‘Advances in AI for Positioning, Navigation and Timing Applications’

A joint event between the Cambridge Wireless Location SIG & The Royal Institute of Navigation

30 June 2026, Cambridge

CAMBRIDGE TECH WEEK

14-18 SEPT 2026

HOW DEEP TECH CHANGES THE WORLD

CAM TECH WEEK

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1 July **FROM PROMISE TO PRACTICE: THE ONGOING 5G JOURNEY**
Omdia, London

15 July ***MODERN AI FOR A BETTER WORLD***
Cambridge

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Location SIG

The purpose of the Location SIG is to promote and further the adoption of location as a value-added facility for a range of applications.

SPECIAL INTEREST GROUPS

SIG Champions

David Bartlett

Bob Cockshott

Ramsey Faragher

The Royal Institute of Navigation

Ben Tarlow

Qualcomm Technologies International

With additional support for the creation of this event from

Matteo Ciprian

Welcome & Introduction from our Event Partner
The Royal Institute of Navigation

Ramsey Faragher

CEO,

The Royal Institute of Navigation

https://rin.org.uk

For over 75 years we have:
Brought together everyone interested in navigation,
to advance the art, science and practice of navigation,
to promote knowledge in navigation
(to make the world a better place)

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Welcome to the RIN Learning Centre

Explore expert-led courses, gain new skills, and stay ahead in the world of positioning, navigation, and timing.

Explore

https://www.pathlms.com/rin

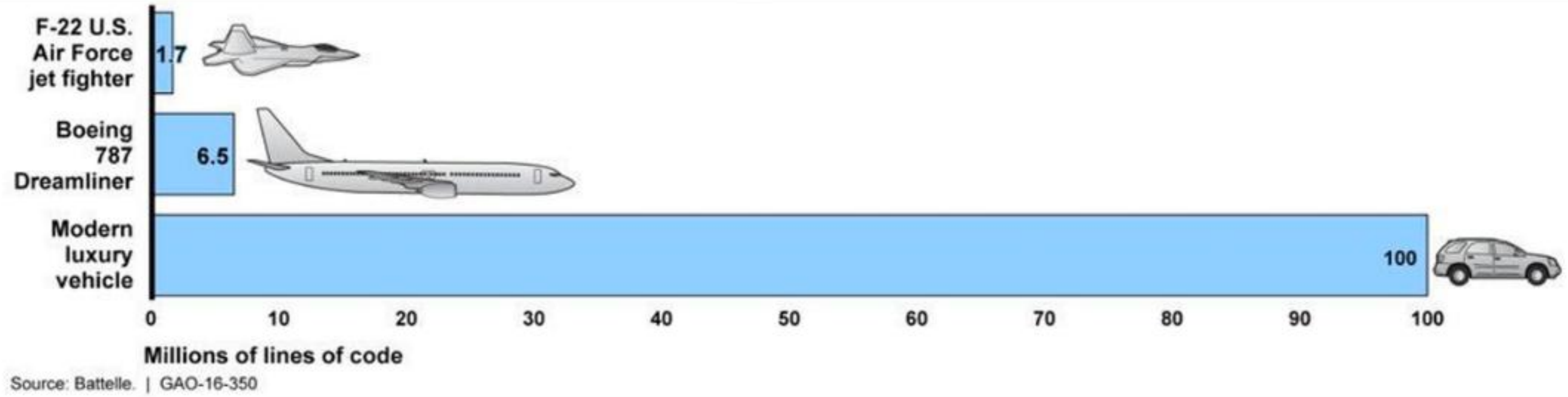
Welcome to the RIN Learning Centre

The Royal Institute of Navigation (RIN) Learning Centre is a new initiative designed to support education for those interested in positioning, navigation, and timing (PNT) across land, air, sea, and space.

The RIN has successfully delivered training for several years; the Learning Centre represents the next step in this journey, enabling us to build on these strong foundations and draw on the depth of experience and expertise across our network.

