

Challenges of Integrated Navigation

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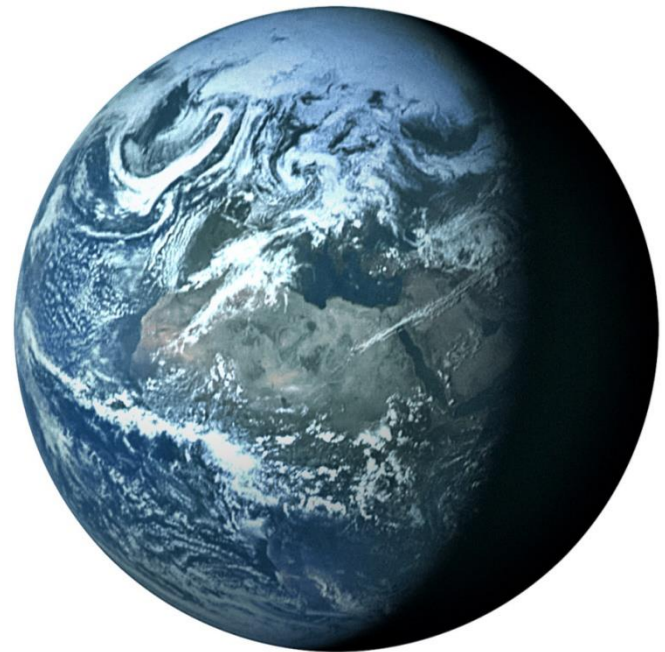
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*Panel: Multisensor Fusion for
Advanced Navigation*

ION GNSS+ 2018

28 September 2018



UCL ENGINEERING

Change the world

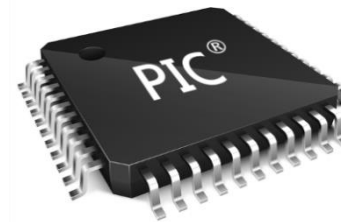
Latest Navigation Requirements

- **Meter accuracy**
 - Autonomous vehicles
 - Drones
 - Visually impaired pedestrians
- **Seamless/ ubiquitous positioning**
 - Pedestrians and vehicles
 - Indoors and outdoors
- **Resilience**
 - Environments with limited signal reception
 - Jamming, interference and spoofing
 - Integrity



Technology Background

- Smaller cheaper sensors
 - IMUs in every smartphone
 - HD video cameras in every phone
 - Magnetometers, barometers, ambient light
- More processing capacity
 - But *for how long?*
- More data available
 - 3D mapping
 - Streetview
 - Signal databases



PNT Technology Developments

GNSS

- New signals and multi-frequency receivers
- Shadow matching and 3D mapping aided ranging
 - *Please come to Session E6 at 3:20 this afternoon ☺*
- Extended coherent integration and synthetic aperture beamforming



Other technologies

- Wi-Fi Round Trip Time (802.11mc)
- Magnetic anomaly matching
- 5G communications
- LEO communication satellites
- Better visual navigation
- More accurate pedestrian dead reckoning
- Better MEMS inertial sensors and quantum sensor technology



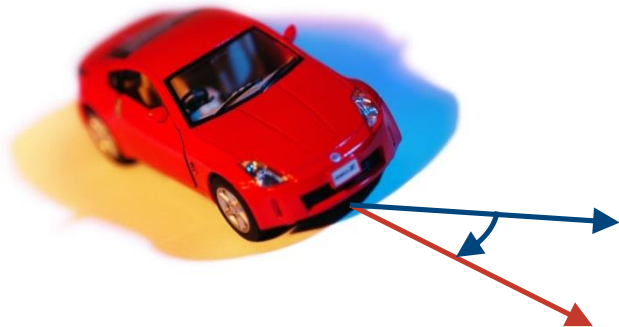
No Single Positioning Technology is Reliable

GNSS and Other Radio Signals:

Jamming
Spoofing
Interference



Signals not
always
available



Dead Reckoning:
Errors grow with time



Visual Navigation:
Landmarks are not
available everywhere

Things Break:



The Quantum Sensor Myth

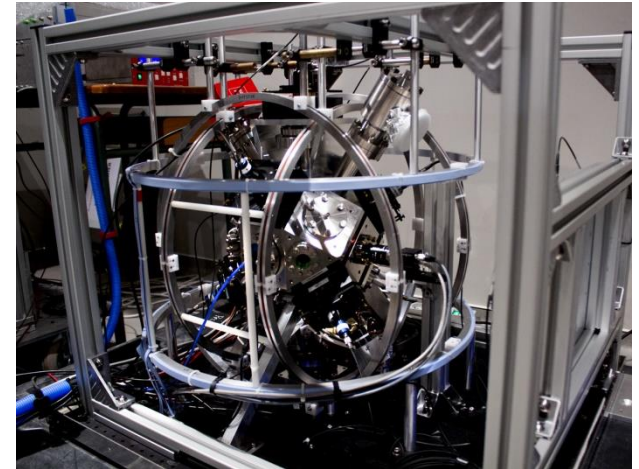
Performance claims include

“One meter per month” inertial navigation drift

BUT... even with perfect sensors, we have:

1. Initialisation errors
 - A **1 mm** height initialisation error will grow to **1 km** after **75 minutes**
2. Errors due to mounting misalignment
 - Flexure effects not easily calibrated
3. Gravity modelling errors
 - EGM2008 accuracy equivalent to **20m** position error after **1000s**
4. Errors due to bandwidth limitation
5. Numerical rounding errors

∴ Error-free inertial navigation is not possible



Top: LP2N Bordeaux and LNE-SYRTE Paris
Bottom: University of Birmingham

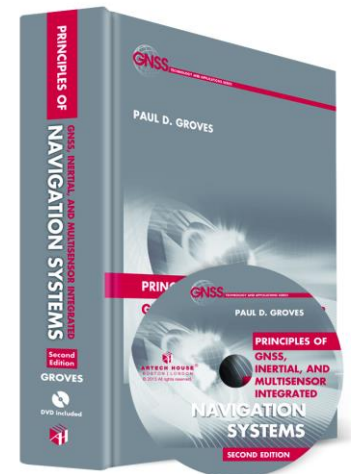
We still need Integrated Navigation

Benefits:

- **Resilience:** With enough different technologies, we can always maintain a navigation solution
- **Accuracy:** More information enables greater accuracy *and* better sensor error calibration
- **Integrity:** More information makes faults easier to spot

Increased complexity brings challenges:

- **Expertise:** Bringing together knowledge of many different technologies
- **Upgrades:** How to incorporate new technology without a complete redesign
- **Integrity:** How do we ensure the navigation solution can be trusted

