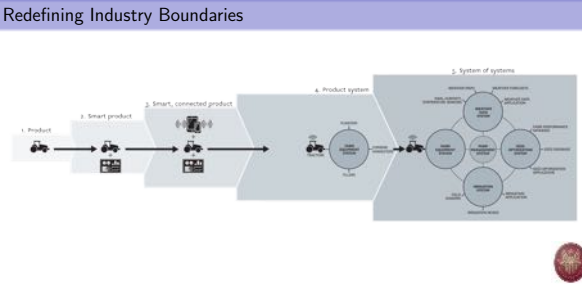
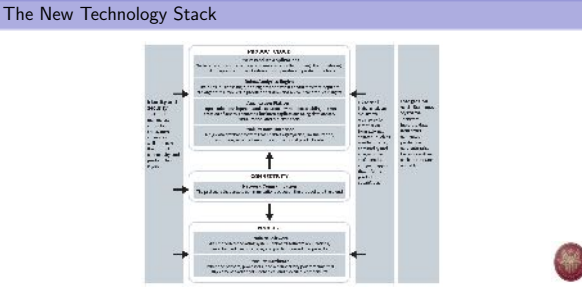


Redefining Industry Boundaries



The Value of Sensor Data

The New Technology Stack



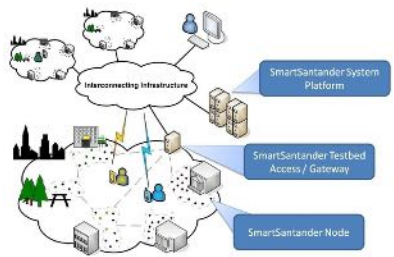
SmartSantander: A City-Scale IoT Infrastructure



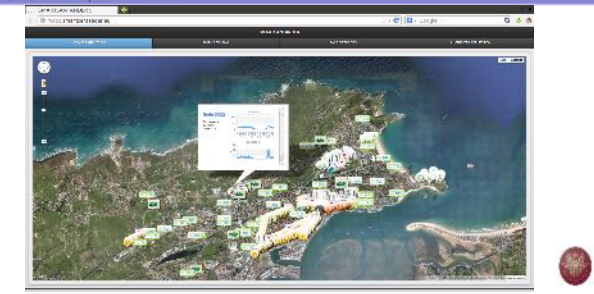
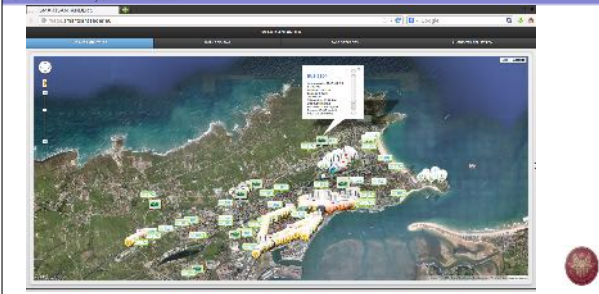
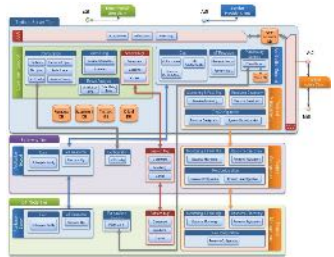
- City-scale IoT deployment.
- 18,000 sensing points.
- Outdoor deployments, Mobile nodes, Human interaction.
- Integrated City Services – Continuous operation.
- Large variety of sensors – Large data.
- Business models and sustainable exploitation combining research & service support.

2010 ... 2013 – FP7-ICT-2009.1.6 - Future Internet experimental facility and experimentally-driven research.

Platform Architecture & Services



Platform Architecture & Services



Data gathering: a general problem

- It is impossible to reach every corner of every neighborhood in the city.
- Even if you choose to do it . . .
- We need a secure, reliable infrastructure that enables interconnectivity and scale.
- Building this infrastructure is difficult, expensive and time-consuming.
- Maintenance of such an infrastructure is expensive and requires continuous investments.