Explore a growing portfolio of courses spanning fundamental principles


TKU 944


F-22 U.S. Air Force jet fighter
1.7
Boeing 787 Dreamliner
6.5
Modern luxury vehicle
100
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20
30
40
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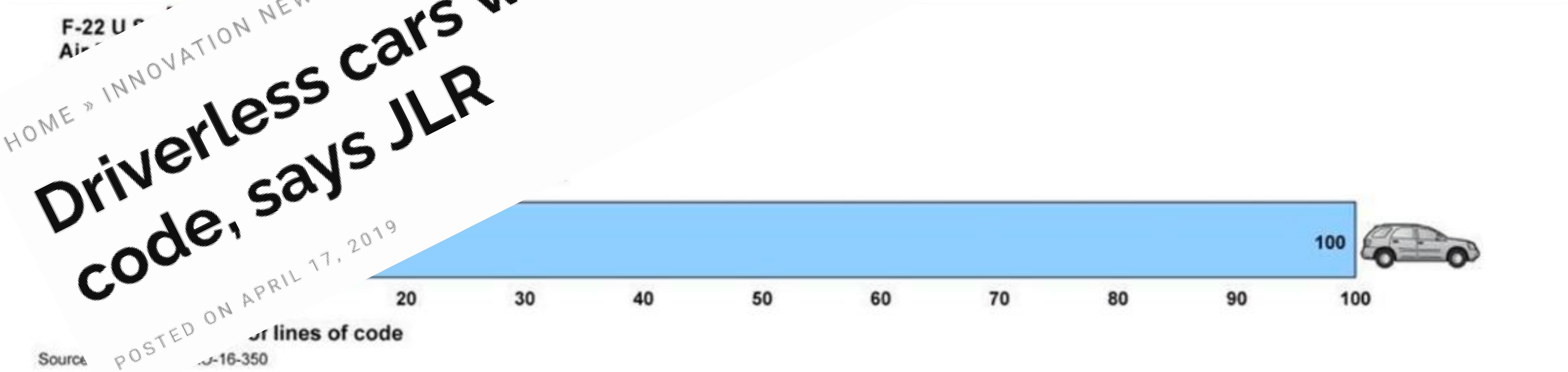
60
70
80
90
100
Millions of lines of code
Source: Battelle. | GAO-16-350

HOME » INNOVATION NEWS

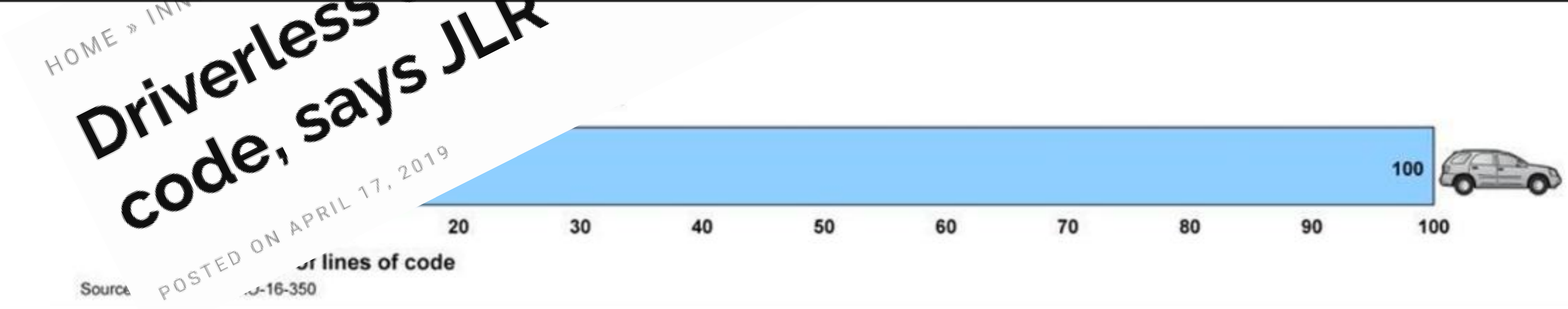
Driverless cars will require one billion lines of code, says JLR

