





Al between the Edge and Cloud Leveraging IoT and Analytics for Smart Cities

Cloud Computing

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Me and my research

Josep Lluís Berral García, from Barcelona and BSC

Education at UPC:

- 2007 Informatics Engineer
- 2008 Master on Computer Architecture
- 2013 PhD on Computer Sciences → ML + HPC



Away from academia:

- Attempt to create a Digital Goods Distribution Platform → Didn't go far ⊗
- Work in Industry, as QA on Medical Machinery

Back to research:

- BSC-UPC with David Carrera (2014)
- Activity Leader for "Applied Machine Learning"
- Teaching and Advising PhD + Master students
- Data Mining/Machine Learning
- Operating Systems
- Computer Engineering



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Introduction

1. Deploying the Smart City

- User and Citizen-centric services
- Internet of Things → Computation in local & personal devices

Data Analytics

- Data from users/systems → Analytics and AI models
- ... for systems optimization/research/business



Introduction

Edge Computing

- Move the data processing and analytics to devices close to data source
- Avoid transmission of sensitive data
- Amortize computing power in local devices
- Provide faster services

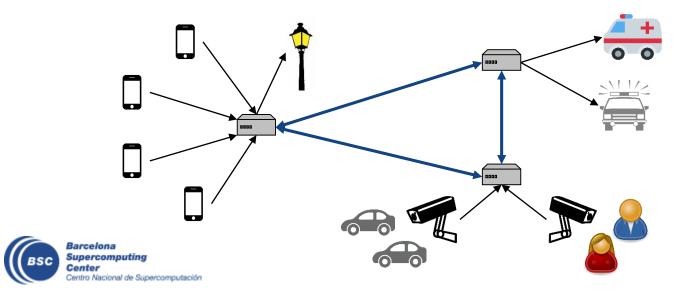
4. Distributed Analytics

Federated Machine Learning paradigms



Smart Cities

- Smart Cities
 - Use of technology to improve citizen services
 - From reducing consumption of street lights...
 - ... to provide emergency assistance to private citizens in the street
 - Pervasive Computing
 - Everything has a computer
 - ... and sensors also actuators
 - Also users → mobile devices
 - Services collect data from users to optimize city services



Internet of Things

- Everything has a Computer
 - Edge Devices → Devices collecting data, or close to data
- Edge Devices
 - Low power → Computing and Consumption
 - Unreliable → May disconnect, private devices, ...



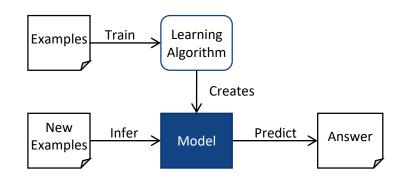
- IoT vs the Cloud
 - Devices connect to send information and receive instructions
 - Change of Paradigm: Edge Computing



Analytics, AI and Machine Learning

"Collecting data from devices for what?"

- Data Analytics
 - Extract information
 - Learn the behavior of the system/users/vehicles/...
 - Then improve the system/make profit
- Machine Learning
 - Automatic modelling
 - Learn from examples
 - Create a prediction model
 - Knowledge discovery & Data mining
 - Extract patterns from data



- Artificial Intelligence
 - Automatization of decisions and management
 - ... including Analytics and Learning services

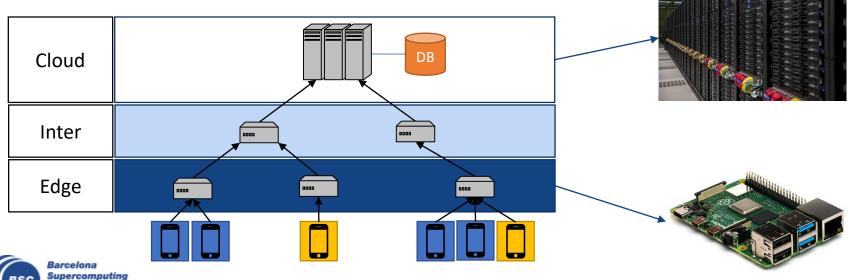


Edge-Cloud Architecture

- The Cloud:
 - High performance nodes
 - Concentrate data computing in "far-away" data-centers
- The Edge:
 - Low power nodes