- Water:** "U.N. has a limited success to get accurate information on water infrastructure and treatment systems".
 - Poor data, weak agencies hamstring U.N. environmental oversight, NY Times, 2009.
- Food:** "Agricultural statistics has deteriorated over time" - weak estimation of global rice/wheat productions - fisheries data outdated.
 - Food and Agriculture Organization, Audit 2009.
- Health:** "Exposure measures are sometimes completely lacking, frequently incomplete or otherwise uncertain".
 - Uncertainty and Data Quality in Exposure Assessment, World Health Organization, 2008.

An Example: Monitoring Pollution

- Important environmental issues in cities
- (long term) health, social and economic impacts
- An increasing problem, especially in developing countries
- Growing public concern & effort (European Directive -2002)
- but limited success of environmental policies.
- Complexity of monitoring the real exposure of the population.



Los-Angeles

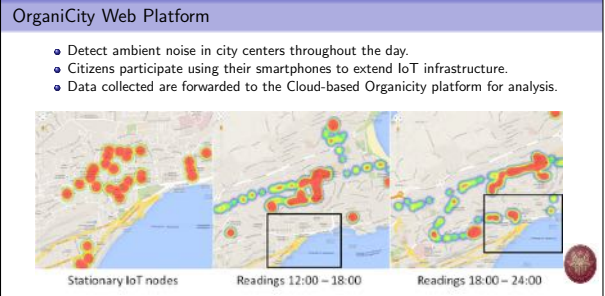
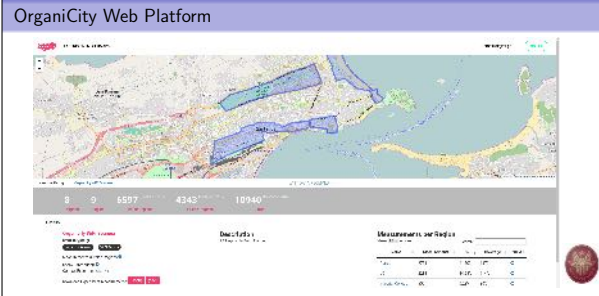
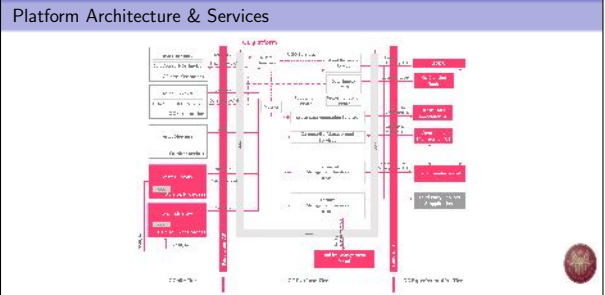
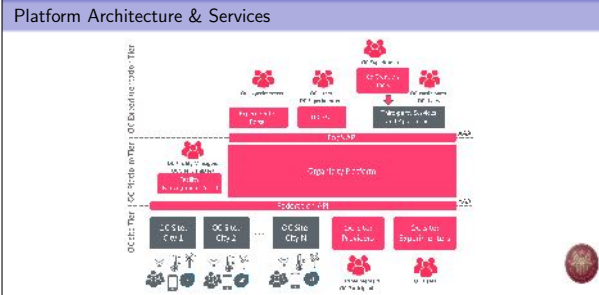


Mumbai

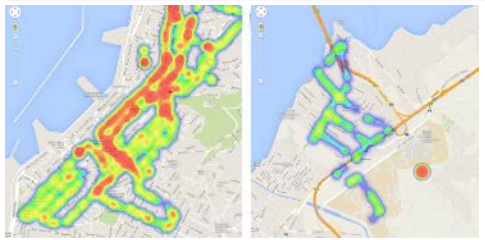
OrganiCity: Enabling Co-Creation of Smart City Services

- Expand IoT facilities by involving People: **Participatory Sensing**
- Access to powerful, rich-sensor smartphones.
 - Use sensors for gathering quantitative information.
 - Use people as sensors for gathering qualitative information.