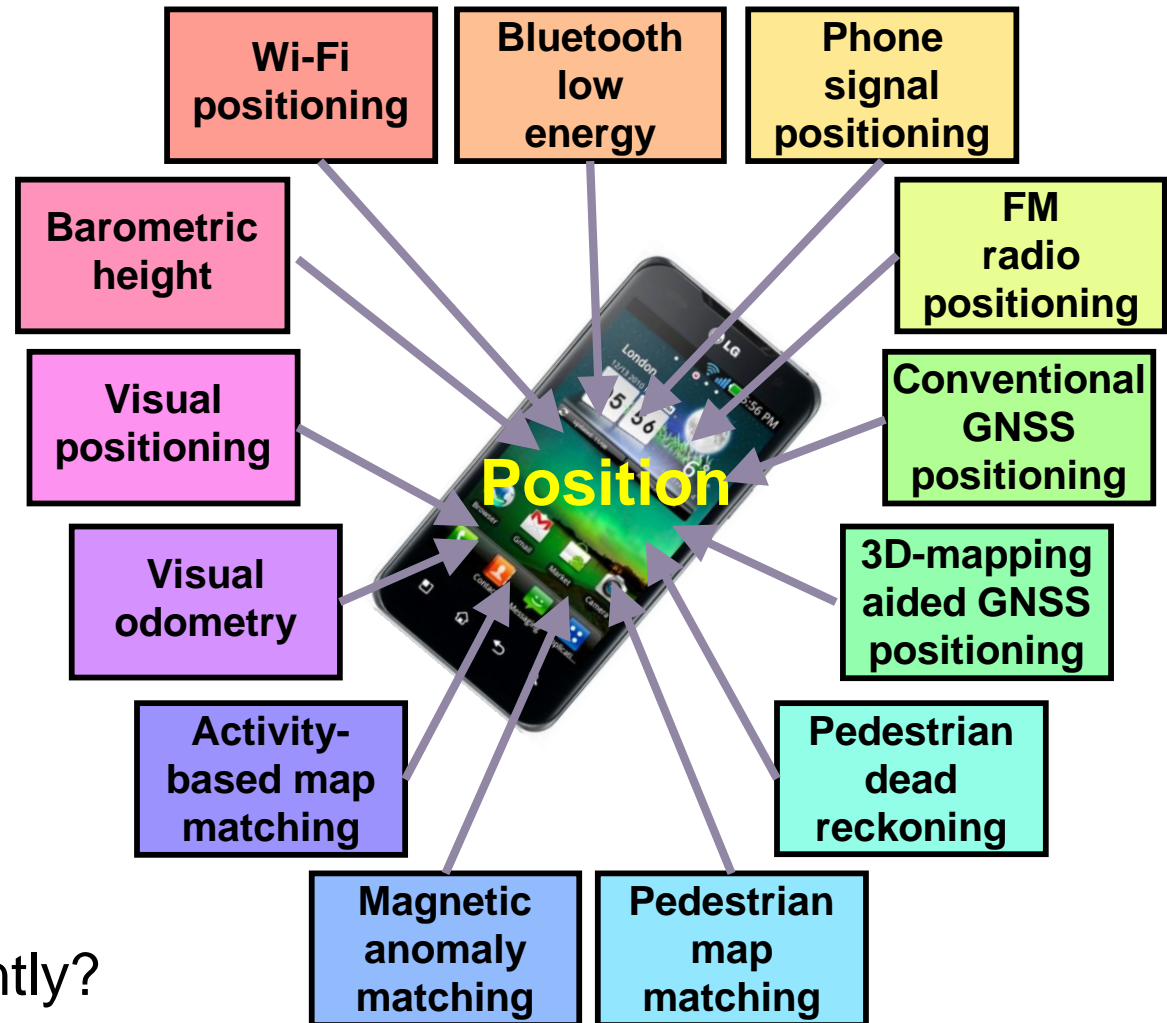


Many Different Navigation Technologies

≥ 13 smartphone
pedestrian
positioning
techniques

Other platforms
use other
techniques

How do we select the
best techniques and
combine them efficiently?



Context is Important

It determines which navigation technologies work best

Environment



Open: Standard GNSS works well



Urban: Use 3D-mapping aided GNSS



Indoor: Wi-Fi generally best

Behaviour

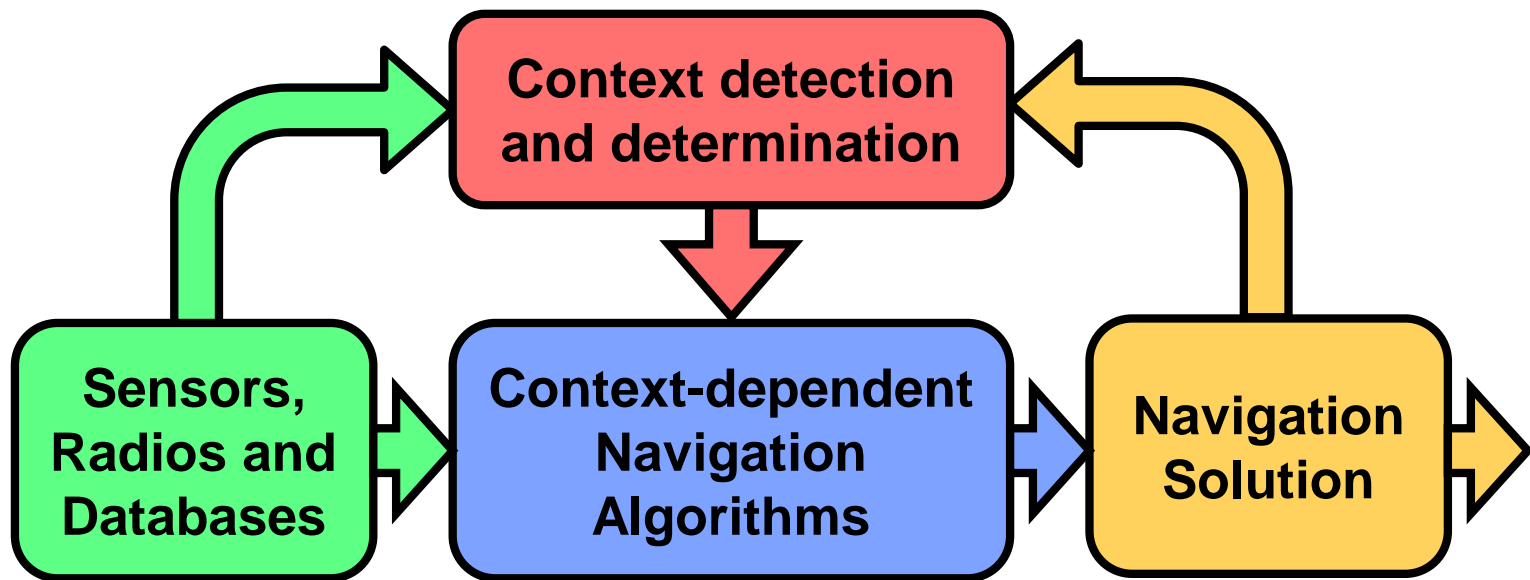


Pedestrians and Vehicles

- Different map matching
- Different motion constraints
- Step detection only works for pedestrians

