sigfox

Machine Learning in IoT

Olivier Isson

Data Science

Contents

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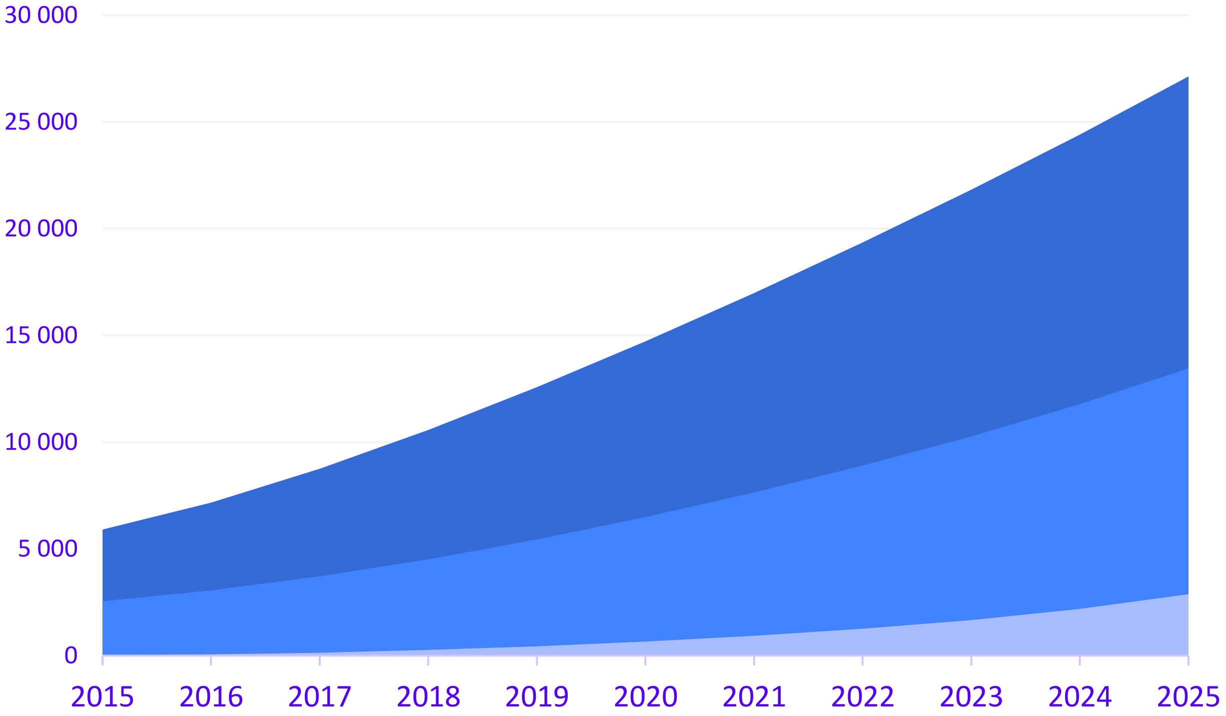
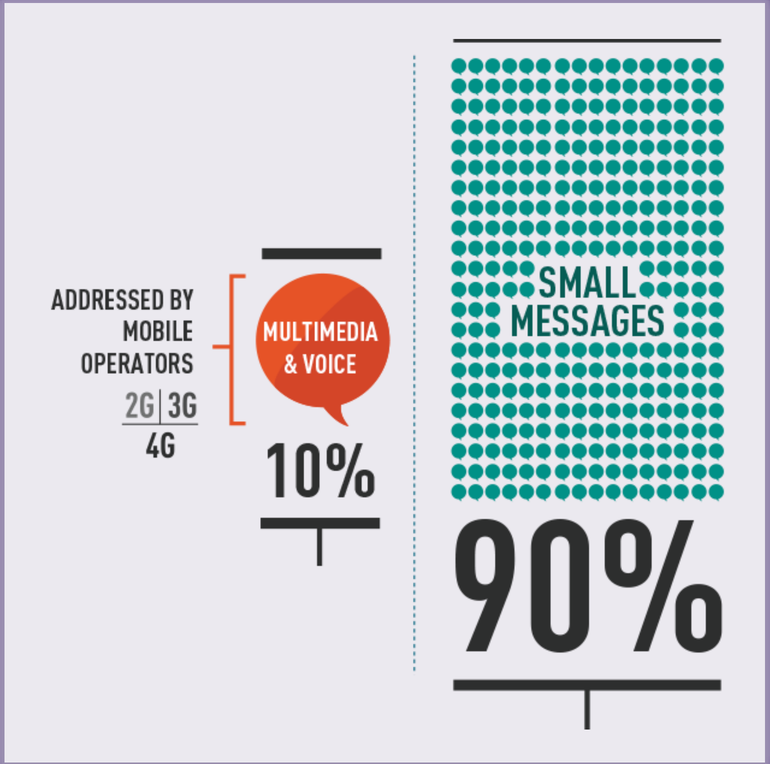
IoT - Sigfox

IoT market size worldwide



Source: Machina Research

The Internet of Things needs its Twitter!



IoT applications need

- ✓ small messages
- ✓ low cost
- ✓ low battery

2G, 3G and 4G are not optimized for IoT

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Small messages…

- ✓ **6 bytes**: GPS coordinates

  Location report with below 3m precision (GPS technical accuracy is above 3m)

- ✓ **2 bytes**: temperature reporting

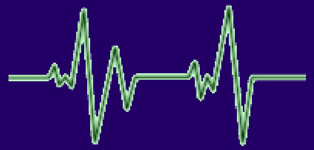
  Lab thermometer with -100°/+200° range, 0.004° precision

- ✓ **1 byte**: speed reporting

  Speed Radar up to 255km/h

- ✓ **1/8 byte**: object state reporting

  Switch report like set in day/night, hot/cold, on/off



- ✓ **0 byte**: heartbeat

  Object is in working state, battery is OK….