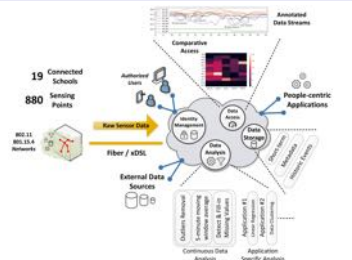


OrganiCity Web Platform



City center (left) and suburb/campus (right) average noise levels between 18:00-24:00

Platform Architecture & Services



GAIA: Green Awareness in Action

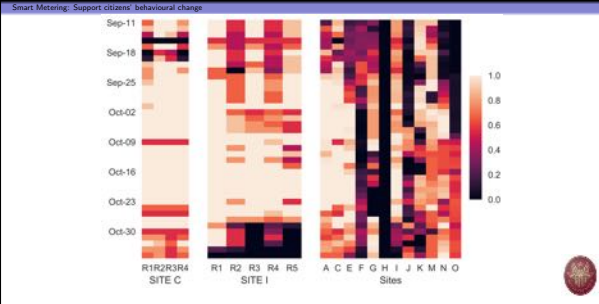
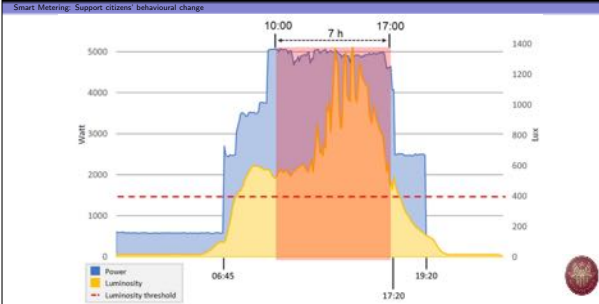
- Educational buildings constitute 17% of the non-residential EU building stock
- Wide variety of buildings of different ages (some built around 1950s)
- Expensive to renovate existing buildings
- Affect the behavioral characteristics of the buildings users.



2016 ... 2019 - H2020-EU 3.3.1 - Reducing energy consumption and carbon footprint by smart and sustainable use.

Platform Architecture & Services





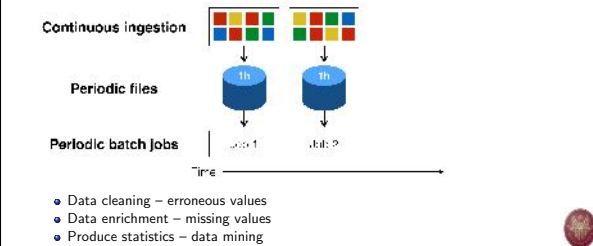
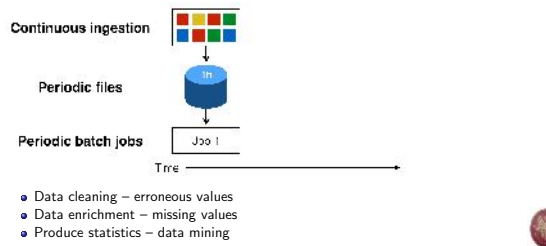
It's all in the Cloud



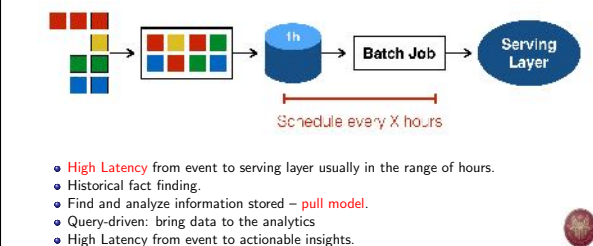
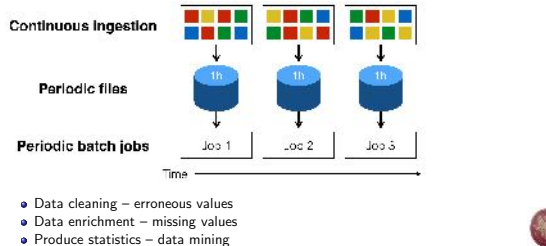
Today's Cloud and its Characteristics

- Common Characteristics:
- Massive Scale
 - Homogeneity
 - Virtualization
 - Low Cost Software
 - Resilient Computing
 - Geographic Distribution
 - Service Orientation
 - Advanced Security
- Essential Characteristics:
- On Demand Self-Service
 - Broad Network Access
 - Resource Pooling
 - Rapid Elasticity
 - Measured Service

