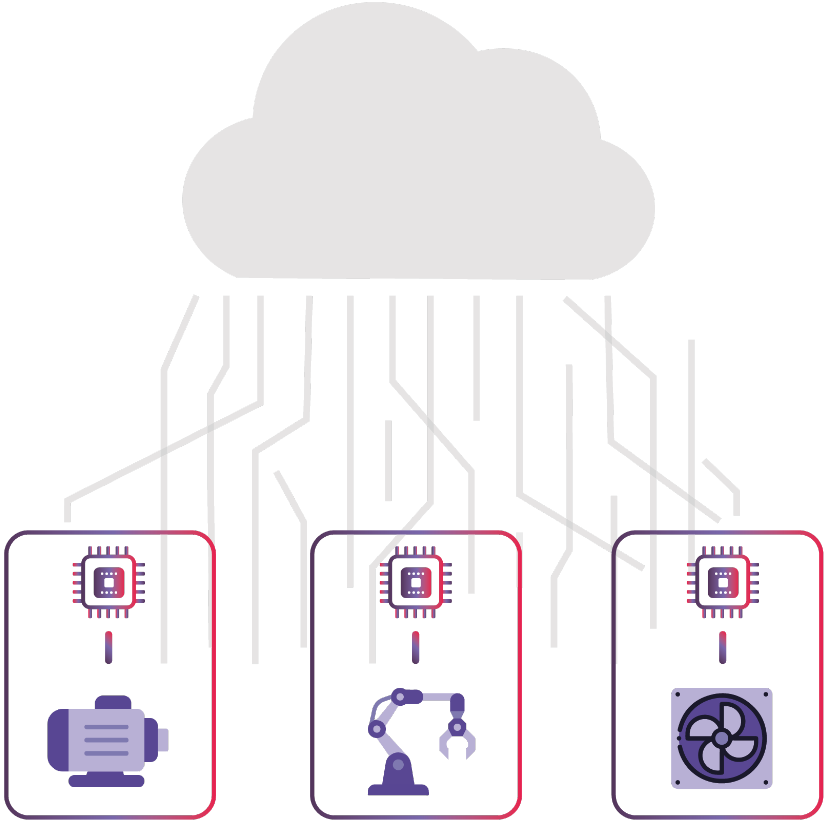
Energy-consuming

High power requirements for running AI models in cloud data centers

High CO_2 footprint

Cloud computing and data centers are a significant driver of carbon emissions

Edge-based analytics



Fast

Lowest latency to inference at data collection point

Cost-effective

Higher bandwidth and no need for large infrastructure and expensive GPUs/NPUs

Secure

Companies keep all of their sensitive data and compute inside their local network