- ✓ **0 byte**: Request for duplex operation

  Do you have some information for me?

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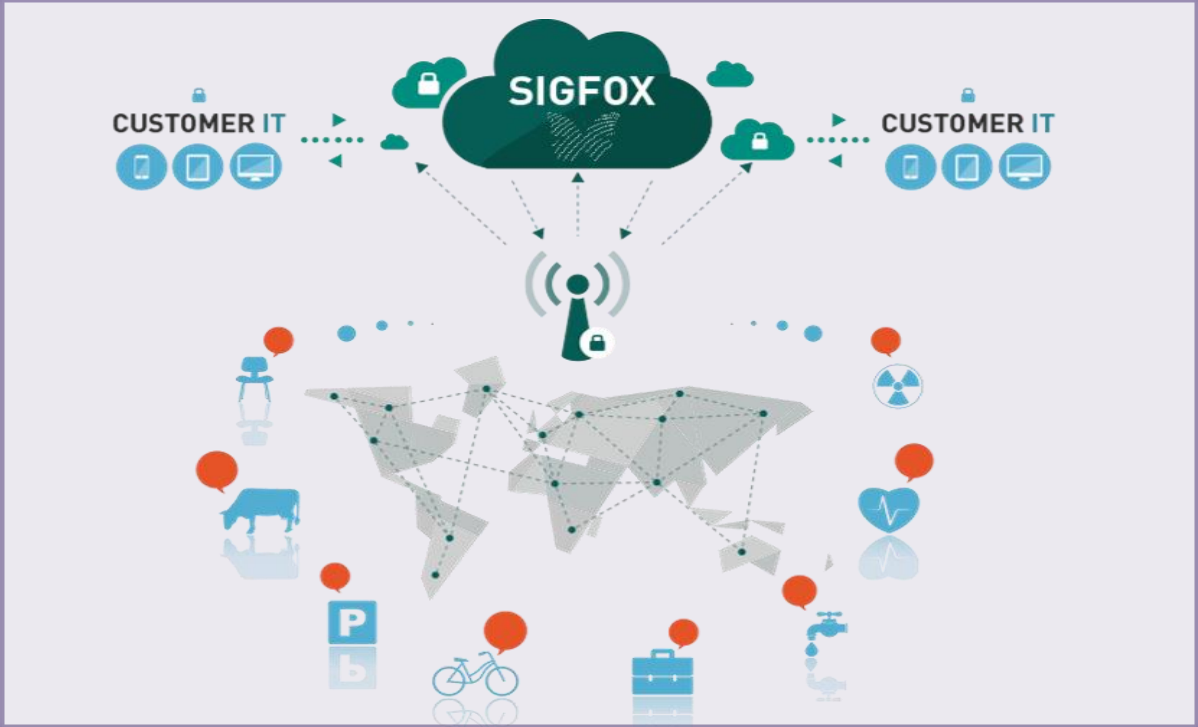
0G - Low Power Wide Area Network

- Ultra low power
- Ultra long range
- Energy efficient
- Cost effective



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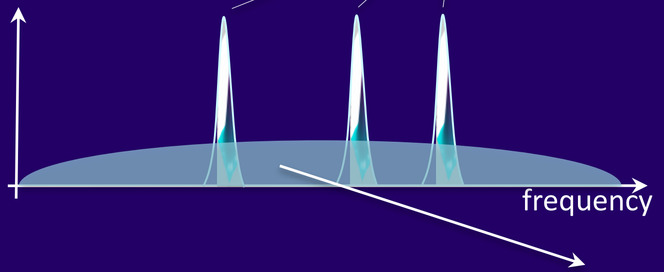
0G, how does it work?

Ultra **N**arrow **B**and signal

100-600 Hz per message

Space & **F**requency & **T**ime diversity

- ✓ High noise resilience
- ✓ Very low energy
- ✓ Long range capabilities



Use of free ISM band (868 MHz in Europe)

0G, how does it work?

Very **Efficient** protocol

- ✓ Low redundancy to transfer a message
- ✓ No negotiation
- ✓ No Handover
- ✓ Bi-directional

12 bytes / message
Up to **140 messages** / day

A device can work up to **20 years** off two AA batteries

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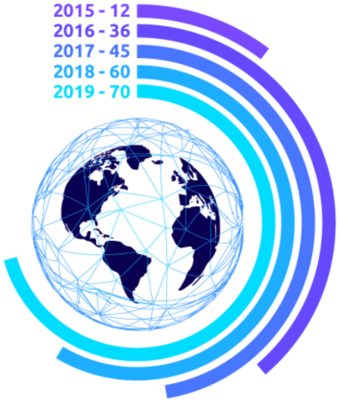

Present in
70
Countries & Regions

2019 **5.3M km²**

2018 **3.6M km²**

2017 **1.2M km²**

1.1 billion people & 5+ million km² covered

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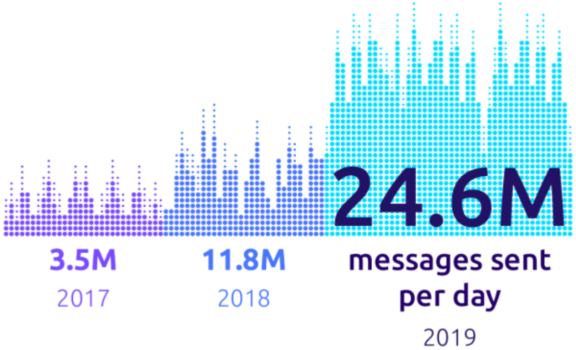
January 2020