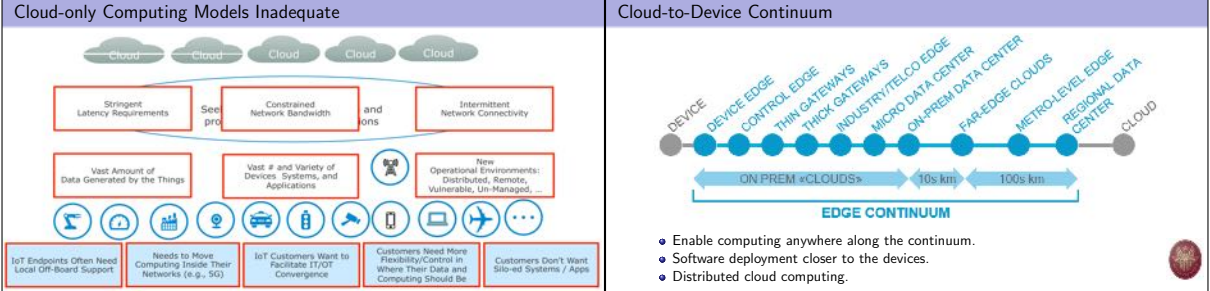
Batch processing of IoT Data



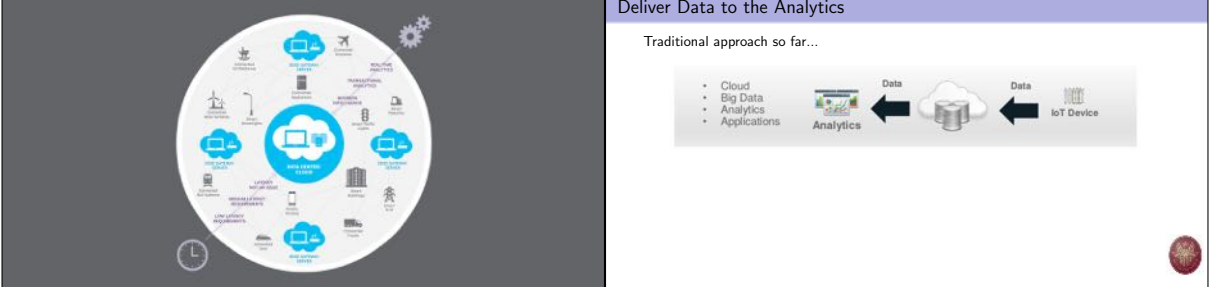
Batch processing of IoT Data



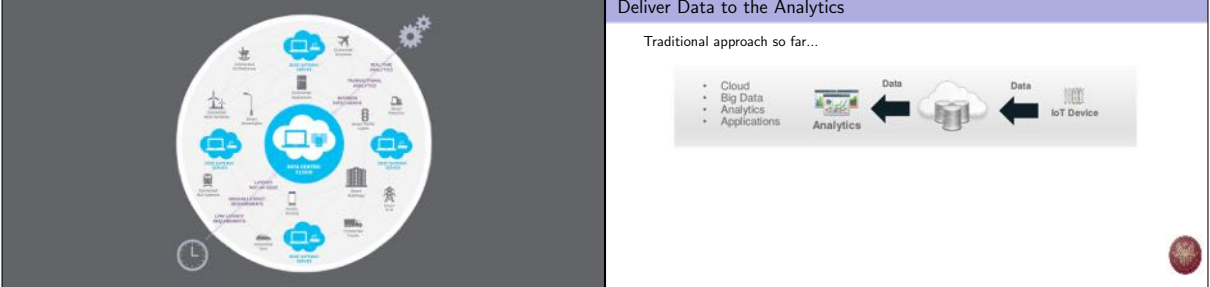
Cloud-only Computing Models Inadequate



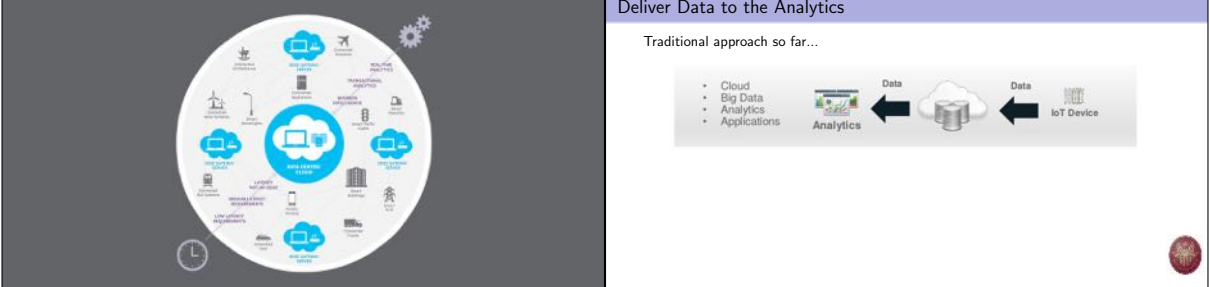
Cloud-to-Device Continuum



Deliver Data to the Analytics



Deliver Data to the Analytics



Analyze Data in the Right place

Traditional approach so far...

- Cloud
- Big Data
- Analytics
- Applications

Fog computing: distributed analytics from Cloud to Source

Heterogeneity Challenges in Cloud-to-Device Continuum

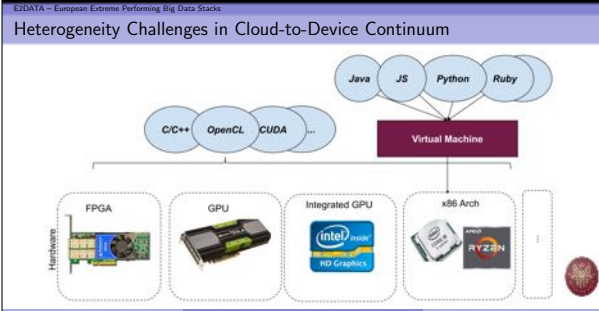
CPU	GPU	FPGA
Intel Ice Lake (10nm) 8 cores HT, AVX512 SIMD ~1TFlops* (including the iGPU) ~ TDP 28W	NVIDIA GP 100 – Pascal - 16nm 60 SMs, 64 cores each 3584 FP32 cores 10.6 TFlops (FP32) TDP ~300 Watts	Intel FPGA Stratix 10 (14nm) Reconfigurable Hardware ~ 10 TFlops TDP ~225Watts