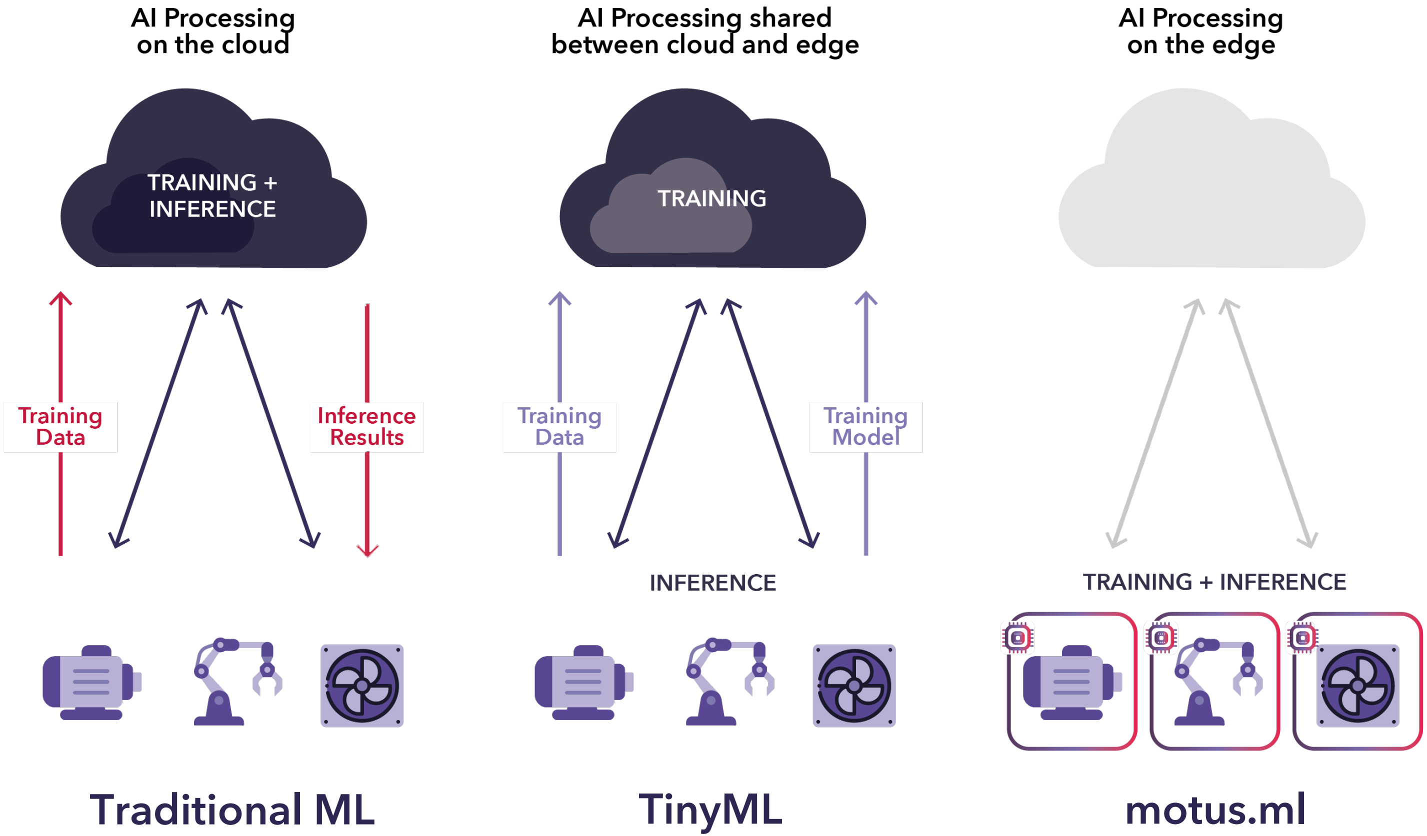
Energy-efficient

Efficient AI targeting battery-powered and portable applications

Low CO_2 footprint

No network connectivity and cloud-based AI minimize the total carbon footprint

Training and Inference @ Edge



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How do we achieve **edge machine learning**?

We combine 2 main technologies:

Streaming Machine Learning	Tiny Machine Learning
We design AI systems able to learn in time-varying situations	We move intelligent systems as close as possible to where data are generated
Our Unique Value Proposition	**A key add-on we master**

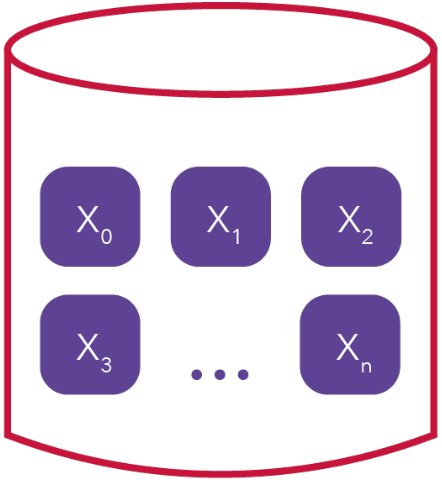
Streaming Machine Learning

Traditional approach: data

Batch: **a finite static** set of data, usually tabular, that does not evolve over time, and describes **historical past events**.

Random access to data

No restrictions on memory/time for training



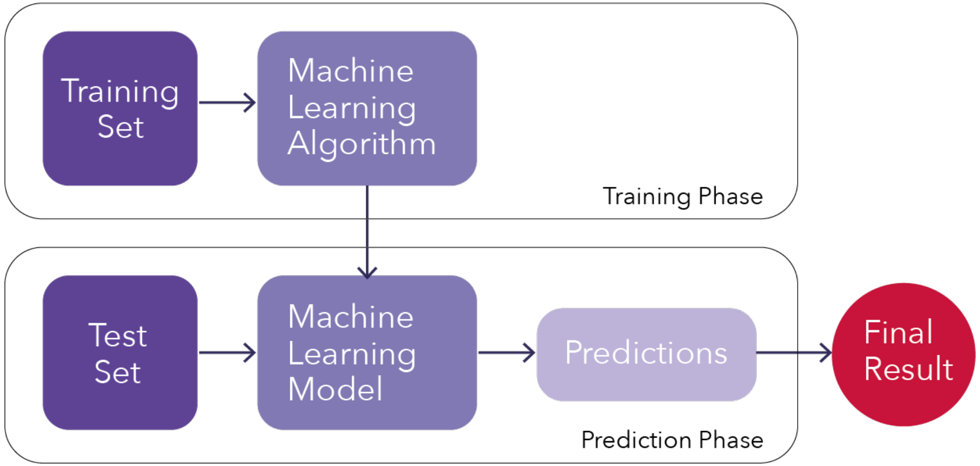
Well defined training phase

Access to all labeled data used for training

Traditional approach: ML setting

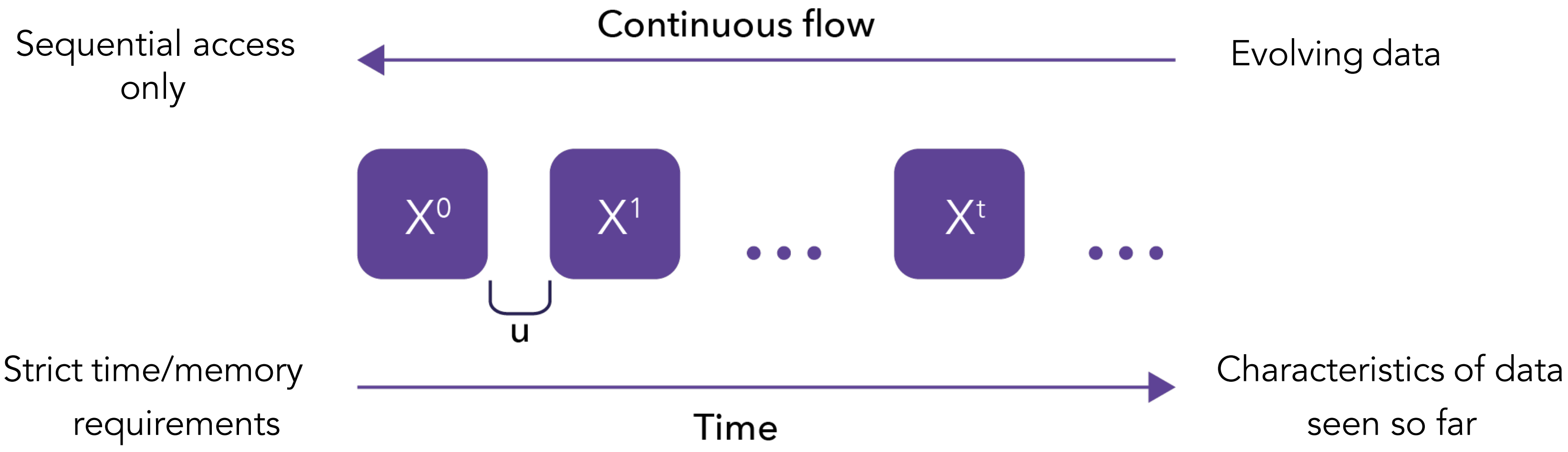
Manual, Stateless Retraining

ML team focuses mainly on developing ML models, updating existing ML models takes a backseat. The process of updating a ML is **ad-hoc** and usually **manual**.