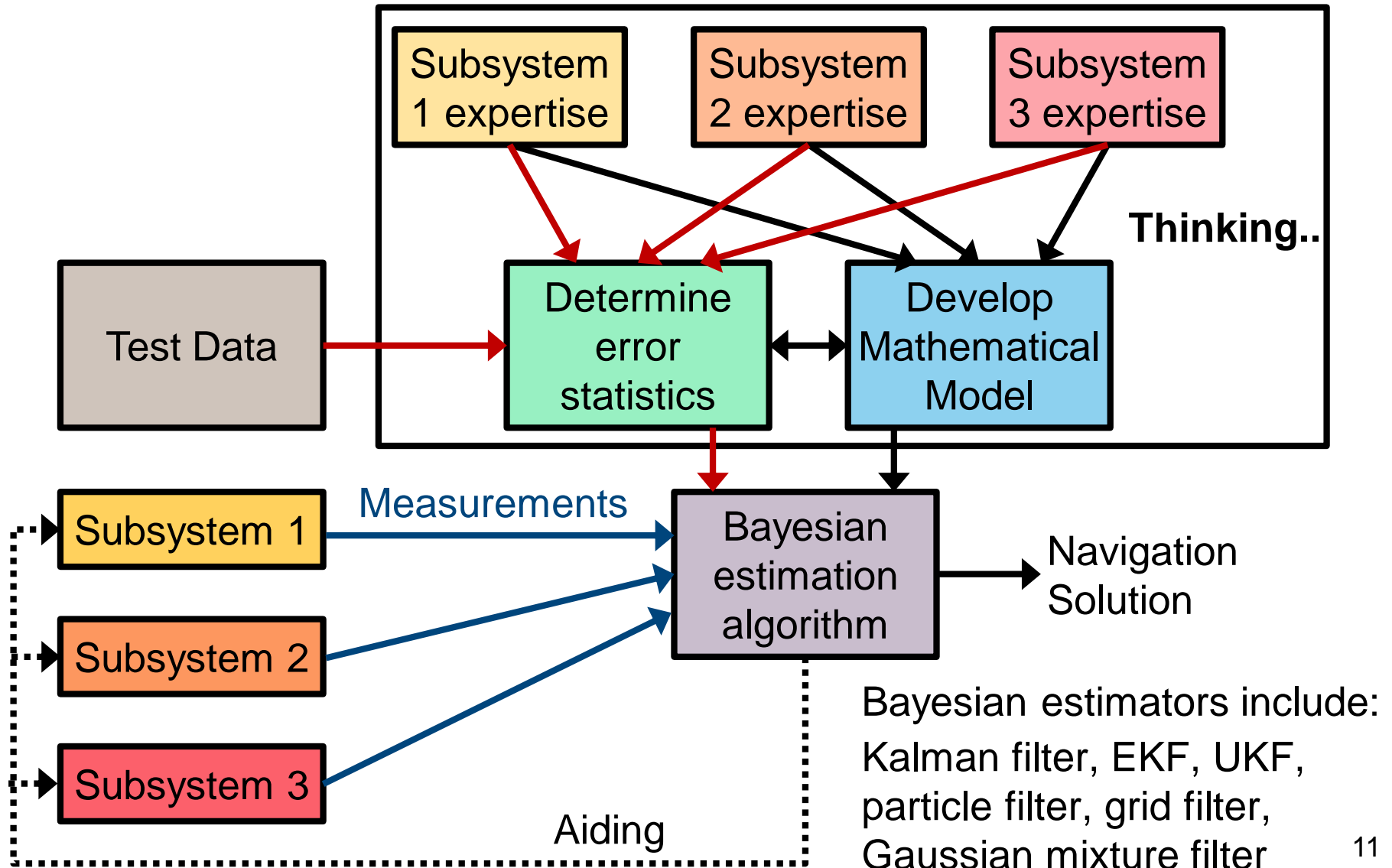
Context-Adaptive Navigation

- Detects the environmental and behavioural context.
- Selects the appropriate navigation techniques



Please come to Han Gao's presentation at 1:50 in Session E6 ☺

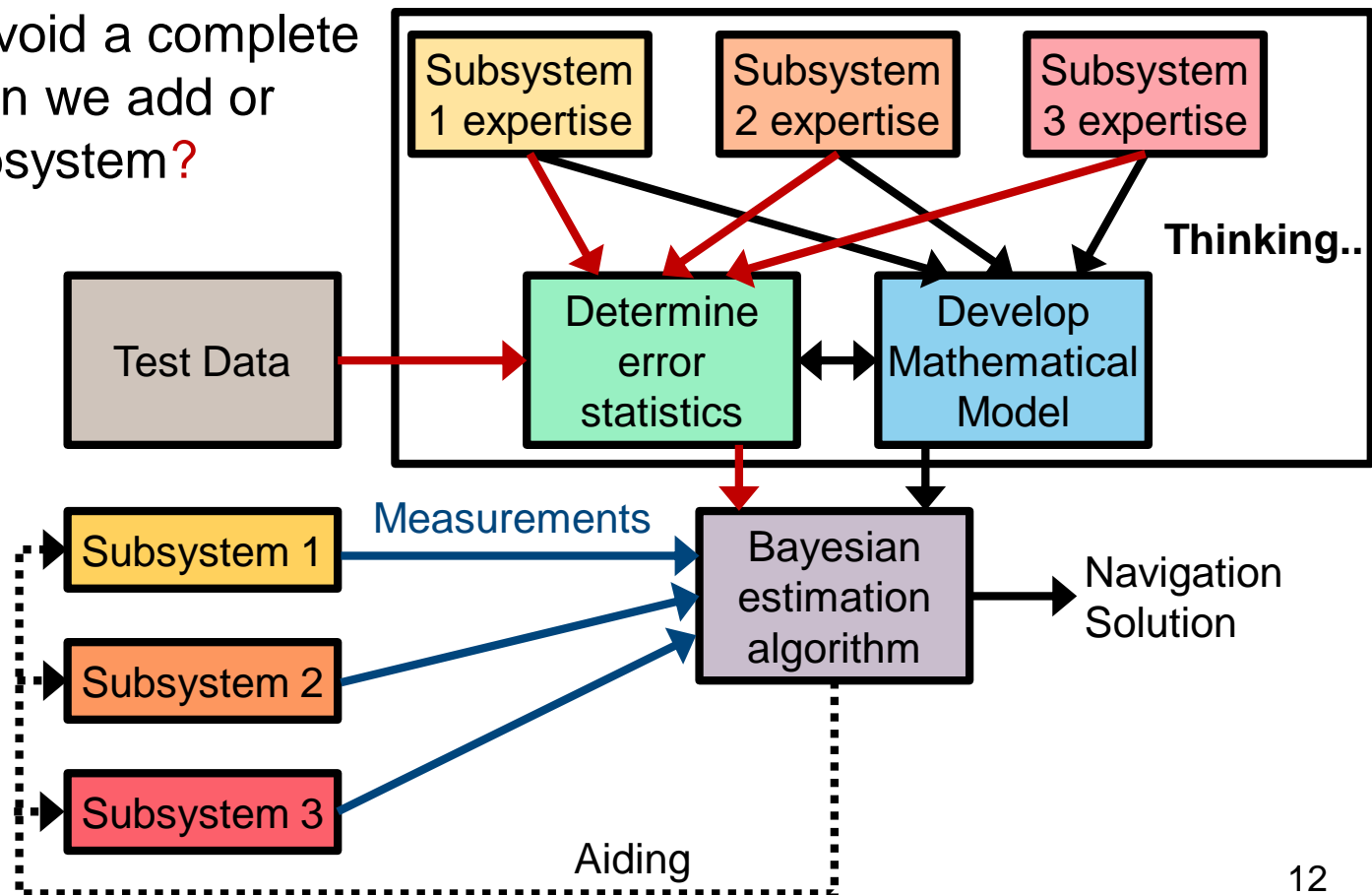
Conventional Integrated Navigation (1)