Stream-based Data Processing

- Stream-based processing is enabling the obvious: continuous processing on data that is continuously produced.
- Current fact finding – Monitor data and react in real time.
- Analyze data in motion – push model
- Data-driven: bring analytics to the data
- Low Latency from reception of event to actionable insights.

Heterogeneity Challenges in Cloud-to-Device Continuum

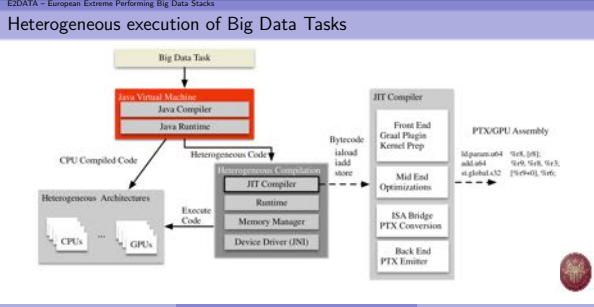
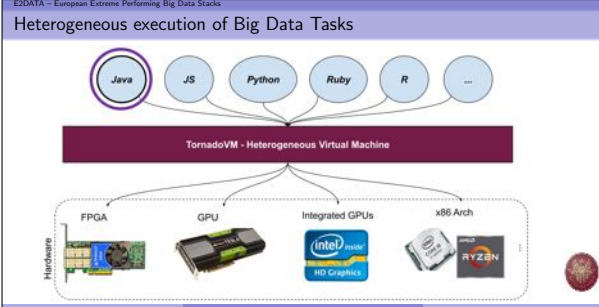
The diagram illustrates the heterogeneity challenges in a cloud-to-device continuum. It shows a CPU with its own cache and a Northbridge Memory controller connected to Main Memory. The CPU is connected via PCI-e to a GPU, which has its own cache and Global Memory. The GPU is also connected via PCI-e to an FPGA, which has its own Global Memory. This setup highlights the challenges of data movement and processing across different hardware architectures.