motus.ml approach: data

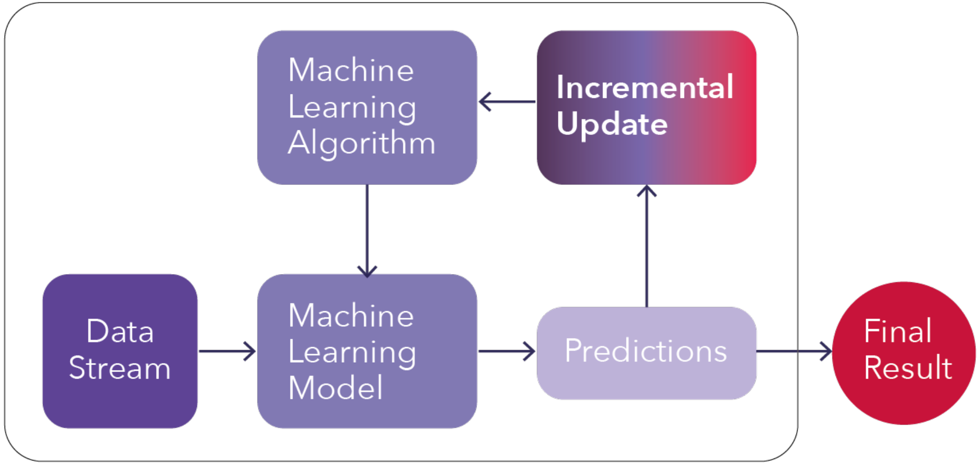
Data Stream: a **continuous** flow of data generated at **high-speed** in **dynamic, time-changing** environments.



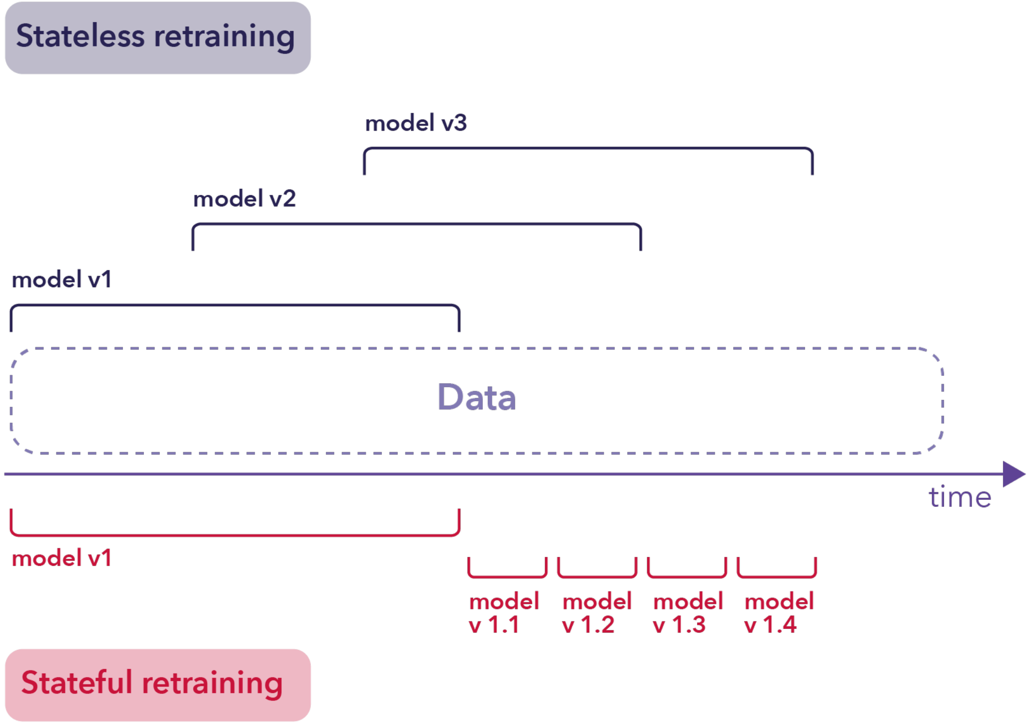
motus.ml approach: SML setting

Automated, Stateful Training

With stateful training, you continue training your model on new data instead of retraining your model from scratch. The process of updating a ML is **automated.**



Stateless retraining vs Stateful training



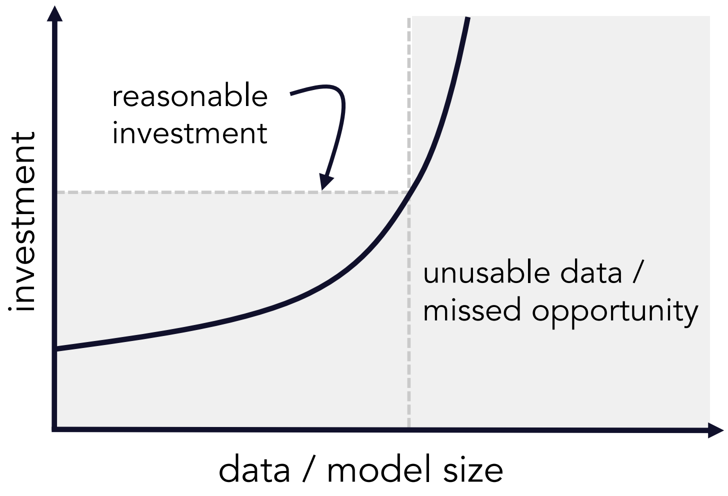
Grubhub, after switching from stateless daily retraining to stateful daily learning, obtained **45x cost decrease**.