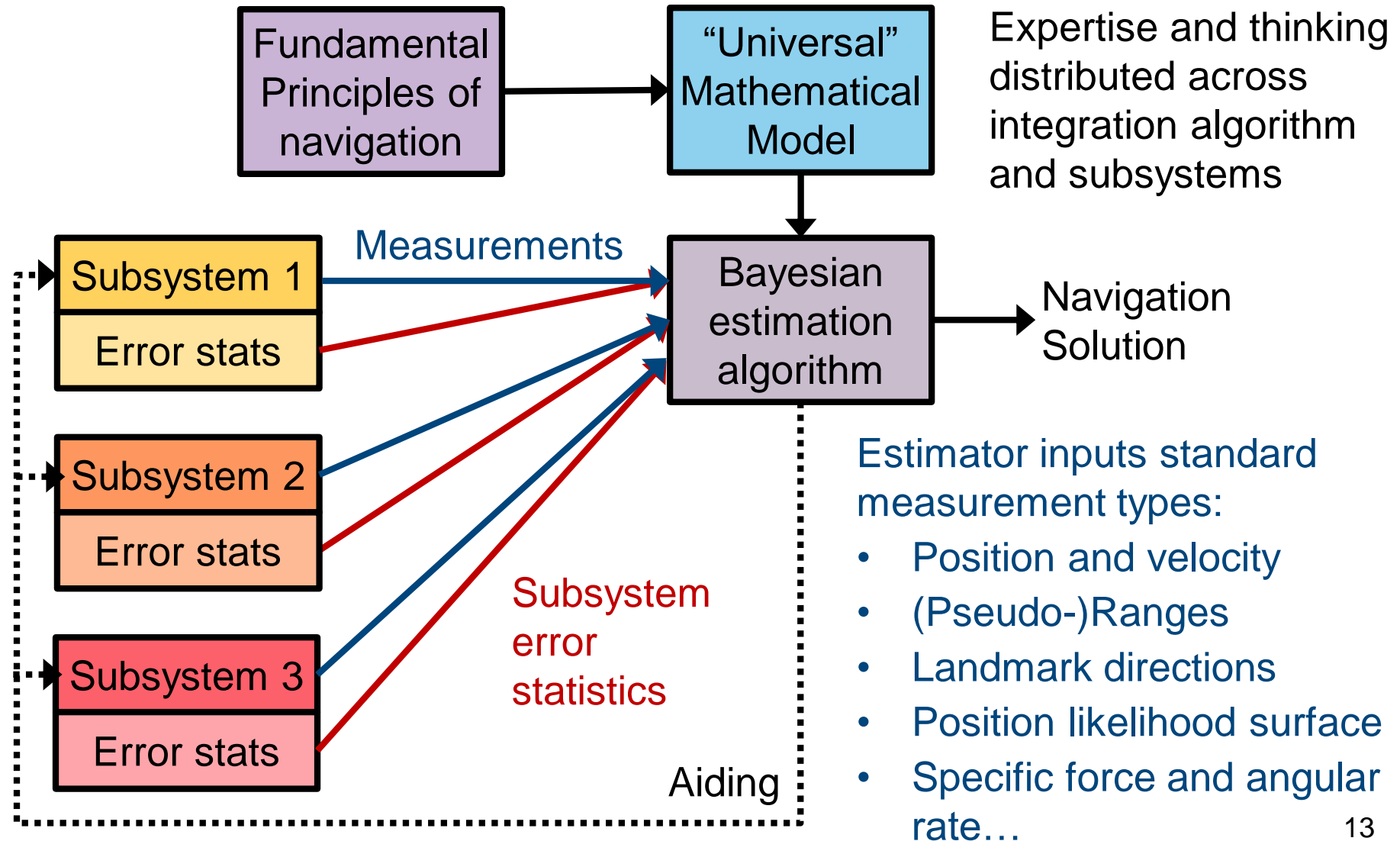
Conventional Integrated Navigation (2)

Challenges:

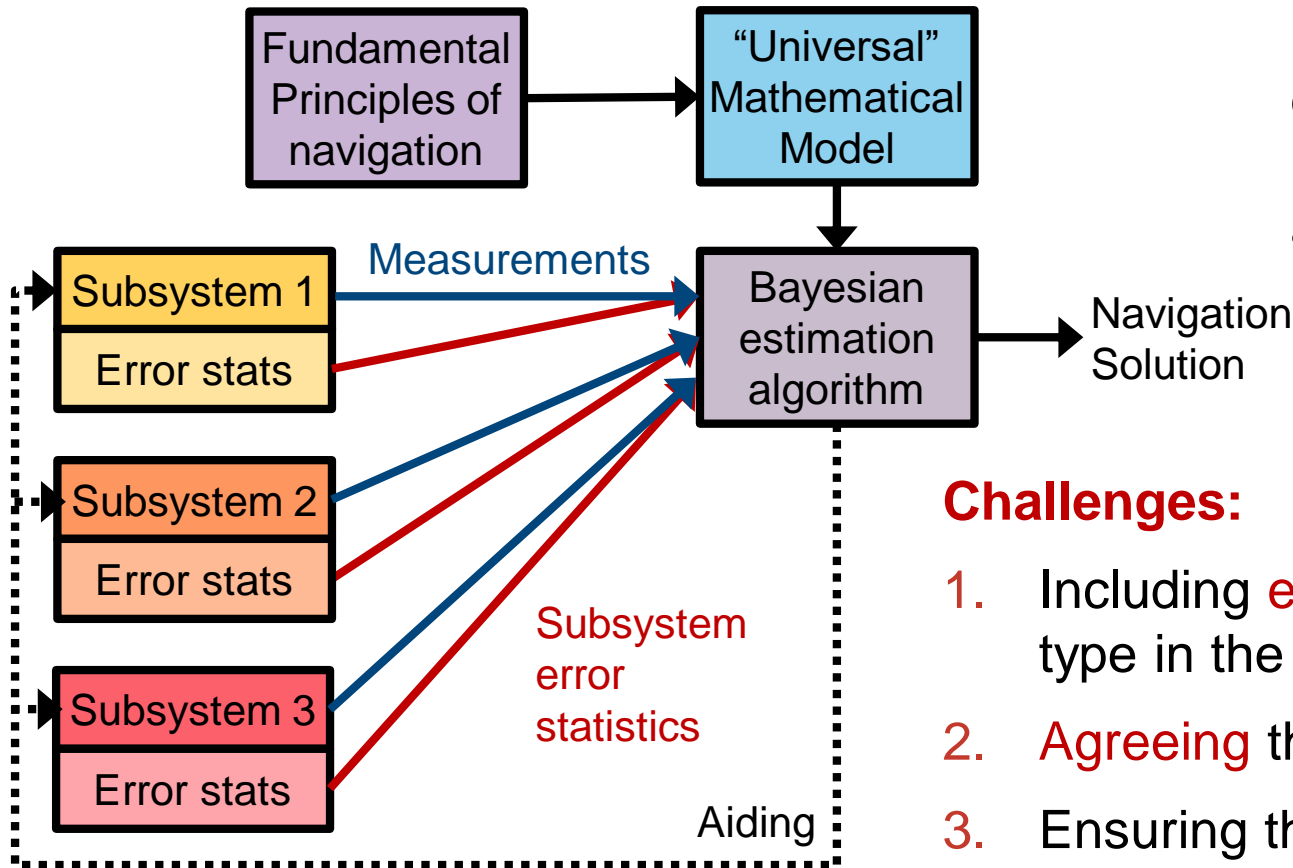
1. How do we bring together all of the subsystem and modelling expertise?
2. How do we avoid a complete redesign when we add or change a subsystem?