15.4M
Connected Devices

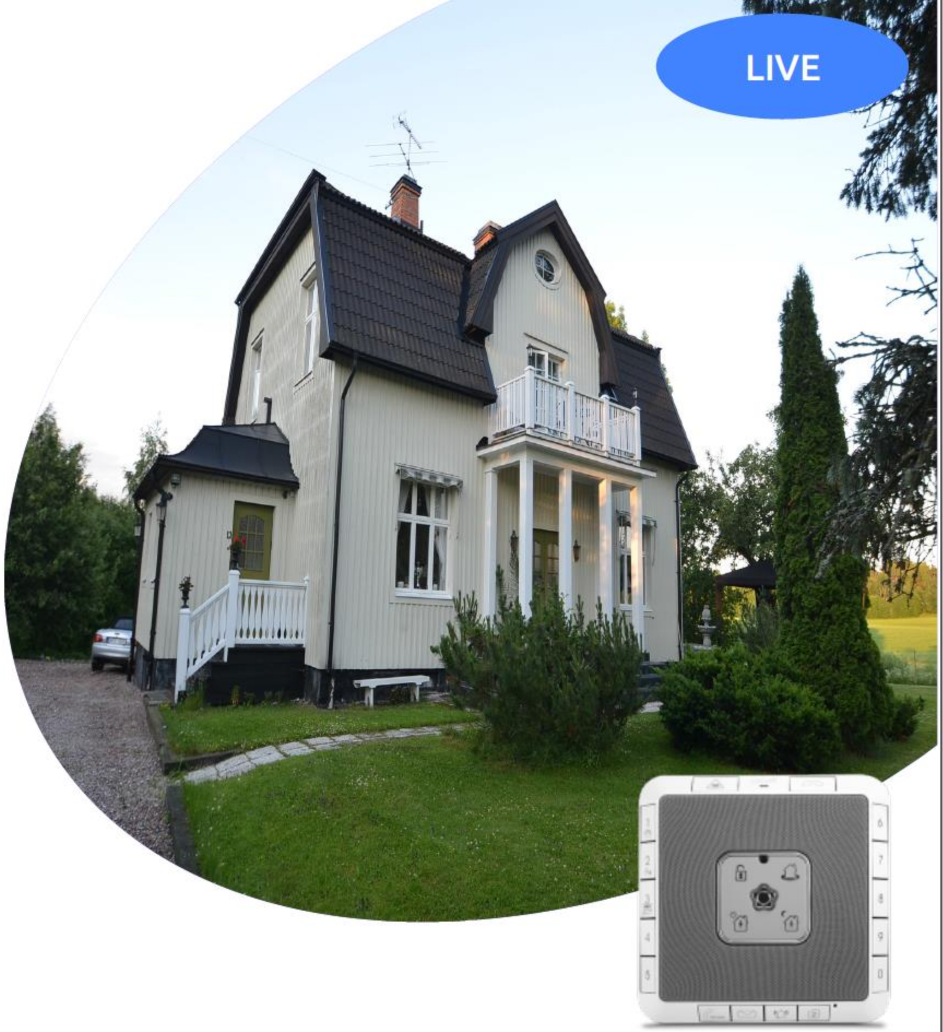



Visible stuff
Water metering
silver economy
Loiret
fastprk
Smart parking
Less visible stuff

Home Alarm System

Challenge

Secure better households



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Stolen Car Recovery

Challenge

Locate and recover stolen assets through a small and discrete GPS tracking device.

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free

2

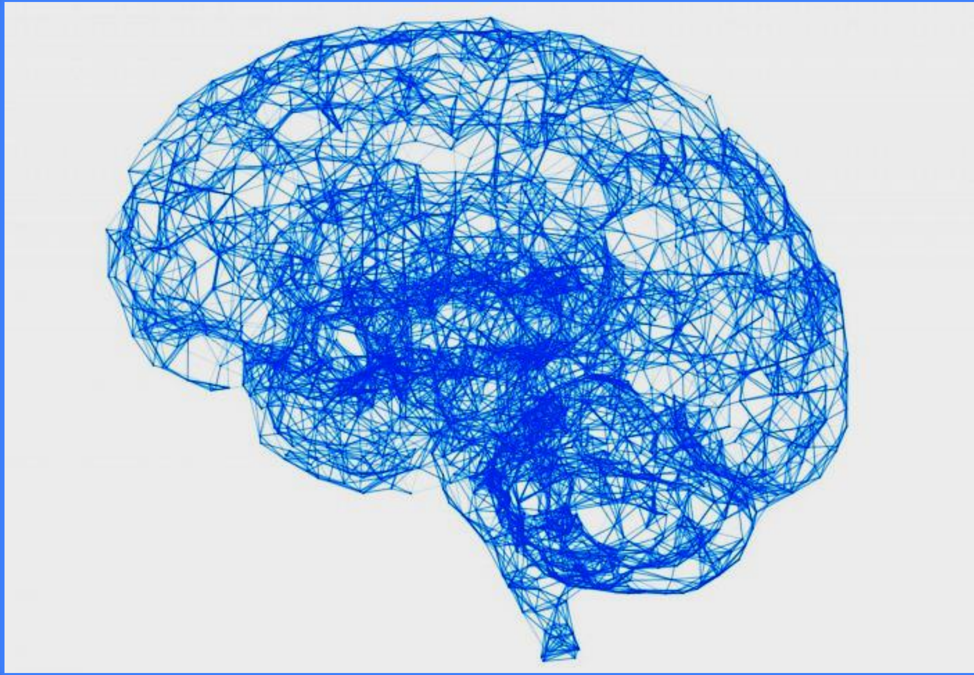
Machine Learning exemples

Data activities

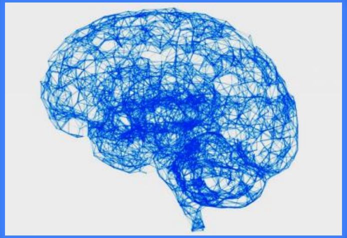
- Data Collection / storage
- Data knowledge / Analytics
- Data Intelligence / Machine learning