Alex Egg. 2021. Online Learning for Recommendations at Grubhub. Fifteenth ACM Conference on Recommender Systems. Association for Computing Machinery, New York, NY, USA, 569–571.

Cost investment of AI processing

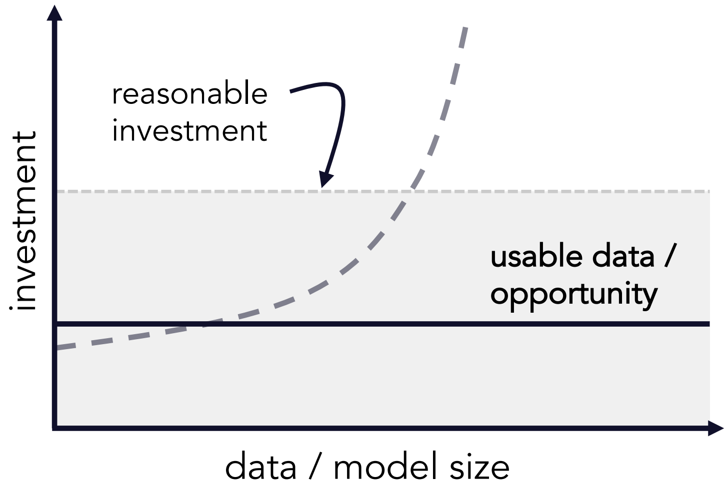
Current AI processing

Often struggles to maintain investment (time, memory, cost) below reasonable level