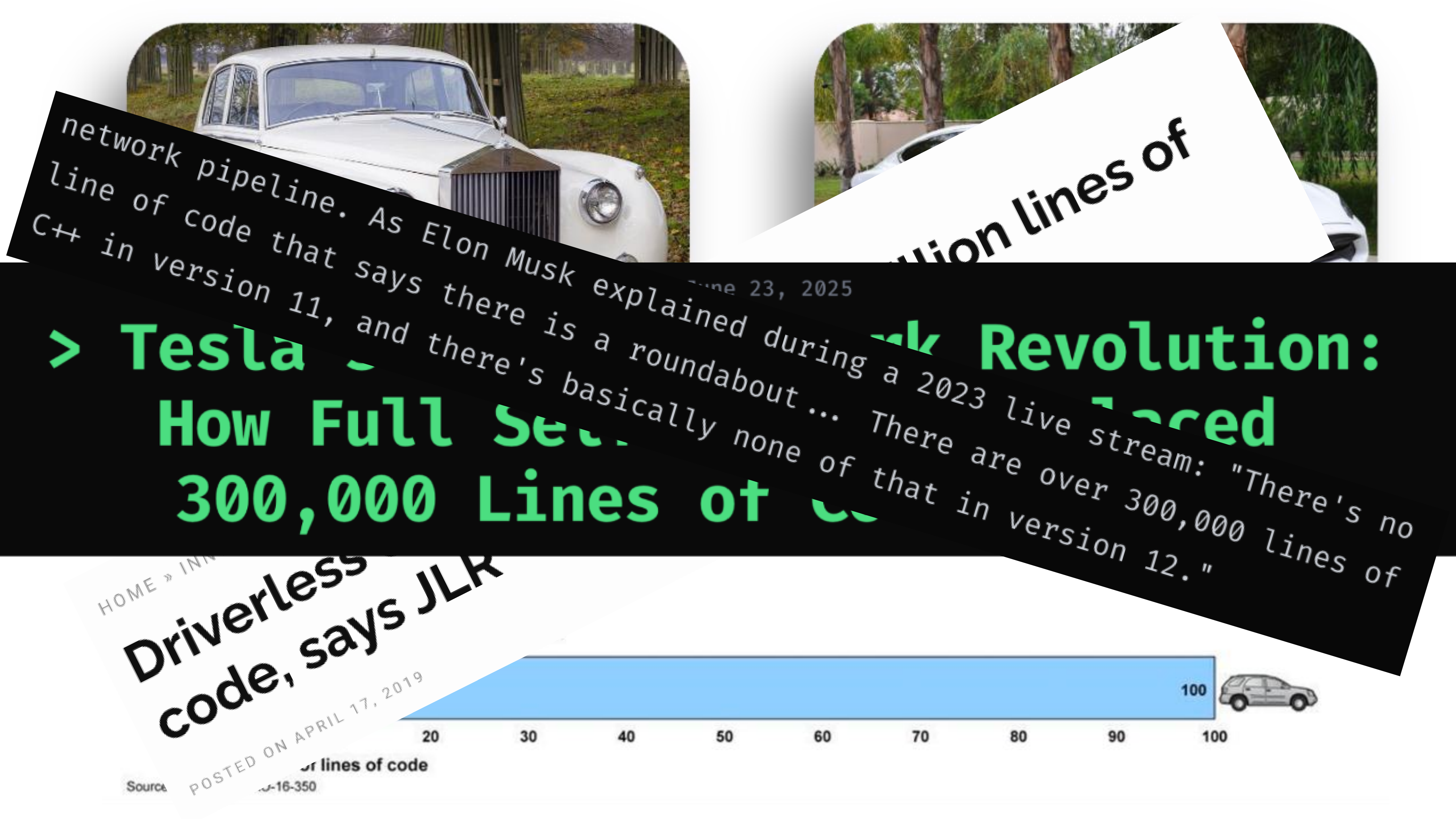
POSTED ON APRIL 17, 2019



Monday, June 23, 2025

> Tesla's Neural Network Revolution: How Full Self-Driving Replaced 300,000 Lines of Code with AI





network pipeline. As Elon Musk explained during a 2023 live stream: "There's no line of code that says there is a roundabout … There are over 300,000 lines of C++ in version 11, and there's basically none of that in version 12."
lines of
23, 2025
> Tesla
Revolution:
How Full
300,000 Lines of
HOME »
Driverless
code, says JLR
POSTED ON APRIL 17, 2019
100
20
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lines of code
Source