Data activities

- Data Intelligence / Machine learning



Data type

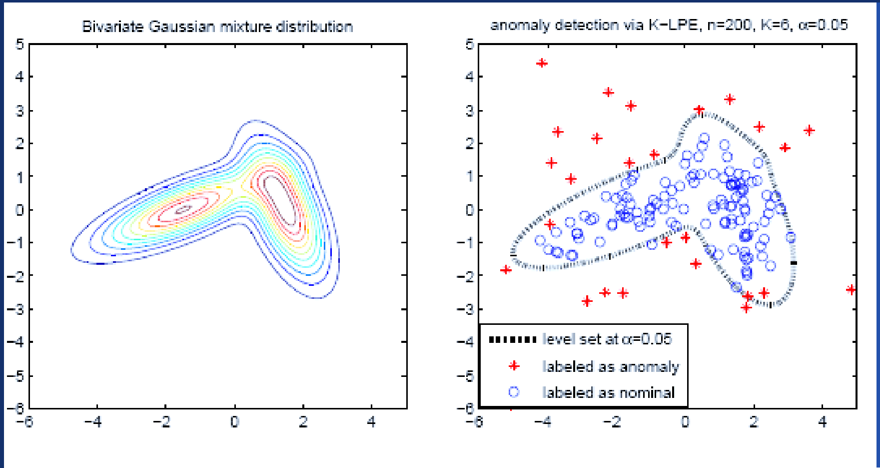


- Machine learning using data in the network
  - Payload data: the value of the transported data
    - Temperature, pressure, position,…
  - Metadata: all about data except its value
    - Reception date
    - Reception level
    - …

Data Intelligence / Machine learning

Anomaly detection /

Predictive Maintenance



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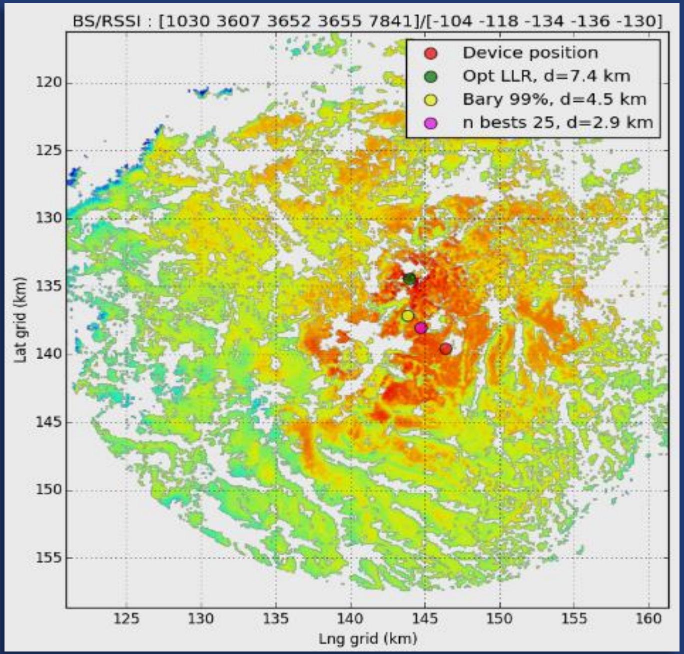
Data Intelligence / Machine learning

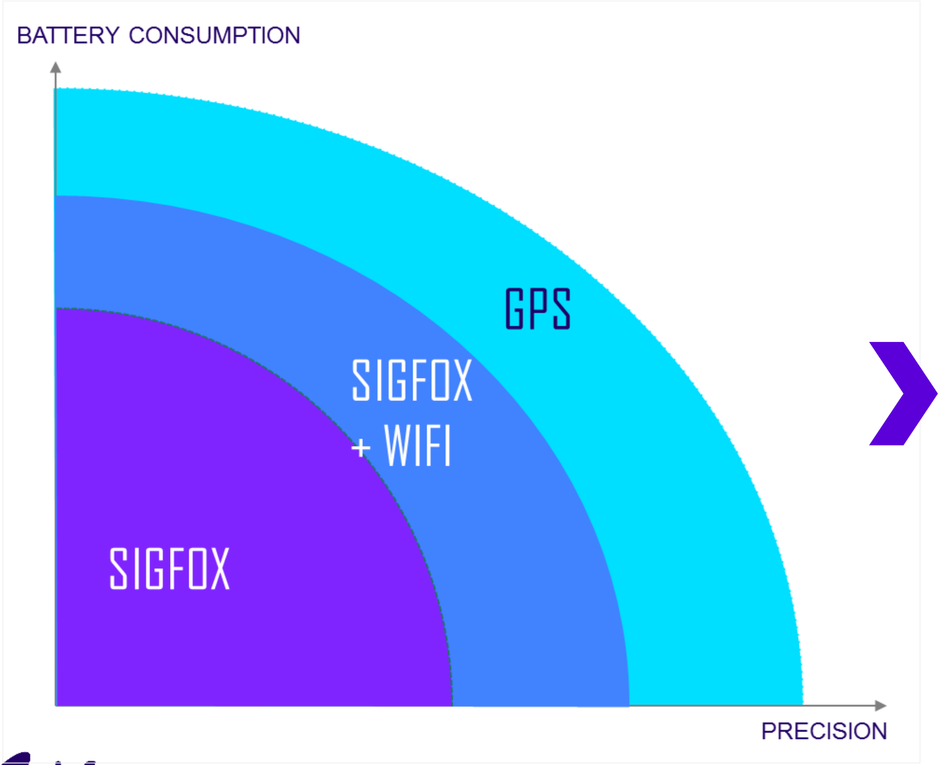
Geolocation



Geolocation business case: Louis Vuitton

DHL
DHL
DHL
NH

The Geolocation Challenge



Need for a location solution without GPS:

- *Low cost module*
- *High battery life*
- *Precision target ~ 1km*

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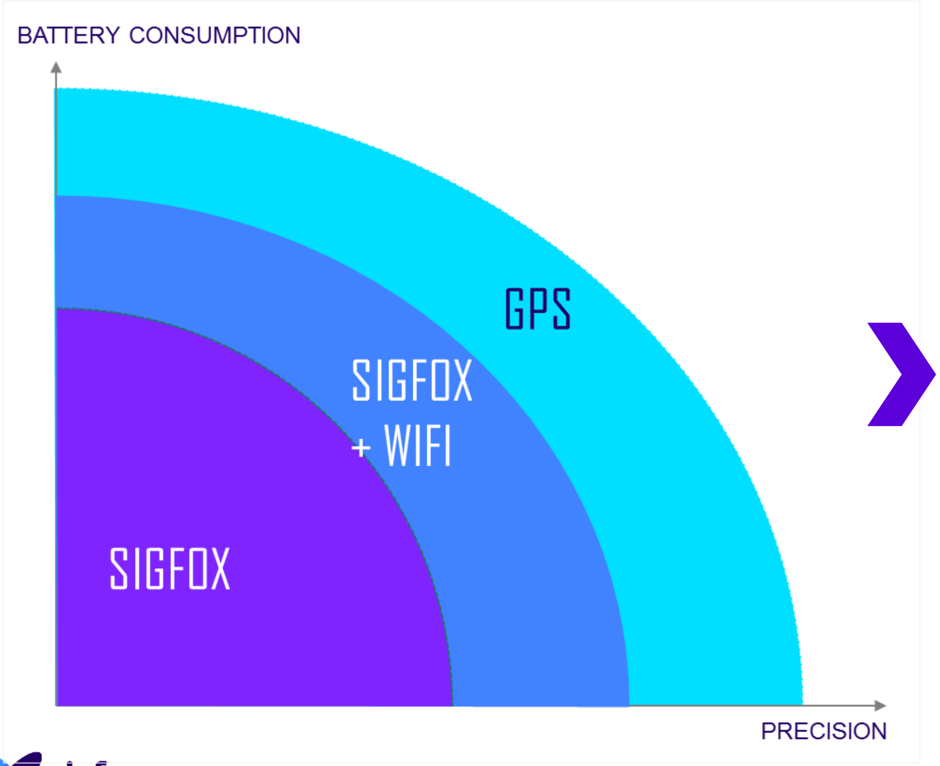
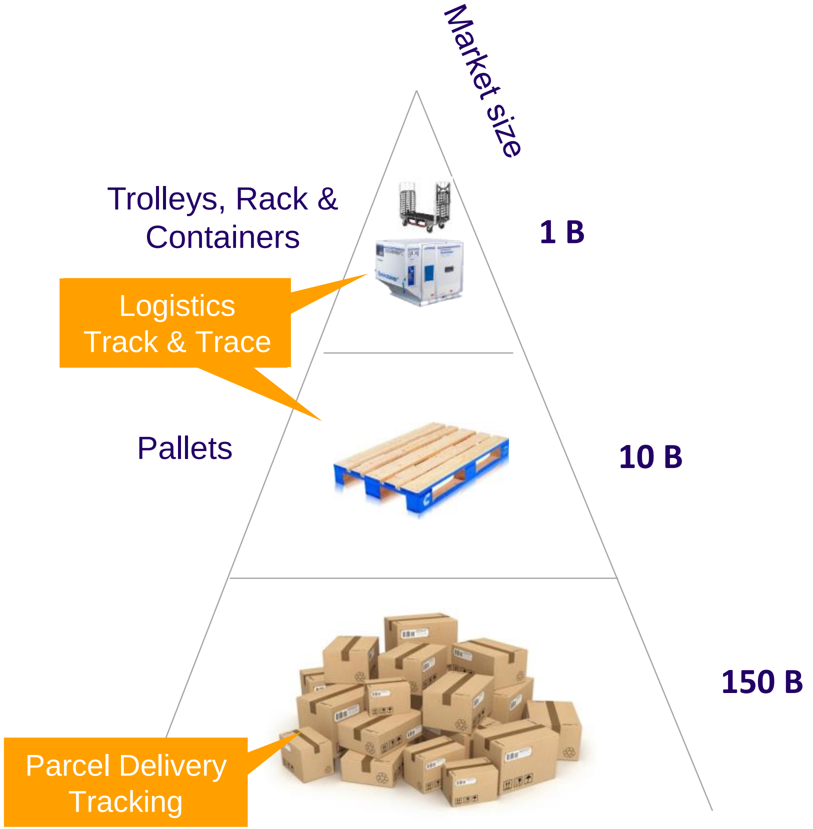
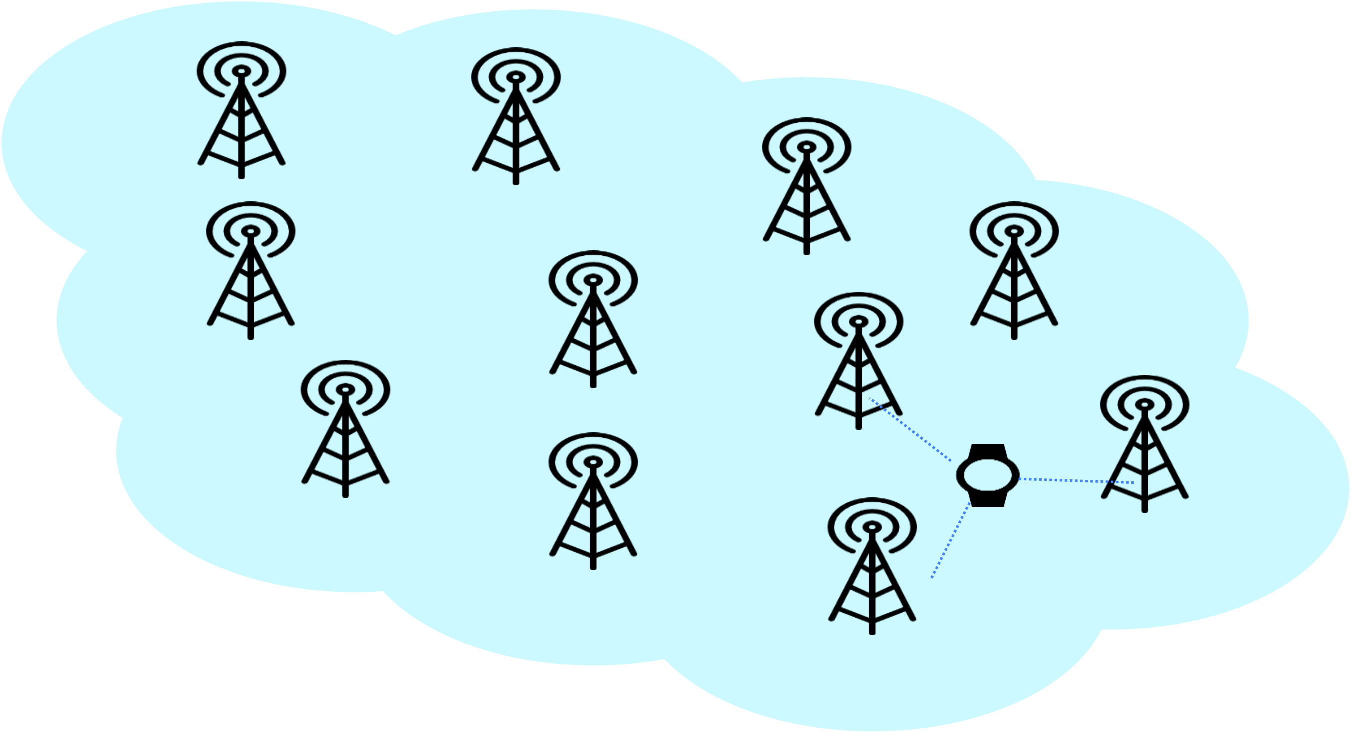
The Geolocation Challenge