motus.ml AI processing

Efficiently generates incremental models from data streams

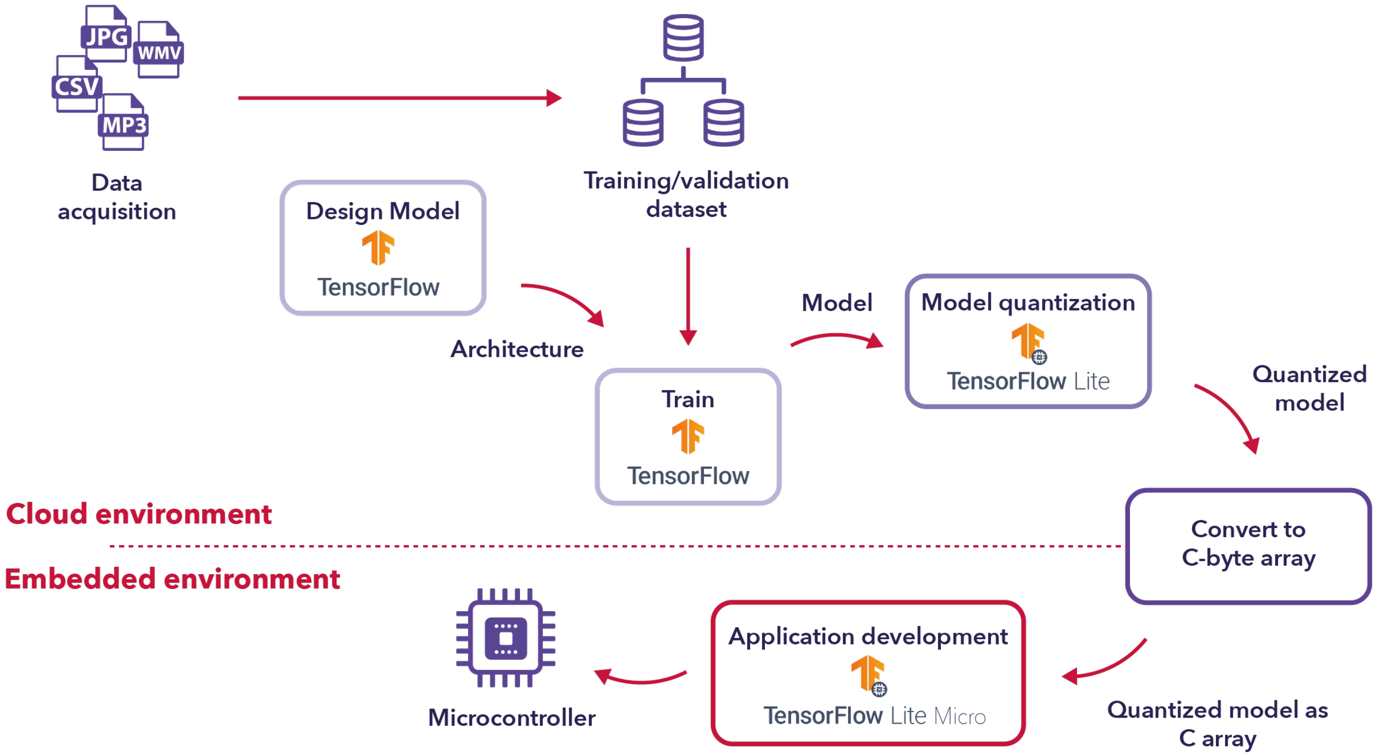


SML in a nutshell

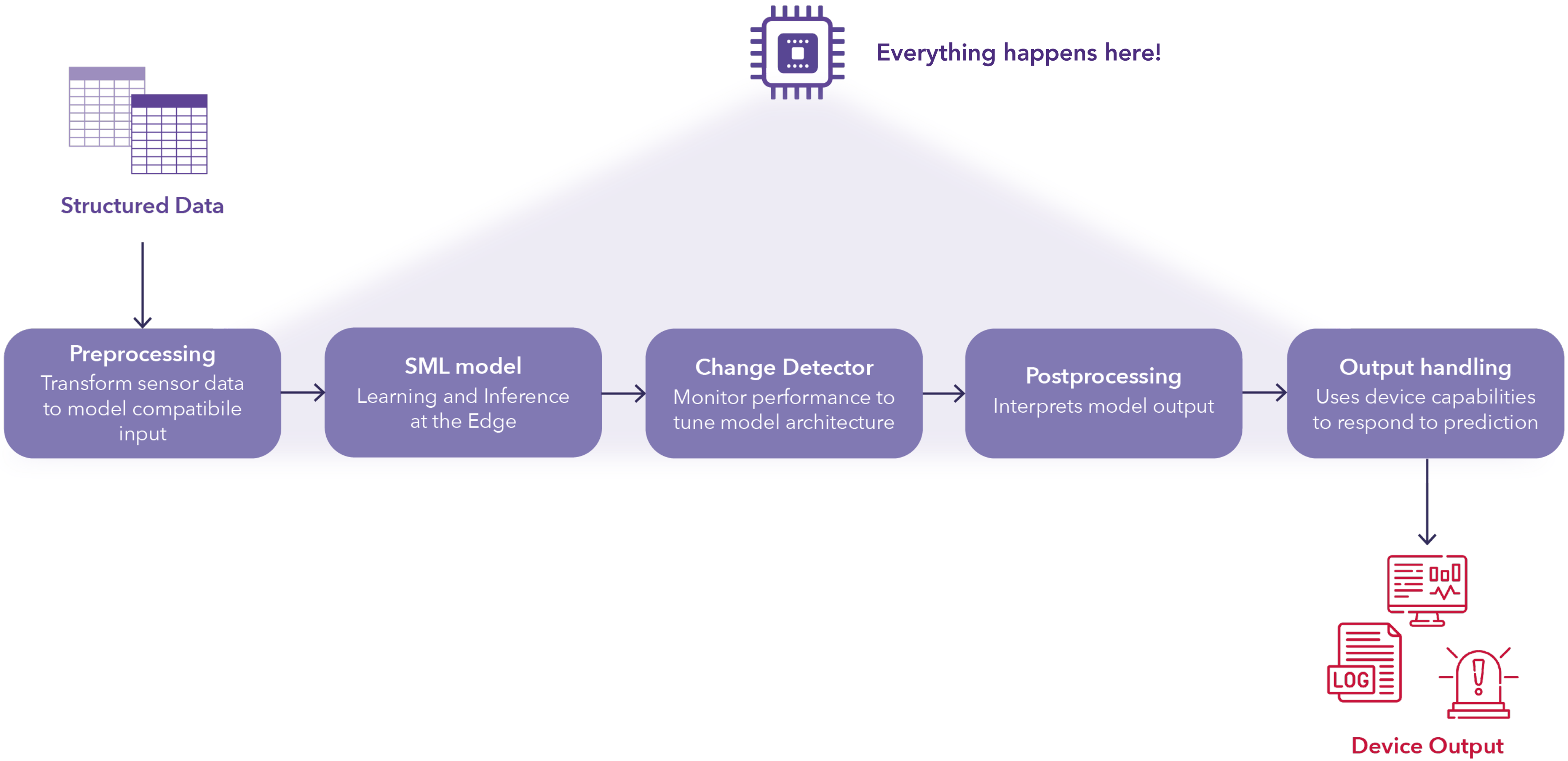
- SML can be applied to **unbounded real-time data**
- **Incremental learning**: SML models can incorporate data on the fly, i.e., one sample at a time
- SML techniques are **resource efficient**
- **Dynamic models**: can work in non-stationarity environment