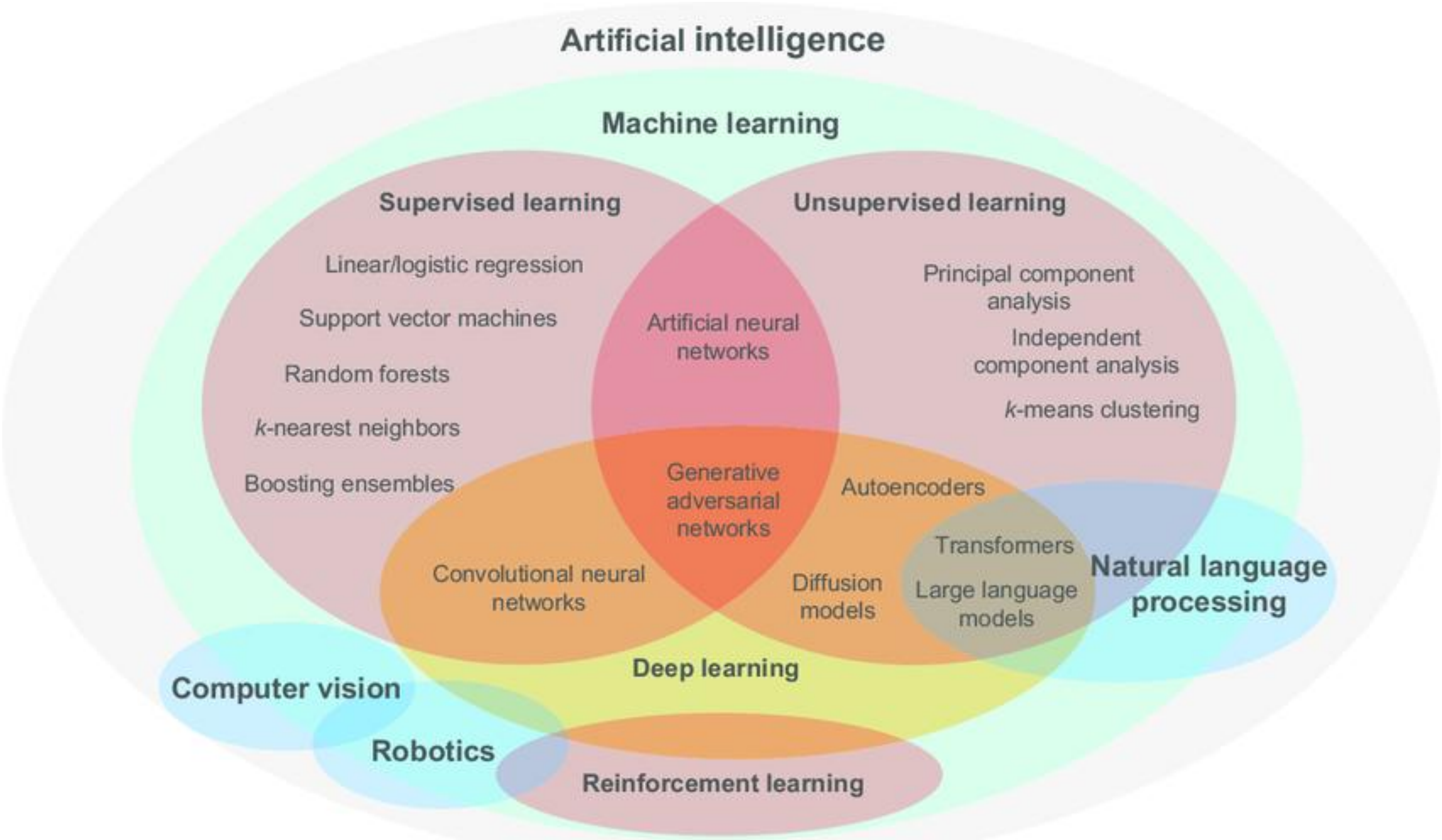
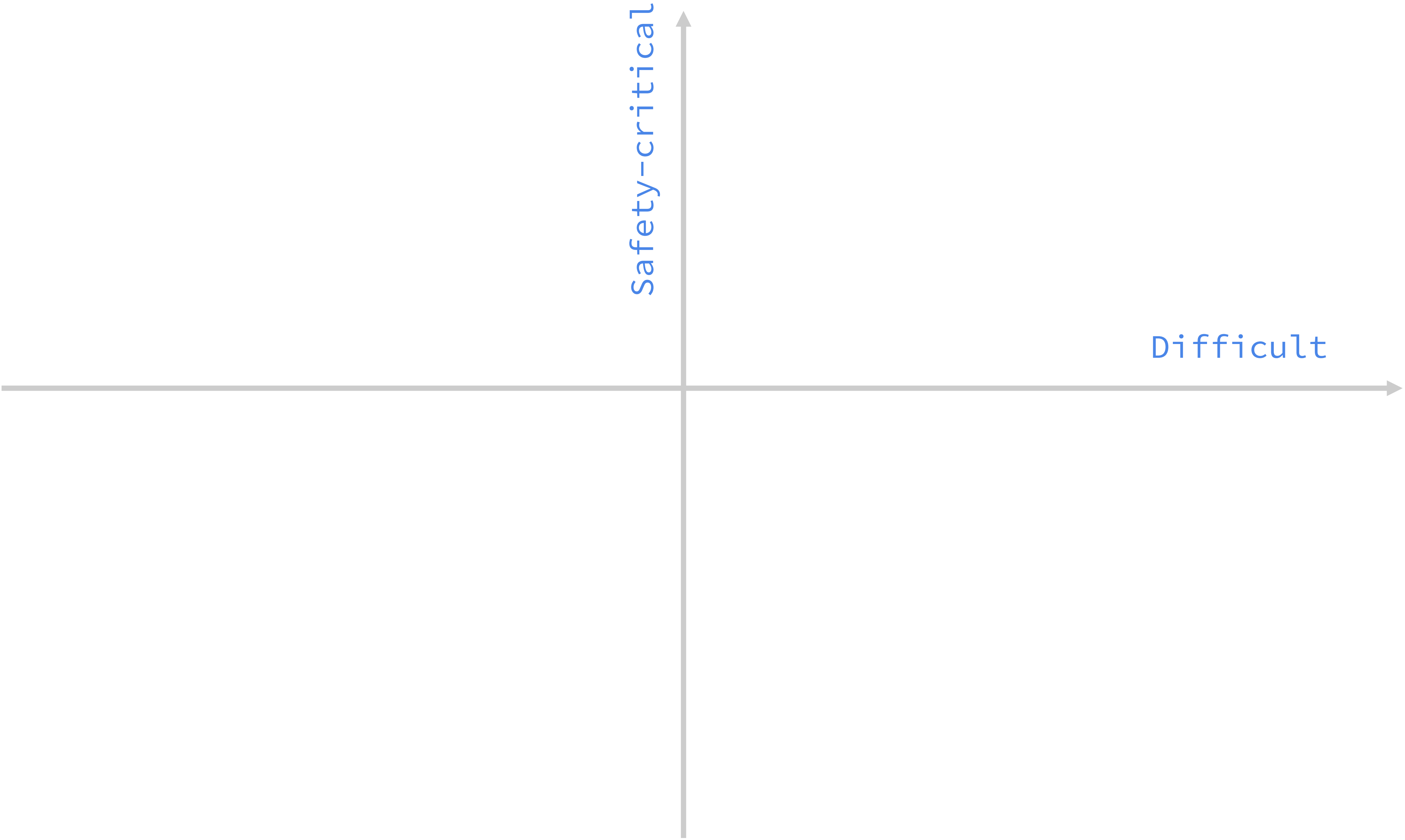