Plug'n'Play Integrated Navigation (1)



Plug'n'Play Integrated Navigation (2)



Expertise and thinking distributed across integration algorithm and subsystems

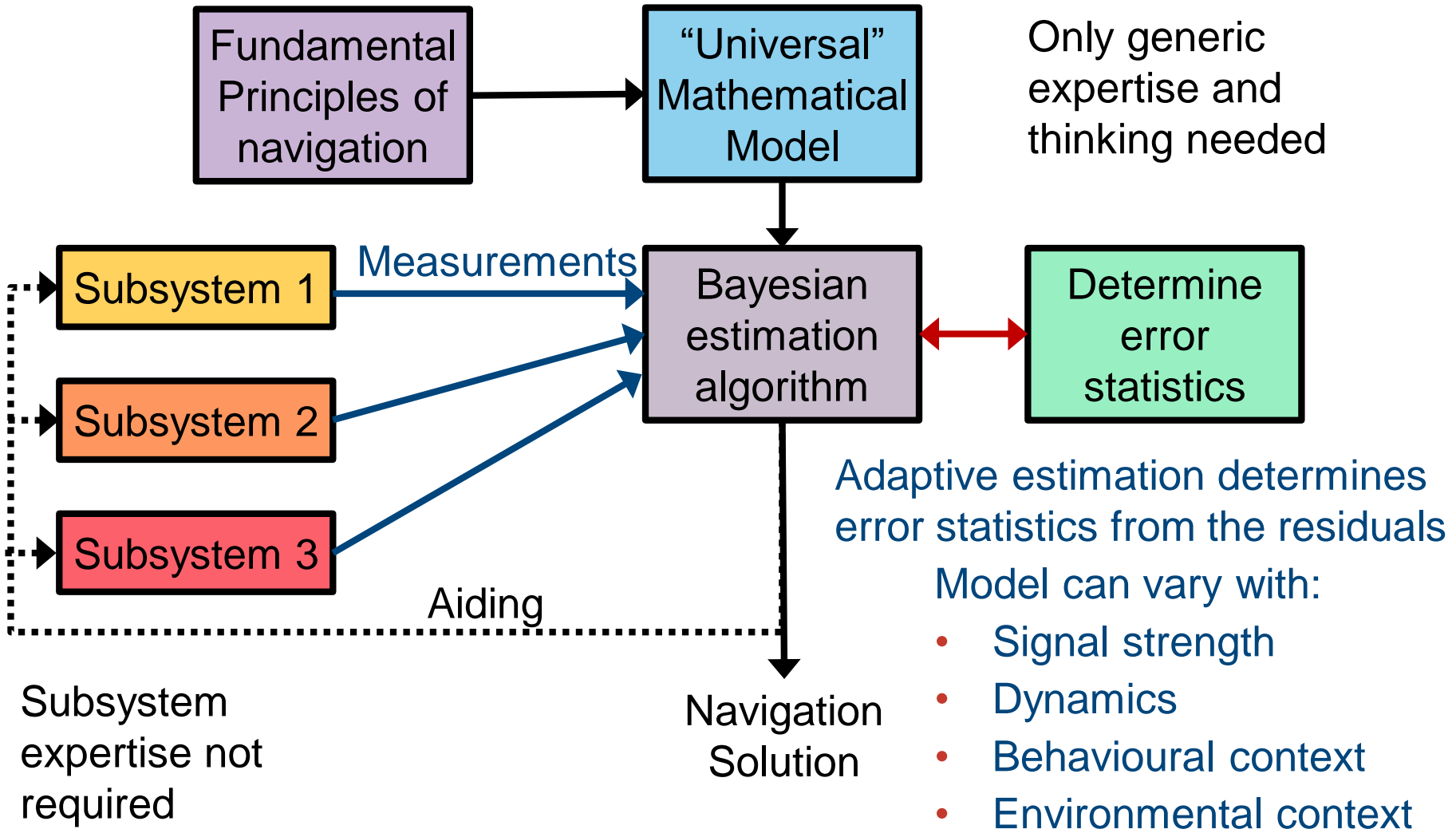
Challenges:

1. Including **every** measurement type in the “universal” model
2. **Agreeing** the interface
3. Ensuring the subsystem manufacturers' error statistics are **trustworthy**

Groves, P. D., The Complexity Problem in Future Multisensor Navigation and Positioning Systems: A Modular Solution. *Journal of Navigation*, 67 (2), 2014, 311-326.

Groves, P. D. et al. The Four Key Challenges of Advanced Multi-sensor Navigation and Positioning, *Proc. IEEE/ION PLANS 2014*.

Self-Calibrating Plug'n'Play Integration (1)