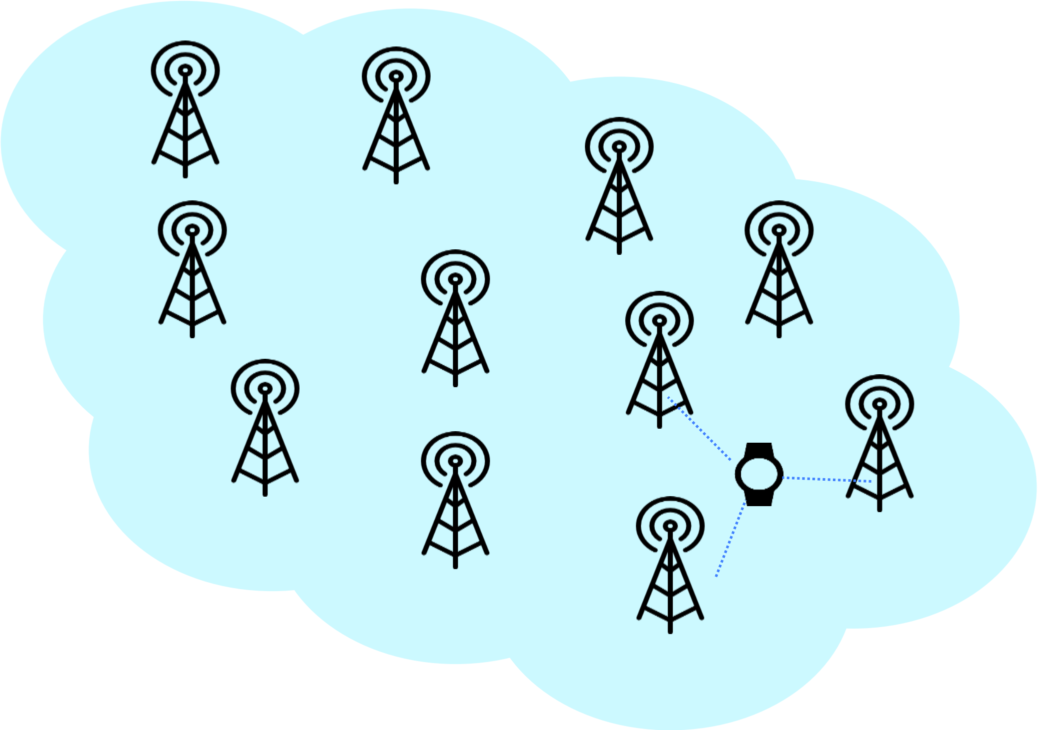




Network based geolocation



Geolocation state of the art – Time of flight



Calculate signal Time of Flight

- *Use of TDOA*
- *Estimate distances BS - Device*
- *Solve equation system: device area*