Learning & Inference @ Edge

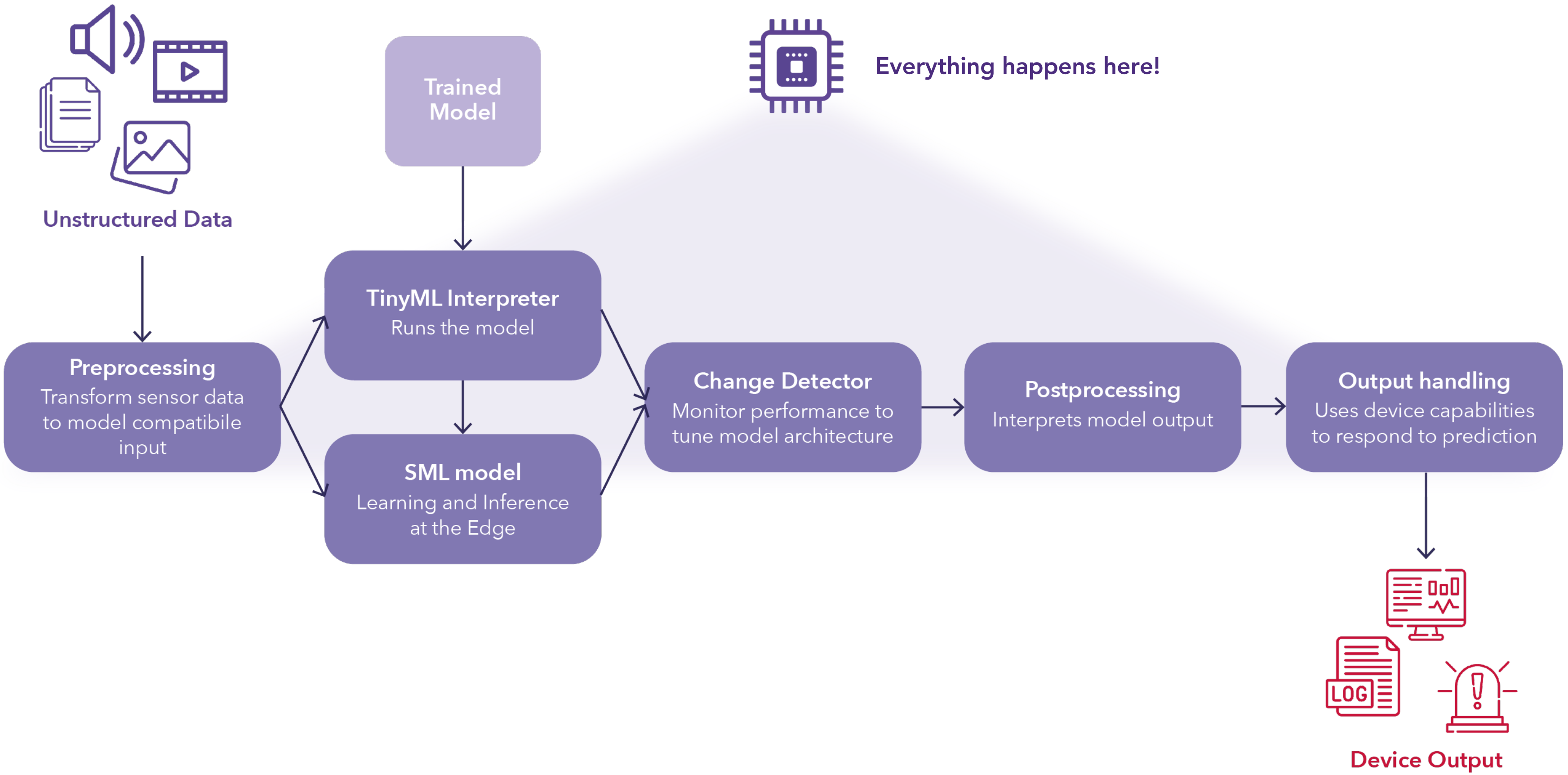
TinyML pipeline



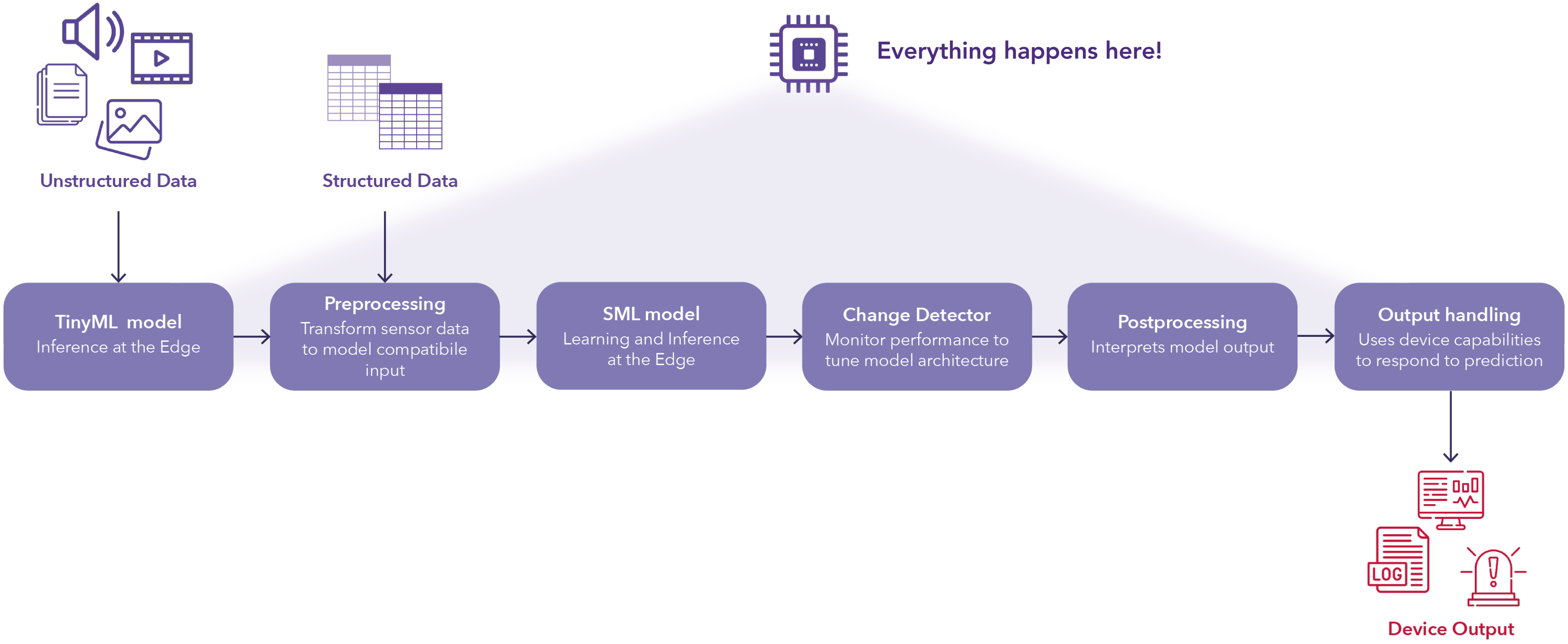
Pipeline for structured data



Pipeline for unstructured data



Pipeline for streaming data



Performance of SML@Edge

Edge device: Raspberry Pi4b, Quad core Cortex-A72, 4 GB RAM

On-device performance (inference + training on-device)

PEAK LATENCY

0.1 ms

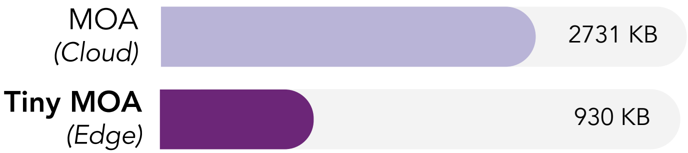
THROUGHPUT

80.7k inst/sec

ACCURACY

No loss w.r.t. cloud

Software Library



MEMORY USAGE

- 66% lighter

Use Cases

Predictive Maintenance

1

Sensors

The first step is having high quality sensors that are streaming live data. Sensors will ideally be collecting a wide variety of metrics, without bias.