Heterogeneity Challenges in Cloud-to-Device Continuum

- Today a variety of mature stream processors are available: Flink, Spark
 - Data analytics stacks cannot exploit heterogeneous hardware dynamically.
 - Rely on existing, pre-compiled operators or kernels for specific HW resources.
- Enabling dynamic compilation of arbitrary code to any* heterogeneous hardware device.
- Designing an intelligent elastic system where applications are executed on the best hardware resource


2018 ... 2020 - H2020-ICT-16-2017 - Big data PPP: addressing technology challenges of the data economy.



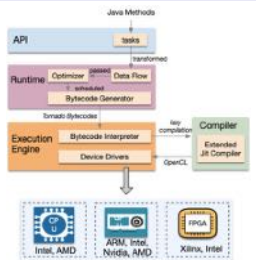
Heterogeneous execution of Big Data Tasks


```

public static void matrixMultiplication(final float[] A, final float[] B,
                                       final float[] C, final int size) {
    for (@Parallel int i = 0; i < size; i++) {
        for (@Parallel int j = 0; j < size; j++) {
            float sum = 0.0f;
            for (int k = 0; k < size; k++) {
                sum += A[(i * size) + k] * B[(k * size) + j];
            }
            C[(i * size) + j] = sum;
        }
    }
}
    
```



Fog-Computing based Smart Metering




- Data Analytics stack executed directly over TornadoVM.
 - Suitable for applications that require hardware acceleration but do not benefit from or fit a Big Data framework.
 - Enables hot swapping of underlying runtimes with TornadoVM.
- 

Fog-Computing based Smart Metering

Performance Evaluation

- On average 15 sensing devices are available on each school.
- Each of them is equipped with 1 to 5 sensors.
- Sensing rate is 30sec thus on average each edge device is receiving 2.5 sensor updates every second.

	ARM	Intel	Intel Xeon
Processor	Cortex-A53	i3-3120M	E5-2630V4
Frequency	1.2Ghz	2.2Ghz	2.2Ghz
Cores	4	2	8
Memory	1 GB	8 GB	24 GB
Disk	64GB	120GB	600GB
Type	SD Card class10	SSD	SSD



Performance Evaluation

- Data engineering over windows of data
 - Min/Max/Average/Sum.
 - Outliers Detection with a Hampel Filter.
- Maximum number of messages processed per second

Device	Processing Rate (Msg/Sec)
Cortex-A53	15,36
i3-3120M	2,692.31
E5-2630V4	5,833.33

- Processing time per message (Sec)

Service	Cortex A53	i3-3120M	E5-2630V4
Window Setup	1.620	0.016	0.004
Data Engineering	63.817	0.186	0.145

Performance Evaluation

- Tesla V100-SXM2-32GB GPU available on the Intel Xeon.
- Data engineering over windows of data
- Speed-up from 75x to 449x

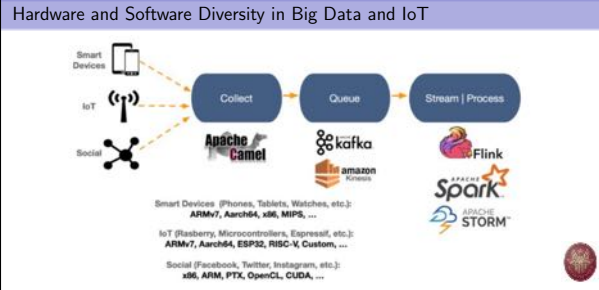
Green Buildings TomadoVM Kernels Runtime on Tesla V100-SXM2-32GB

Performance Evaluation

- AArch64 Mali G71 MP8 GPU available on the ARM Cortex-A.
- Data engineering over windows of data
- Speed-up from 3.5x to 9.3x