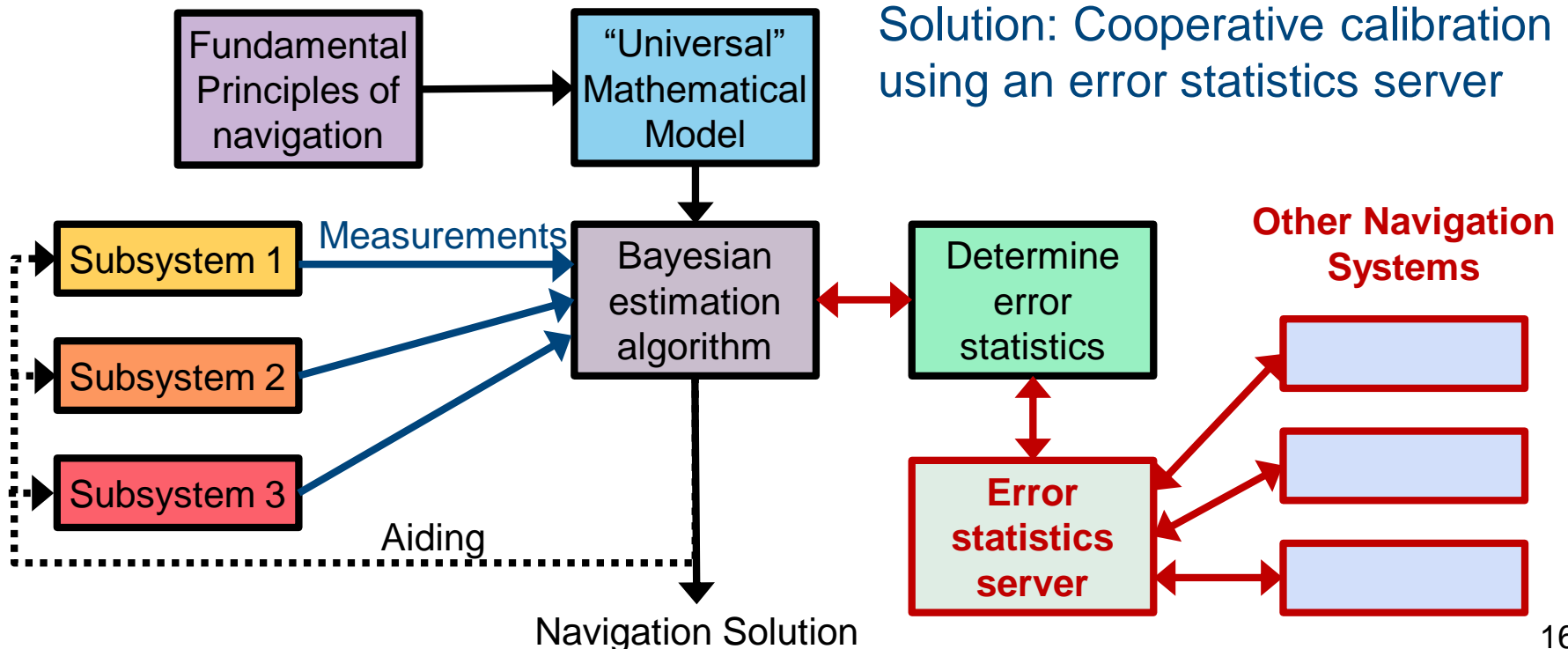


Self-Calibrating Plug'n'Play Integration (2)

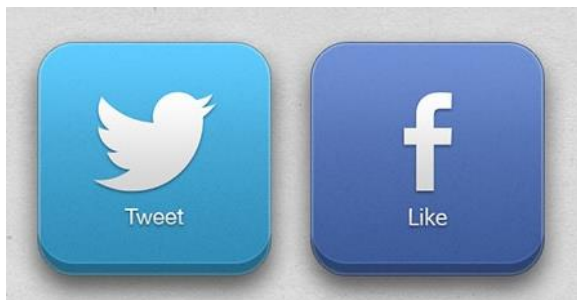
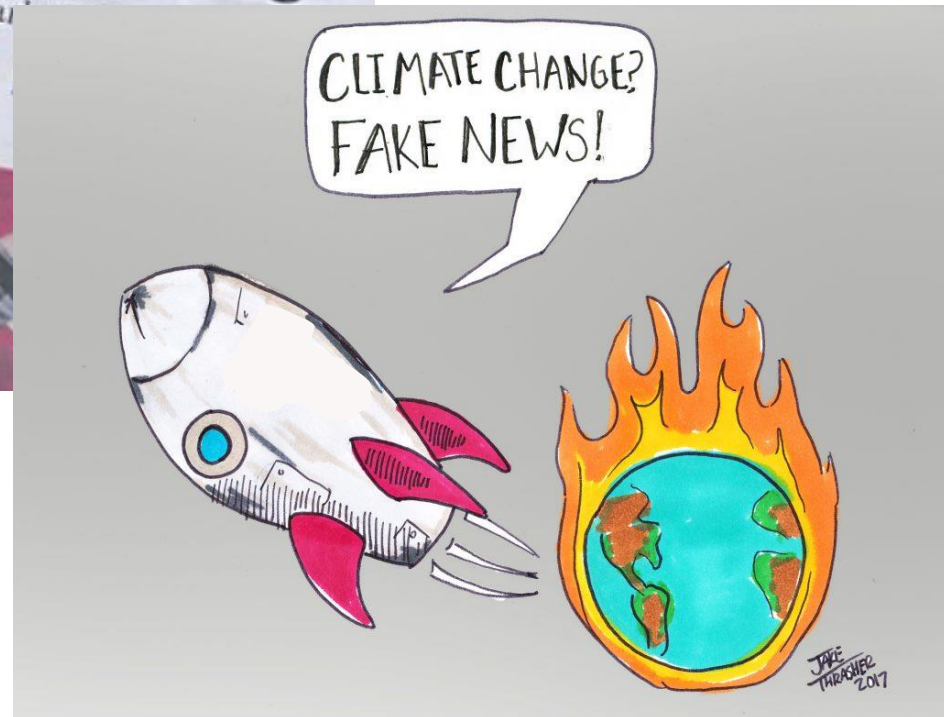
Challenges:

1. Including **every** measurement type in the “universal” model
2. **Agreeing** the interface (though at least it's simpler)
3. Capturing enough data to **reliably** determine the error statistics

Solution: Cooperative calibration using an error statistics server



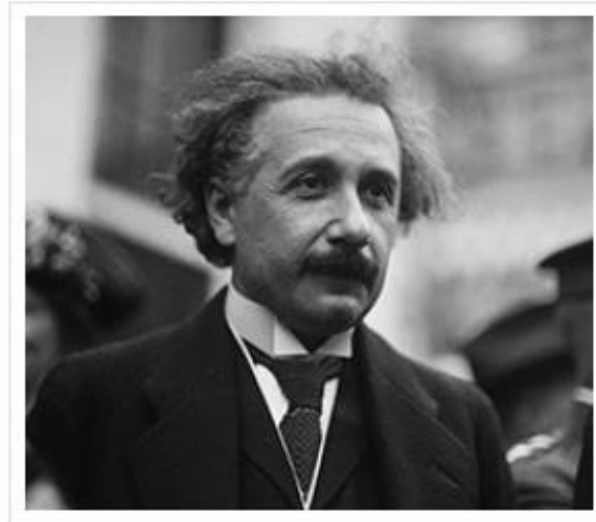
Thinking is Now Deeply Unfashionable



Rational Thought has been made a Disease

Was Albert Einstein Autistic?

The boy was an odd one, that was something his family could agree about. When he was born, the back of his head was enormous. His grandmother thought he was just fat, but his parents were worried it was a sign of some problem. But within a few weeks, he'd managed to grow into it somehow, so at least he didn't look strange.