2

Data Communication

The next critical component is a secure system by which data can flow between assets and the motus.ml algorithms.

3

Edge-based Predictive Analytics

Powered by novel streaming artificial intelligence, motus.ml algorithms will ingest, aggregate and synthesize data, with the ability to recognize complex patterns and generating detailed insights.

4

Time to Failure and Root Cause

Predictions will provide time-to-failure and root cause analysis alerts and insights. This will ease a quick identification of the action required for predictive maintenance.

5

Increased Uptime

With motus.ml you can eliminate unscheduled maintenance and instead plan for it with optimal material and staff resourcing, resulting in increased productivity and profits.

Maintenance of broadcasting antennas

Remote locations

Limited internet connection

High maintenance cost

Maintenance of radio navigation technologies (DME)

Sensible data

High site variability

High speed of intervention

Water Network Optimization

On-site specialized solution

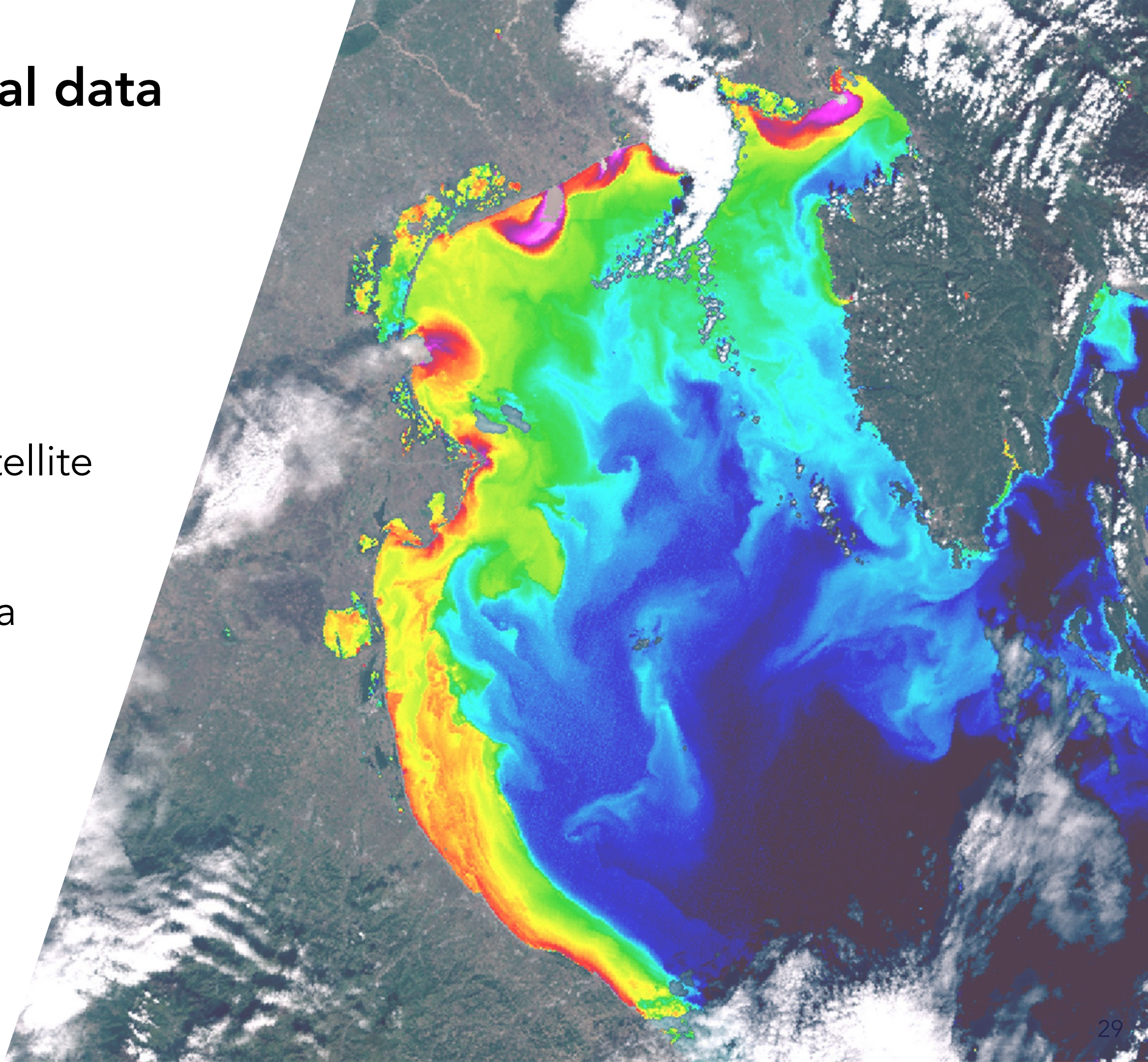
Water flow control

Preventing flooding

Analysis of environmental data

Use motus.ml to analyze environmental data:

- unstructured data (video, satellite images)
- flood, sea, tide, weather data



Conclusion

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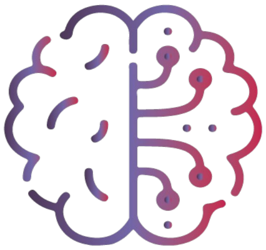
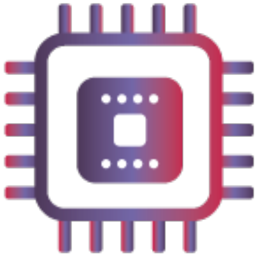