Green Buildings TomadoVM Kernels Runtime on Mali G71 MP8

Hardware and Software Diversity in Big Data and IoT



Hardware and Software Diversity in Big Data and IoT

- Big Data and IoT have separate development routes
 - Diversification of the programming models
 - Big Data – Map/Reduce paradigm
 - IoT – Event-driven
 - Lack of interoperability
 - Big Data – Java/Python
 - IoT – C/C++
- Big Data and IoT have separate orchestration approaches
 - Cannot dynamically select which parts of the code should run on which side
 - Big Data – Rich orchestration tool-chain
 - IoT – Limited to Over-The-Air-Programming

Hardware and Software Diversity in Big Data and IoT

Big Data
Apache Flink Existing Java Operator

```

Dataset<...> stream = ...
Dataset<...> sorted = stream
    .sortPartitions(8, Order.ASCENDING);
    
```

Edge

ARM, x86 C Code

```

int values[] = {...};
int compare(void * a, void * b) {
    return *(int*)a - *(int*)b;
}

int main () {
    qsort(values, 5, sizeof(int), compare);
    return 0;
}
    
```

Espressif MicroPython Code

```

array = [...]
def partition(array, begin, end):
    pivot = begin
    for i in range(begin+1, end+1):
        // Split array
        array[pivot], array[i] = array[i], array[pivot]
    return pivot

def quicksort(array, begin=0, end=None):
    if end is None:
        end = len(array) - 1
    def _quicksort(array, begin, end):
        pivot = partition(array, begin, end)
        _quicksort(array, begin, pivot-1)
        _quicksort(array, pivot+1, end)
    return _quicksort(array, begin, end)
    
```

Secure and Seamless Edge-to-cloud Analytics

- Developers will be able to view an IoT/Big Data deployment as a single system.
- Provide a unified API for data operators
 - Can be executed on both the IoT devices and the data analytics side.
 - Using a uniform orchestration process.
- Intelligent orchestration of code motion between IoT and cloud analytics
 - Gather profiling information of all devices
 - Gather profiling information of all data operators
 - Scheduling decisions regarding execution
 - Instruct code motion

Secure and Seamless Edge-to-cloud Analytics

```

graph TD
    subgraph IoT_Side [IoT Side]
        IoT_API[IoT-customized API]
        ELEGANT_IoT[ELEGANT Elastic Runtime (IoT mode)]
        IoT_Devs[IoT Devices]
        IoT_API --> ELEGANT_IoT
        ELEGANT_IoT --> IoT_Devs
    end

    subgraph Big_Data_Side [Big Data Side]
        Flink_API[Vanilla Apache Flink API]
        Flink_Exec[Apache Flink Execution]
        ELEGANT_High[ELEGANT Elastic Runtime (High-Execution mode)]
        Cloud_Dep[Cloud Deployment]
        Flink_API --> Flink_Exec
        Flink_Exec --> ELEGANT_High
        ELEGANT_High --> Cloud_Dep
    end

    IoT_Devs --> DF[Data Flow representation]
    DF --> EO[ELEGANT Orchestrator (Scheduling and Optimizations)]
    EO --> Flink_Exec
    EO --> ELEGANT_High

    subgraph ELEGANT_API [ELEGANT API (Java based similar to Apache Flink interface)]
        Stream_map[Stream.map() reduce() complex logic]
    end
    subgraph ELEGANT_IoT_Runtime [ELEGANT Elastic Runtime (IoT mode)]
        Stream_map_IoT[Stream.map() reduce() complex logic]
    end
    subgraph ELEGANT_High_Runtime [ELEGANT Elastic Runtime (High-Execution mode)]
        Stream_map_High[Stream.map() reduce() complex logic]
    end
    
```

Our Vision: Unify IoT and Big Data fragmentation concerns

- Utilize such software and hardware diverse deployments as a single system
 - Heterogeneous hardware capabilities
 - Operate on demand depending on their specific use case requirements
- Enable computing anywhere along the continuum
 - Not just at specific edge devices.
 - Using a uniform execution environment.
- Orchestrate resources in clouds, fogs, and devices
 - Not just at isolated edge devices, systems, or apps
 - Using a uniform orchestration process.



... could be analogous to previous Internet revolutions



Thank you!

Questions ?