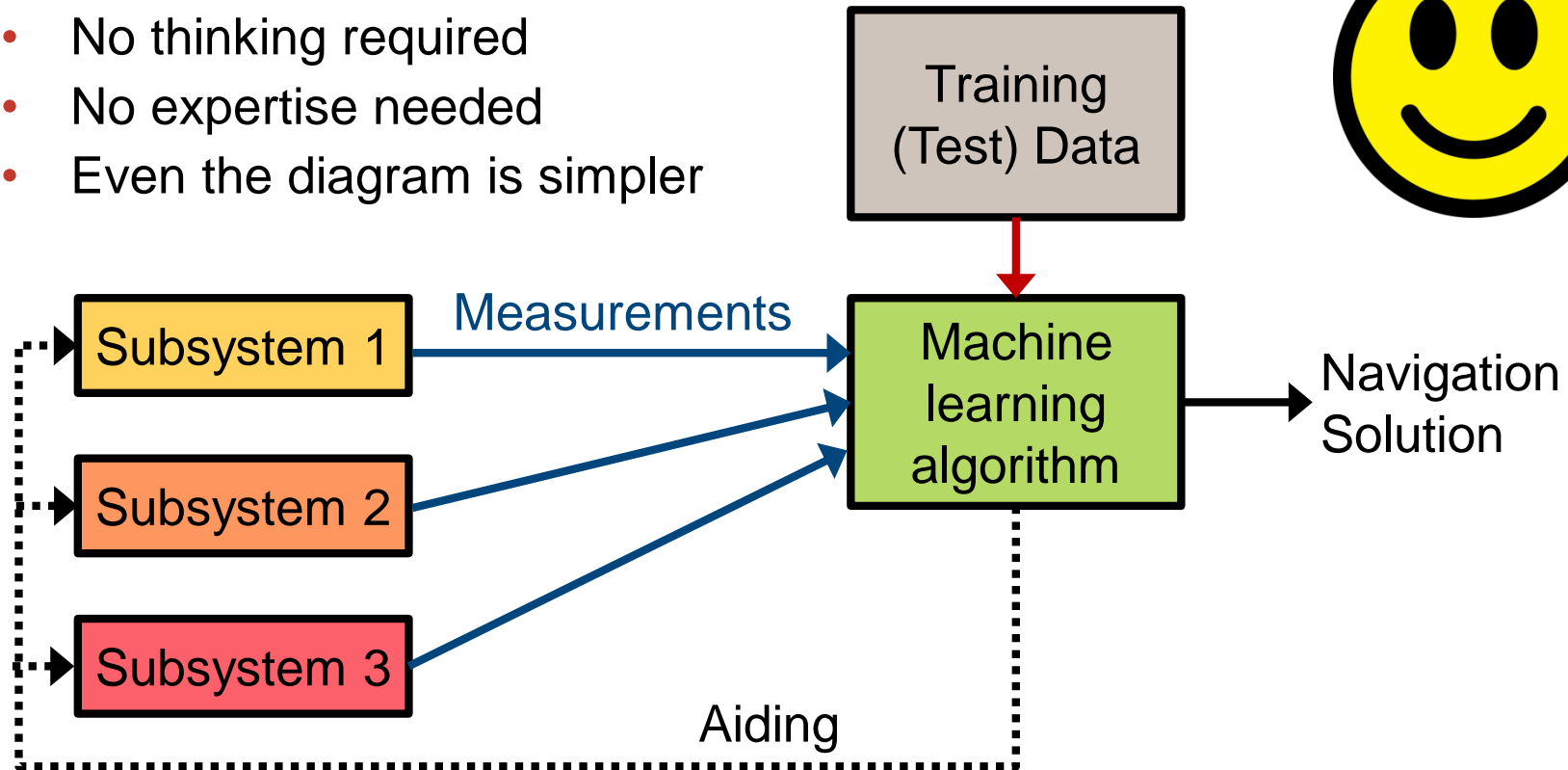


But then, as he grew older, he wouldn't speak!

As others his age were learning words and then assembling them into sentences, he

The Artificial Intelligence Approach

- No thinking required
- No expertise needed
- Even the diagram is simpler



Challenge: Can we **trust** the navigation solution?

Solution: If you don't employ expert engineers, no-one will ask the question

GNSS Positioning Using Machine Learning (1)

Assuming no prior GNSS expertise...

Step 1: Collect training data

- Distribute GNSS receivers across entire area of operation
- Space them at the required positioning resolution



GNSS Positioning Using Machine Learning (2)

Step 2: Train your machine learning algorithm

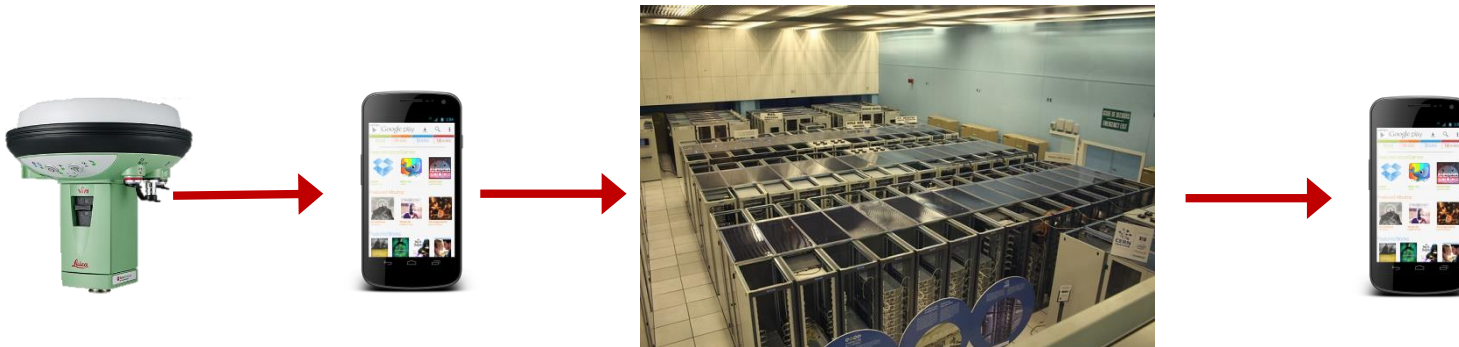
- Input GNSS receiver ADC outputs and true receiver positions
- 4 MB per second per receiver (2 bit sampling at 16 Msamples/s)
- 86,400 s to capture GPS ground track repeat period (longer for other constellations)
- 1m resolution
- 350 petabytes of training data per km² of service area
- This is more data than CERN has



GNSS Positioning Using Machine Learning (3)

Step 3: Positioning service

- Send GNSS receiver ADC outputs (4 kB per ms) to server
- Input to massive deep learning algorithm (too big for a mobile device)
- Return position to user



- Correlating the PRN codes, downloading the ephemeris and computing a least-squares solution is **much much** easier!

Maybe we still need expertise and thinking

Is Machine Learning Useful at all?

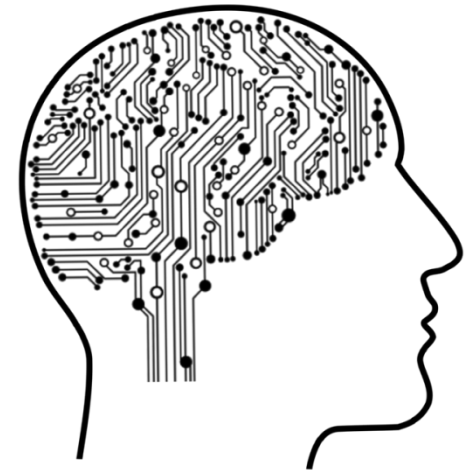
Physics-based mathematical modelling is more efficient for systems we understand