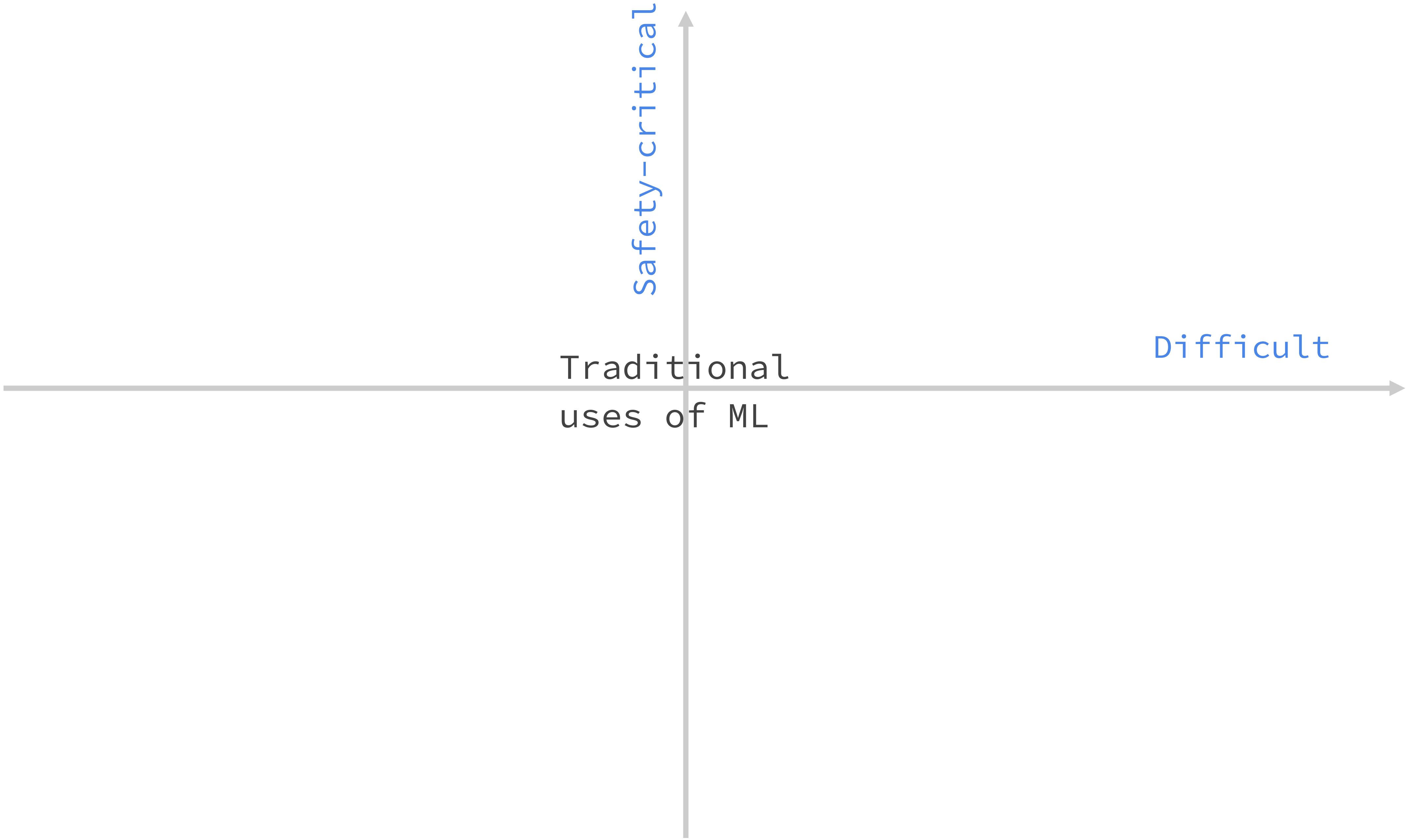
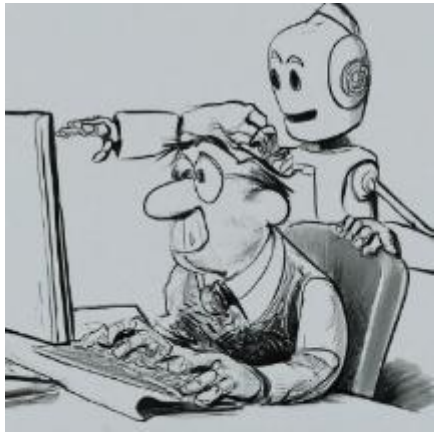