Detachable Artificial Intelligence

- Time critical inference
- Limited to no network access
- On-site specialized AI



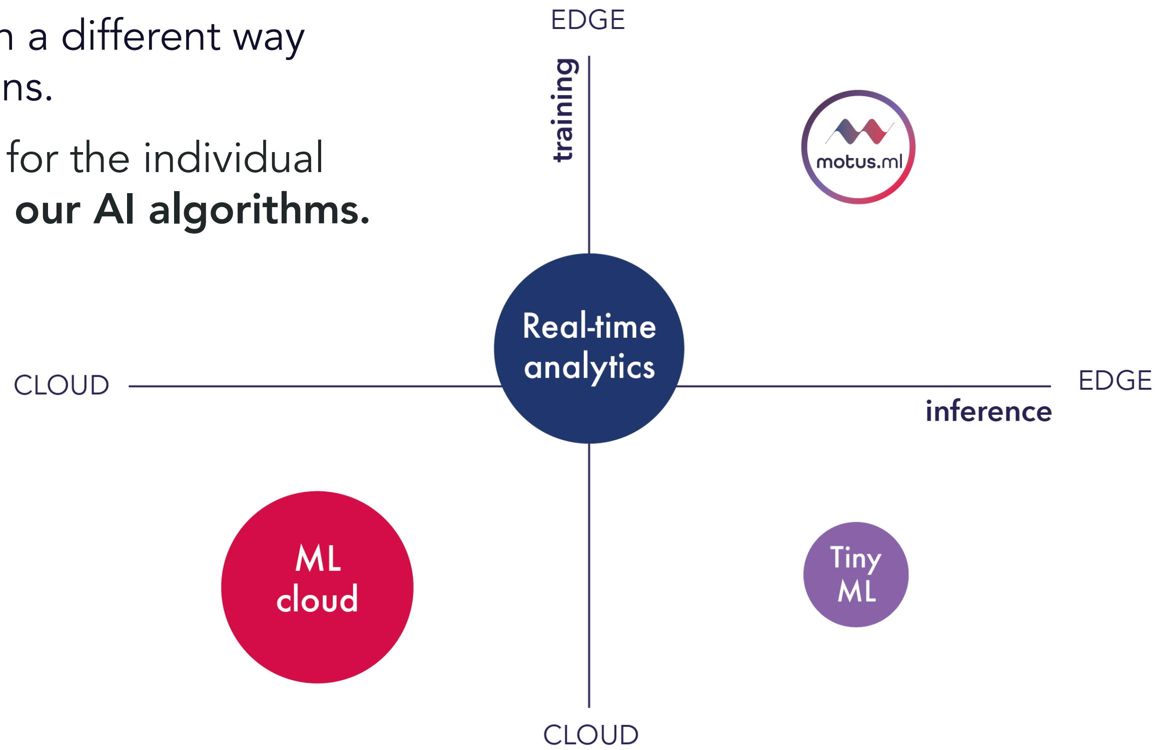
Resource-constrained Hardware

- Suitable for any device (MCU & MP)
- Modular architecture
- OS agnostic

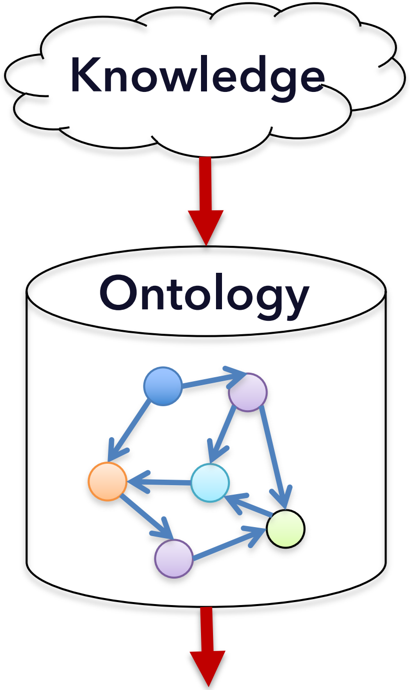
What makes motus.ml unique

motus.ml offers the solution for **IoT automation** by using machine learning in a different way compared to current solutions.

We can learn what's normal for the individual device by **running onboard our AI algorithms.**

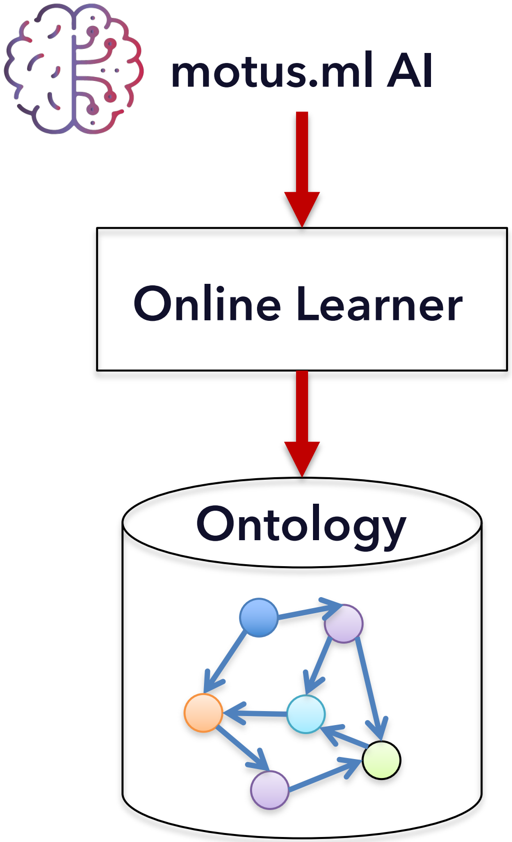


motus.ml + Stream Reasoning



Query

```
PREFIX : <ontology/>
SELECT ?s
```



motus.ml’s team

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