Machine learning is useful for systems that are difficult to model

- Nonlinear inertial sensor errors
- Object recognition
- Context determination

But... thinking is still needed

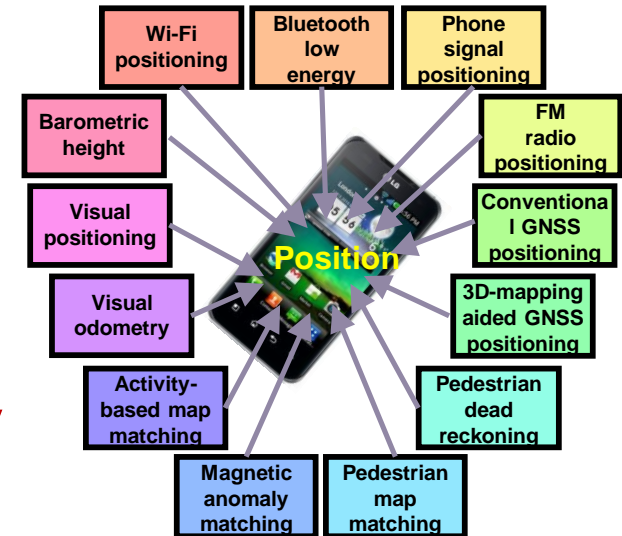
- Define classes to recognise or parameters to estimate
- Select the right machine learning algorithm
- Determine the feature data to input
- Devise a suitable training process



Fault Detection (1)

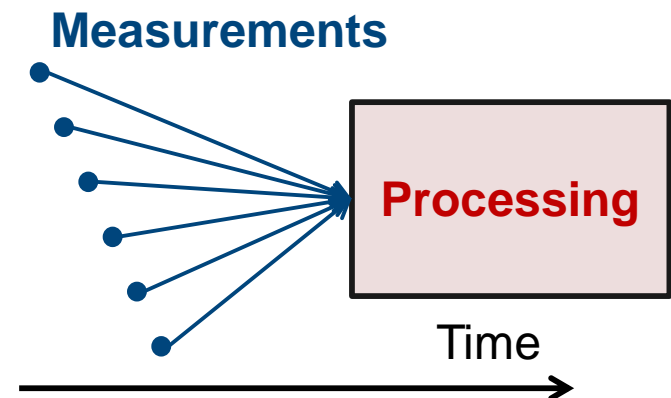
Multi-sensor fault detection

- More measurements improves outlier detection sensitivity
- **But** more measurements also makes simultaneous faults more likely
- **And** simultaneous faults are not necessarily independent



Multi-epoch fault detection

- More measurements improves outlier detection sensitivity
- **But** there are more faults to detect
- **And** faults are often correlated over successive epochs



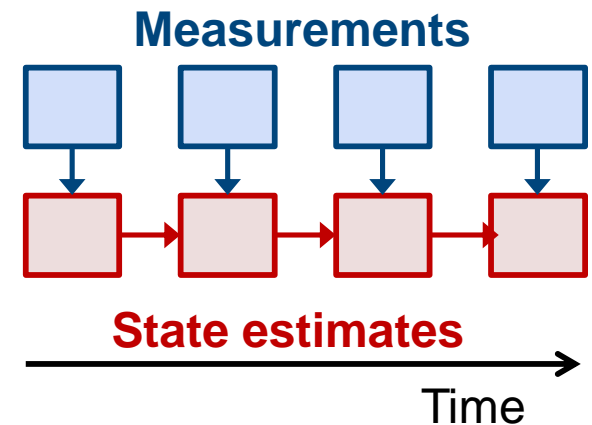
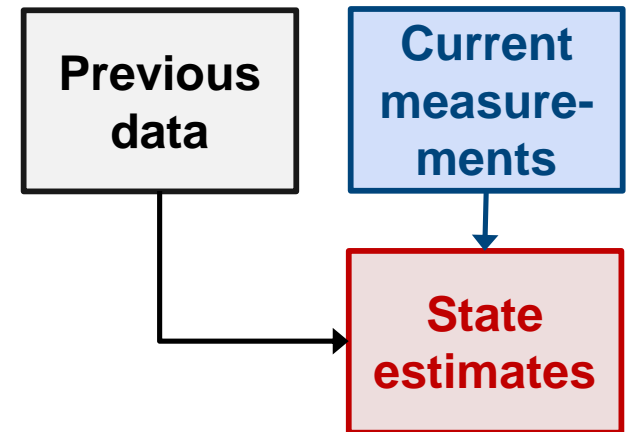
Fault Detection (2)

Recursive Estimator

- Limited processing load for unlimited epochs
- Faults must be detected immediately to avoid contaminating the state estimates

Batch Estimator

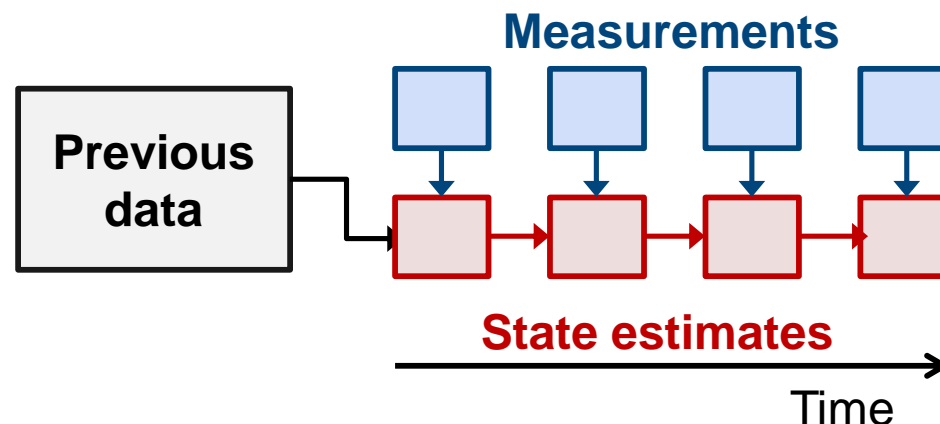
- Processing load increases with number of epochs, effectively limiting the number of epochs
- Faulty measurements can be removed at any time



Fault Detection (3)

Hybrid Batch-Recursive Estimator

- Most recent epochs considered separately with older epochs combined recursively
- Processing load is finite for unlimited epochs
- Faulty measurements can be removed at any time before they are absorbed in the recursive part of the filter



- Fault detection algorithms must consider multiple faults that can be correlated over time and across different measurements

Some Thoughts on Integrity

Formal Integrity Requirements:

- The probability that the position error exceeds x must be less than y otherwise an alert must be raised

This requires real-time calculation of

- *Either* Integrity risk of a position error exceeding x
- *Or* position error corresponding to an integrity risk of y

Which requires..

- Statistical error distribution of all measurements under normal operation *and* for each failure mode
- Probability of each failure mode
- Temporal correlation models for all error sources
- Models of error correlation across measurements for all sources

I don't know how to do this!

Summary and Discussion Points

Context determination allows a navigation system to adapt to different environments and user behaviours

Do you agree?

Plug'n'play multisensor integration helps to manage complexity

But is it practical?

Machine learning is not a replacement for Bayesian estimation

But, does it still have uses in navigation?

A hybrid batch-recursive estimator is a good approach to multi-epoch multi-sensor Fault Detection

Are there any alternative proposals?

Maintaining integrity in a complex multisensor system is very difficult.

Does anyone have any suggestions?