Image shamelessly stolen from: Hanassab et.al. *The prospect of artificial intelligence to personalize assisted reproductive technology*. npj Digital Medicine. 7. 10.1038/s41746-024-01006-x.


Safety-critical
Difficult


Safety-critical
Difficult
Traditional
uses of ML

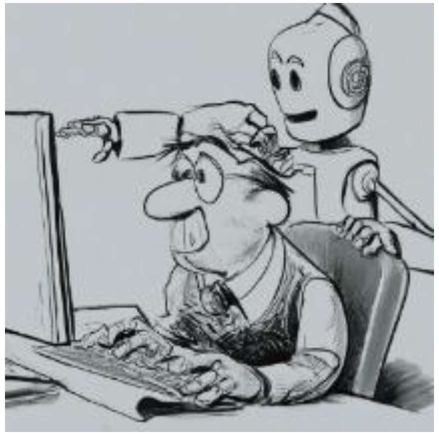


Coding/text-gen/image-gen assistants

Safety-critical

Difficult

Traditional uses of ML



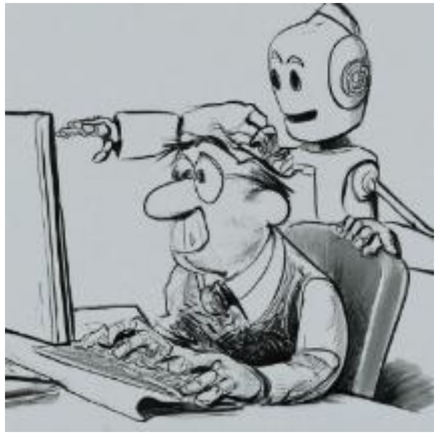
Coding/text-gen/image-gen assistants

Safety-critical

Fully explainable & certifiable & safe self-driving cars

Difficult

Traditional uses of ML



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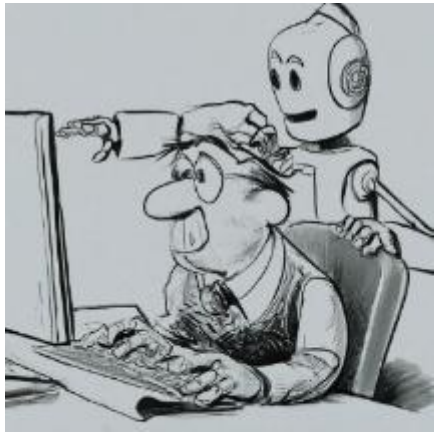

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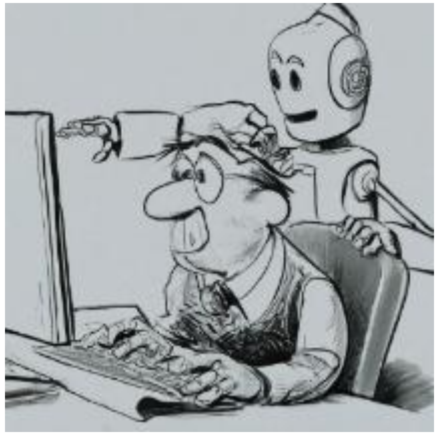
Huge datasets versus overfitting