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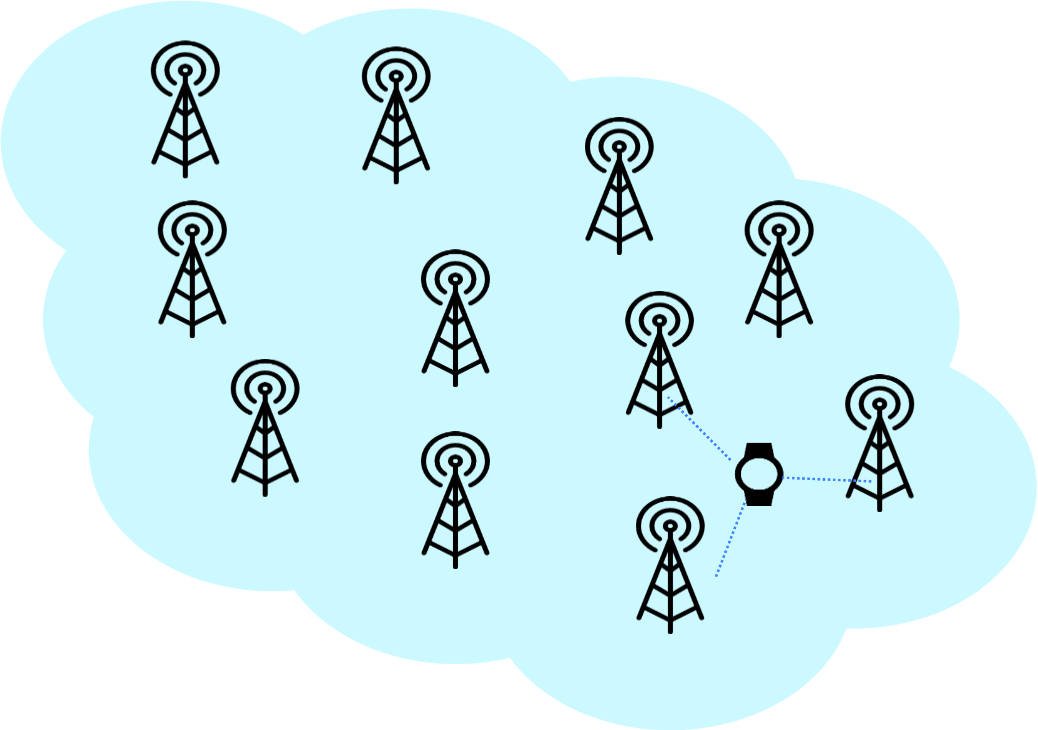
Geolocation state of the art – Time of flight



Calculate signal Time of Flight

- *Use of TDOA*
- *Estimate distances BS - Device*
- *Solve equation system: device area*

Drawbacks for LPWAN

- *UNB not well suited for precise TDOA*
- *Need network synchronization time domain (~µs).*
- *Multipath channel destroy perfs*

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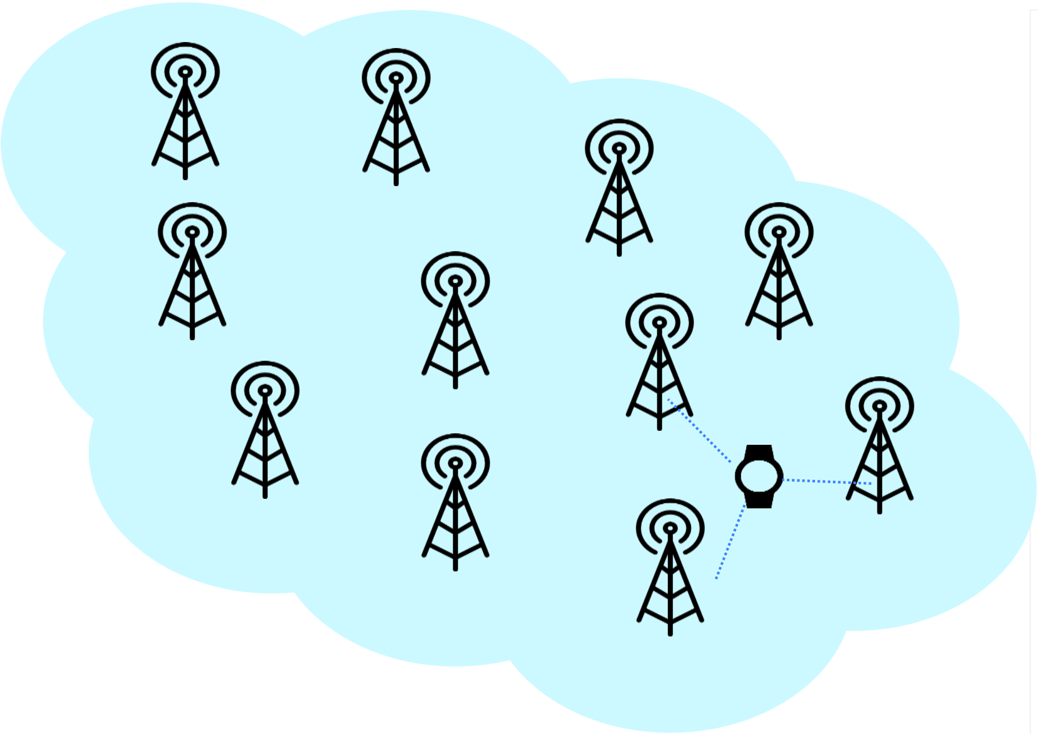
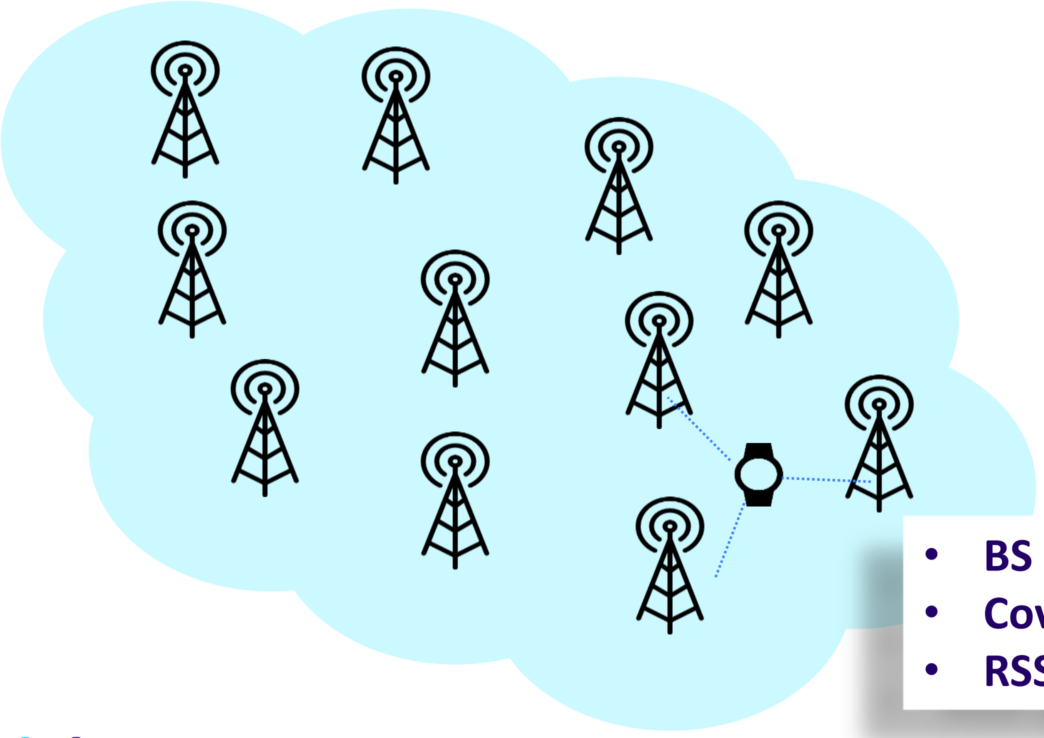
Network based geolocation