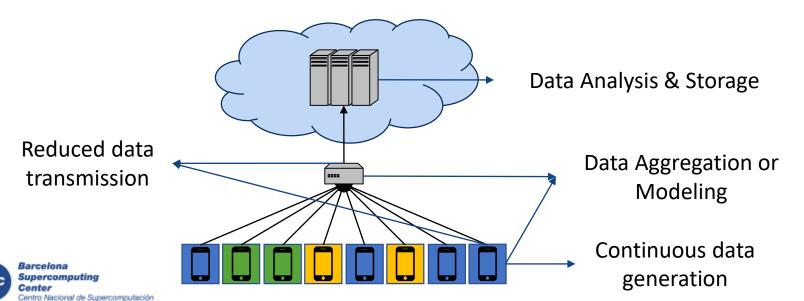
entro Nacional de Supercomputación

- ... or personal devices and appliances
- It is where all data is collected



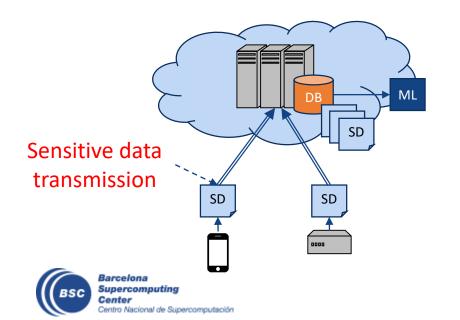
Analytics in the Edge

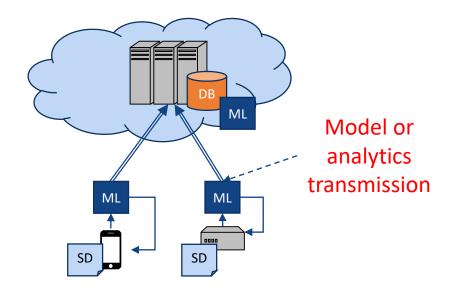
- Efficiency
 - Keeping important data
 - Edge devices aggregate local data
 - Only transmit aggegated data ← usable for analytics
 - Raw data ← can be discarded from origin
 - Service to users
 - User data and analytics/aggregation remain local
 - Energy
 - Edge devices are "always" on-line and low-power. Most of the time, power is amortised



Analytics in the Edge

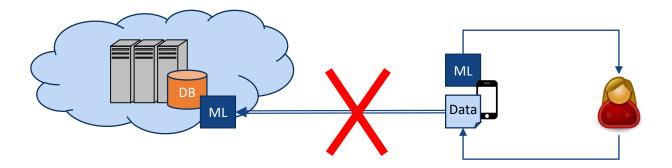
- Privacy
 - Aggregation:
 - Allows anonymization
 - Done in Edge devices or personal devices
 - Sensitive data:
 - Analytics and models are created without transmitting it
 - Companies and government can get informationabout users without it
 - User decides which data is shared, without altering the service





Analytics in the Edge

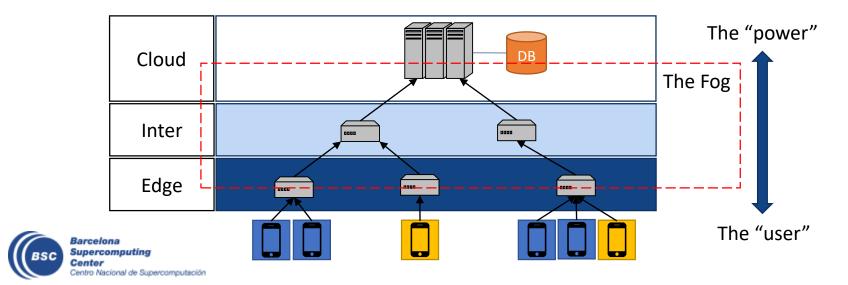
- Autonomy
 - Services for User
 - ... can work in local devices.
 - The user does not need to be constantly connected
 - Network disconnection
 - Local devices keep aggregated data and local analytics
 - Local services can keep working
 - Transmission of aggregated data
 - ... is resumed when connection restablishes