Coding/text-gen/image-gen assistants

Safety-critical

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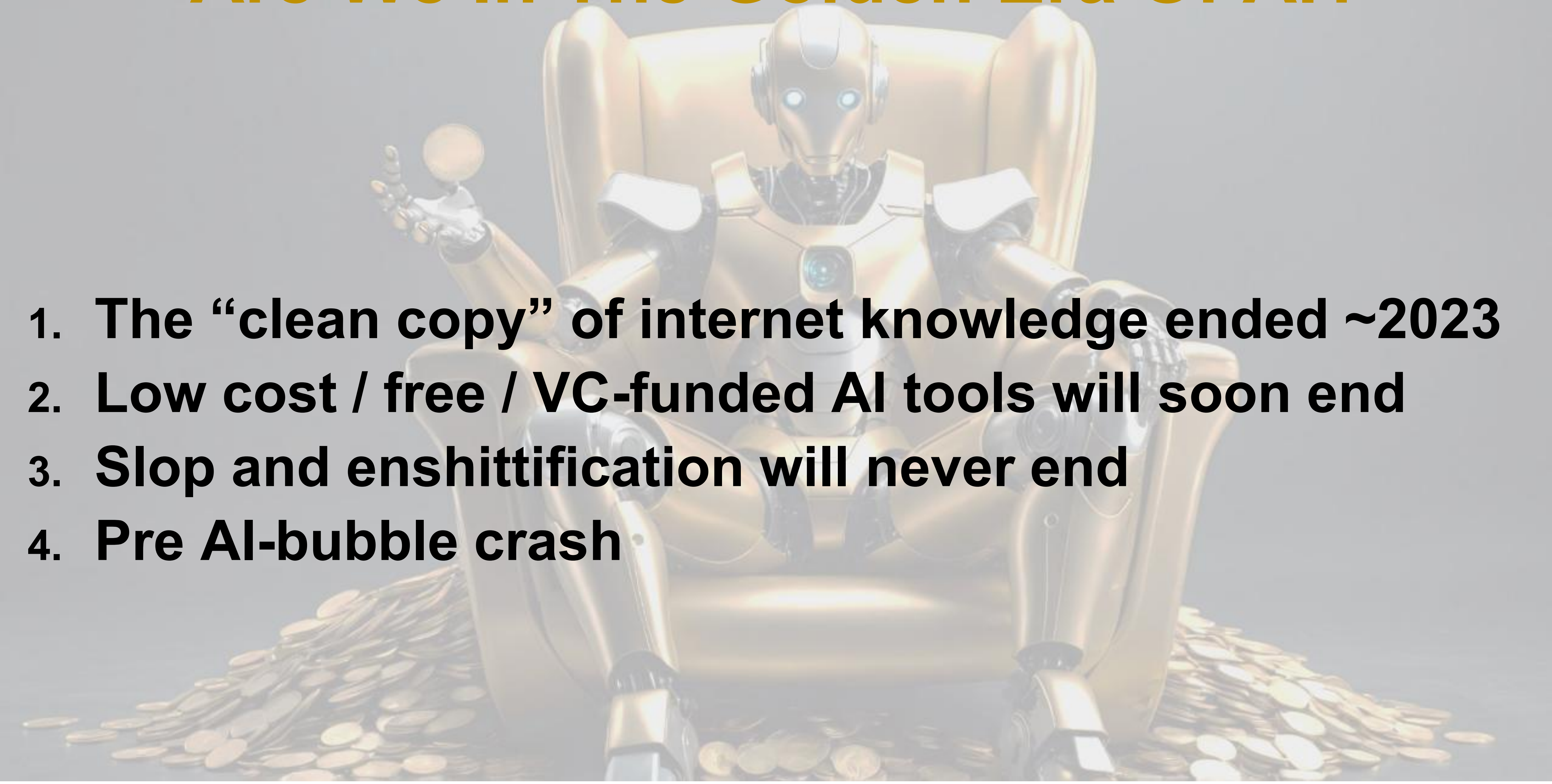
Education

Huge datasets versus overfitting

Are We In The Golden Era Of AI?

Are We In The Golden Era Of AI?



1. The “clean copy” of internet knowledge ended ~2023
2. Low cost / free / VC-funded AI tools will soon end
3. Slop and enshittification will never end
4. Pre AI-bubble crash

POSITION • NAVIGATION • TIMING

Is it possible to build a Foundation Model for PNT?

// THE PARADIGM SHIFT OF THE LAST 10 years

From Narrow AI to Foundation Models

NARROW AI

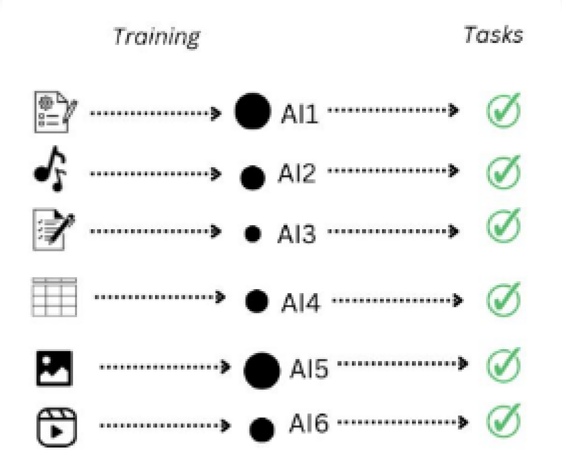
one task, one model

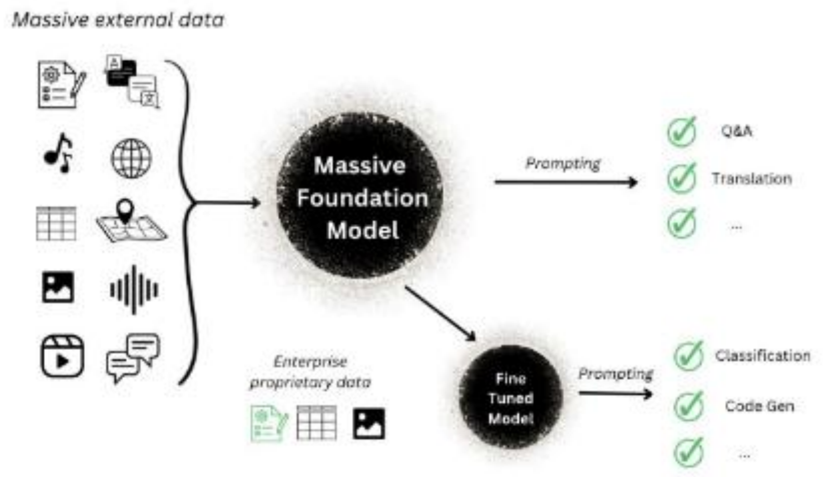
- Built from scratch per task
- Needs labeled task data
- No transfer between tasks

FOUNDATION MODELS

one base, many tasks

- Pretrained once, broad data
- Self-supervised
- Adapt via fine-tune / prompt





// SAME RECIPE, DIFFERENT MODALITY

Foundation Models Across Domains

NLP

GPT • Claude • Llama

next-token over web text

COMPUTER VISION

CLIP • SAM • DINOv2

self-supervised vision + gen

AUDIO & SPEECH PROCESSING

Whisper • Wav2Vec2 • MusicLM

speech-to-text + audio gen

DRUG DISCOVERY

AlphaFold • RoseTTAFold

sequence → 3D structure

POSITION • NAVIGATION • TIMING

Is it possible to build a Foundation Model for PNT?