- **Use of metadata to estimate a device position**
  - *Message reception → feature vector :* X

Network based geolocation– RSSI



Received Signal Strength Indicator

- *Use the received signal power*
- *Try to make a link between RSSI and device position*
- *No need for synchronized network*
- *Hard to link distance – RSSI in multipath environment*

- **BS Locations**
- **Coverage Map of each BS**
- **RSSI @ each BS**

Data oriented geolocation

- Sigfox received message → X a feature vector $X = (x_0,\dots,x_n)$
- x_i : Network information concerning the message
  - Base station position, received power, SNR,…

Data oriented geolocation

- Sigfox received message → X a feature vector $X = (x_0,\ldots,x_n)$
- x_i : Network information concerning the message
  - Base station position, received power, SNR,…
- Let Y be the position of the object (Lat, Lng)
- Then we want to make the link $X \rightarrow Y$

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Lab: Geolocation

Geolocation Train Set

Input:

Message Id

Base station Id

Device Id

Base station position (Lat, Lng)

	messid	bsid	did	nseq	Rssi (dBm)	time_ux (ms)	bs_lat	bs_lng
0	573bf1d9864fce1a9af8c5c9	2841	473335	0.5	-121.5	1.463546e+12	39.617794	-104.954917
1	573bf1d9864fce1a9af8c5c9	3526	473335	2.0	-125.0	1.463546e+12	39.677251	-104.952721
2	573bf3533e952e19126b256a	2605	473335	1.0	-134.0	1.463547e+12	39.612745	-105.008827
3	573c0cd0f0fe6e735a699b93	2610	473953	2.0	-132.0	1.463553e+12	39.797969	-105.073460
4	573c0cd0f0fe6e735a699b93	3574	473953	1.0	-120.0	1.463553e+12	39.723151	-104.956216

Output: device position

	lat	lng
0	39.606690	-104.958490
1	39.606690	-104.958490
2	39.637741	-104.958554
3	39.730417	-104.968940
4	39.730417	-104.968940

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How to apply ML techniques to Geolocation

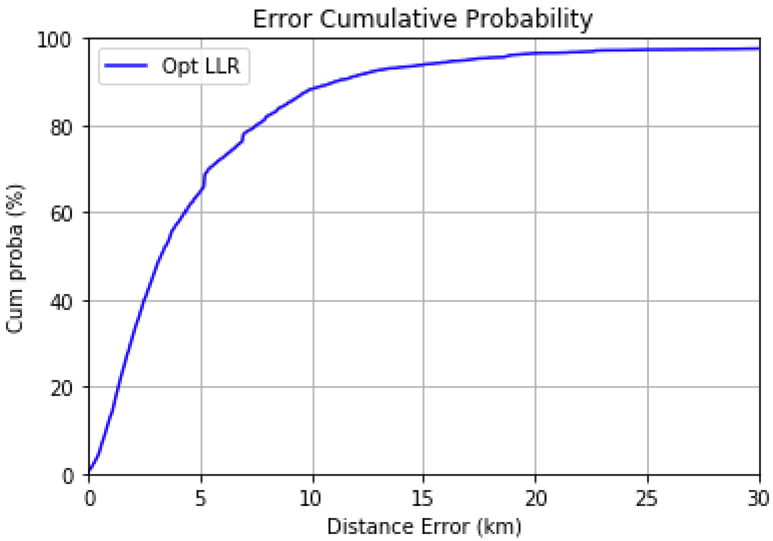
What kind of ML problems do we have?

What is the feature matrix / Ground truth ?

What kind of algorithm will we use ?

Goals

- Build feature matrix
- Build ground truth
- Plot error cumulative probability
- Compute prediction criterion: error @ 80%
- Extract prediction for the test set
  - Save result in csv file
- Cross validation: Build a « leave 1 device out » strategy



Error @ 80% = 7521 m

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Send me your results before 28/02/2020:
Olivier.Isson@gmail.com
Groups of 3-5 people

1. Python code used to generate previous goals
2. Predicted position for test set in csv format: **pred_pos_test_list.csv**
3. Short explanation of your approach and your choices: ~ 1-2 pages, can be included into the notebook or a separate document

Leave 1 device out predictor

- In practice we will not use the same devices to learn and to predict:
  - GPS devices to learn
  - Non GPS devices to predict

- To limit overfitting a « leave 1 device out » strategy must be used
  - To find the best model use cross-validation
    - Do not use the same device for the train and the validation sets

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Thank You