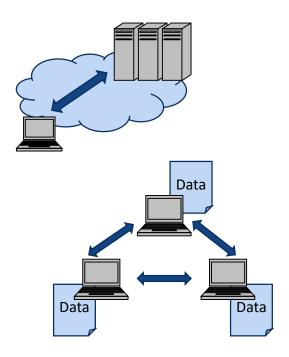
Leveraging Edge-Cloud

- Upward: more power required
 - Lower nodes = Low Power
 - Higher nodes = High Performance
- Lateral: off-loading
 - Unused sibling nodes ← send over-load
- Downward: network/space reduction
 - Higher nodes = More communication / Data-warehousing
 - Lower nodes = Less Network Usage & Lower Latency (Edge Services)



Distributed Analytics

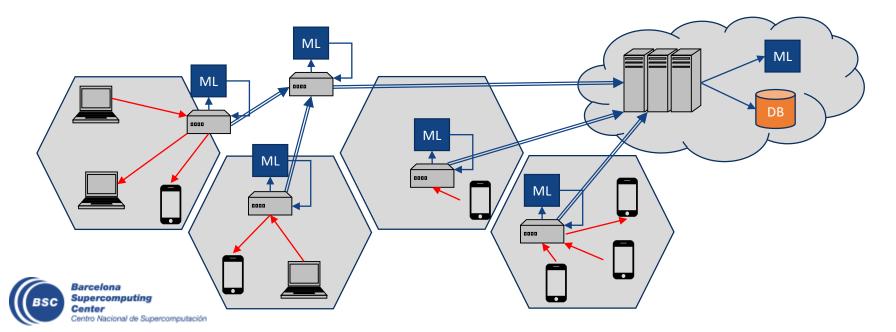
- Analytics:
 - Either general analytics
 - ... or Machine Learning and Al
- Distribution of ML
 - "Where to run Al"
 - Centralized HPC centers
 - Reunion of low-power computing devices
 - Federated Learning
 - "How to share data & efforts"
 - Beware privacy!
 - Beware scarce computing resources!





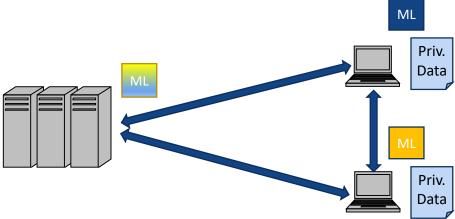
Federated Learning

- Until now:
 - Centralization (Cloud) collects data and models it
 - Models are passed down (if needed)
- Federated Learning
 - Each local node models its data
 - Transmit and query data/models only when necessary
 - Local autonomous nodes



Federated Learning

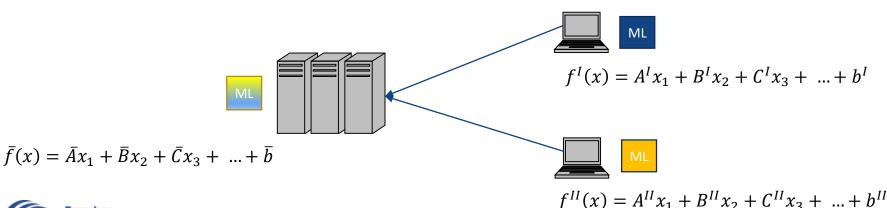
- Distribution of ML load
 - Share analytics/modelling efforts
 - Create local models
 - Share the local models
 - Keep data private in local environments
 - Model aggregation
 - Instead of aggregating data on the Cloud
 - ... aggregate models on the Cloud
 - ... or in neighbor environments (e.g. P2P systems)





Model Aggregation

- Machine Learning models
 - Statistical learning: functions and data representations
 - Neural Networks: matrices and vectors
- Aggregate models
 - Find the average function
 - Find the average matrices and vectors
 - Ensemble models and decide which to keep





New Technologies for Edge + Al

Low-Power Devices

Machine Learning on Limited Environments, and Enhanced Edge Devices



Research:

- Discovering the real limitations vs. advantages of such devices
- Trade-offs between modeling Near-Data vs Near-Power

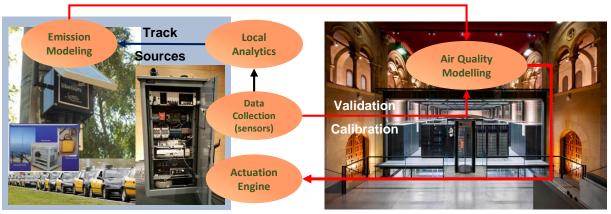


Use case: Traffic and Mobility

Modelling of road traffic towards emissions using Deep Learning

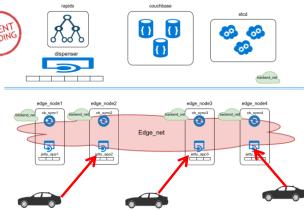
Emission modelling and forecasting based on deep learning





Use of Time Series NNs (Conditional RBMs, ...)

- Discovering traffic characteristics over time
- Input:
 - Floating Car Data (position, speed...)
 - Time/space aggregation
- Output:
 - Future traffic status in certain locations

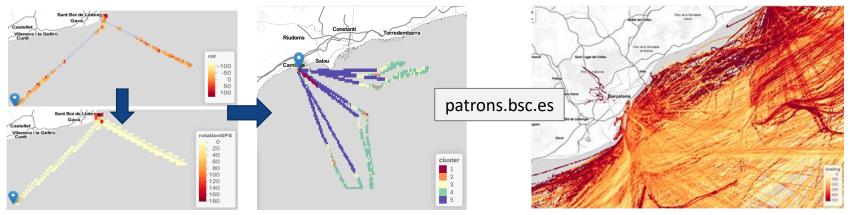




Use case: Maritime Traffic Modeling

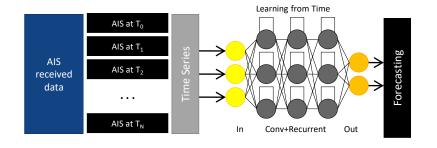
Modelling of Maritime emissions using Deep Learning

Emission modelling and forecasting based on deep learning



Use of CNNs (Convolutional-LSTMs and 3D convolutional NN)

- Learning patterns and forecasting
- Input:
 - AIS traces (position, operation...)
 - Emission modeling (Jalkanen)
 - Time/space aggregation
- Output:
 - Future position and emissions

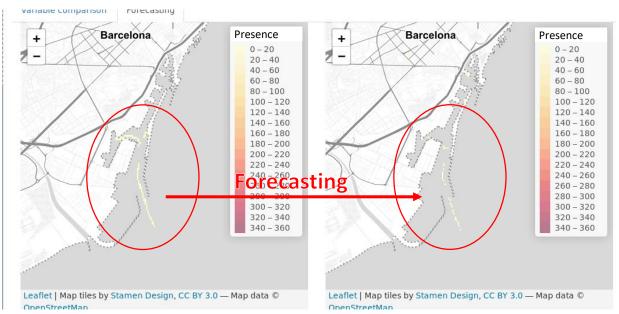




Use case: Port Forecasting

Visualization & Forecasting Tools

Emission modelling and forecasting from AIS & Fog-Computing



Work in Progress:

- Forecasting of occupation and emissions in port vicinity
- Applicability of these techniques to road traffic
 - More complex/chaotic environment



Challenges on Analytics in the Edge

- AI in Exa-Scale & Extreme-Scale analytics
 - Large amounts of data
 - Large amounts of models to run
 - Continuous arrival of new data to process
- Distribution of Analytics
 - Advances of Edge vs Cloud computing
 - Newly arrived Federation of learning models

Preserve Privacy:

- Legal and Ethical restrictions on data and models
- Frameworks & methods to share results without sharing data and models

Maintain Performance:

- Technical restrictions on AI processes, also low resource availability
- Frameworks & methods to share load from experiments



Summary

- Smart Cities and IoT
 - Devices everywhere, collecting data, to manage everything
- Edge Computing
 - Performing analytics, aggregations, models, processing... on near-data devices
- Federated Learning
 - Distributing machine learning processes and load
 - Avoid transmission of sensitive data
- Some examples
 - Analysis of road and maritime traffic
 - Analysis of air quality
 - De-centralised and everywhere-available citizen services