Ontological Issue

Is PNT comparable to Computer Vision or NLP?

Data

Do “PNT Data” share the same corpus?

Physics

Could modelling physical phenomena be a problem?

Unified?

One model for all three legs — or three separate?

// an opening question — not an answer

Agenda

13:55 **Prof Paul Groves, Professor of Positioning and Navigation, University College London (UCL)**
AI and Navigation: Don't Shoot The Physicists

14:20 **Prof Ivan Petrunin, Professor of Signal Processing and Intelligent Systems in the Centre for Space Systems at Cranfield University**
AI-Driven Resilient PNT: Enabling Trusted Navigation and Timing in Challenging Environments

14:45 **Robert Schoonmaker, BootINS Ltd.**
Machine Learning Challenges in Navigation: Technical and Business

15:10 **Refreshment break**

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AI and Navigation: Don’t Shoot The Physicists

Prof Paul Groves
Professor of Positioning and Navigation, University College London (UCL)

AI and Navigation: Don’t Shoot The Physicists

Paul D Groves
Professor of Positioning and Navigation
University College London
p.groves@ucl.ac.uk

Advances in AI for Positioning, Navigation and Timing Applications, Cambridge, 30 June 2026

UCL ENGINEERING
Change the world

Robust Positioning and Navigation at UCL

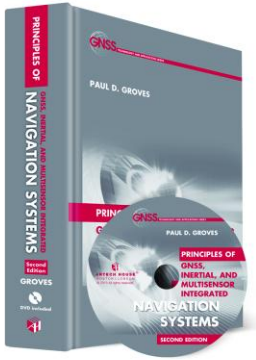
A world with real-time low-cost positioning within 3m in all places at all times needs

- New methods of navigation and positioning
- Improved reliability of existing techniques
- Optimal sensor integration
- Better navigation technology education

Current and Recent Projects

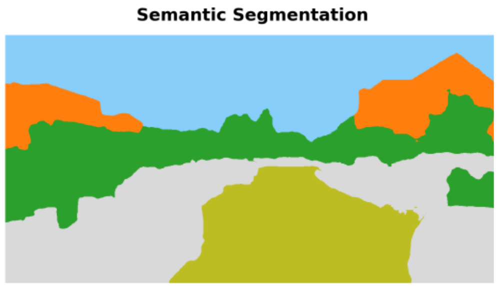
- Wi-Fi Round Trip Timing
- Foot Mounted Inertial Navigation
- Semantic Visual Feature Matching
- Magnetic Anomaly Matching
- 3D Mapping Aided GNSS
- Navigation Doppler Lidar for Aircraft Navigation – with Curtin University, Australia

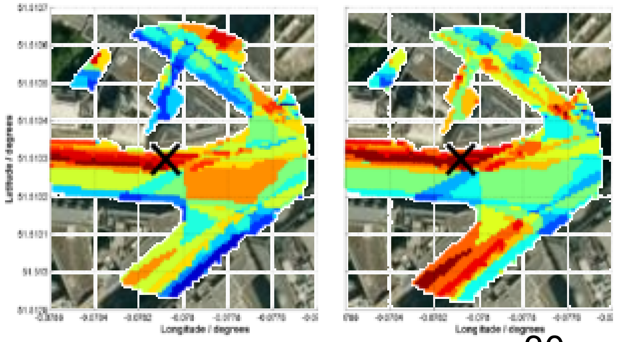




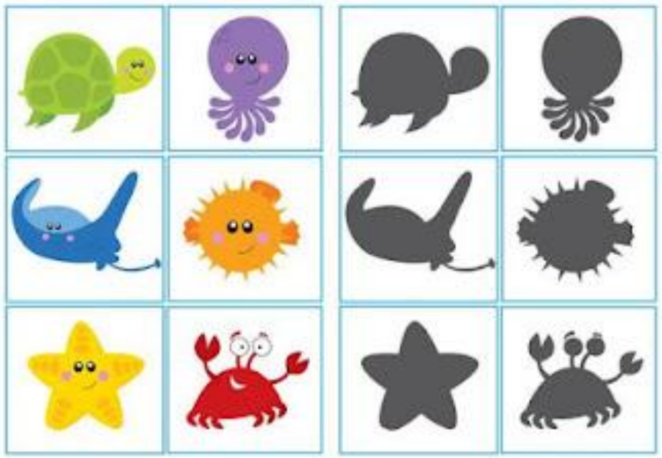




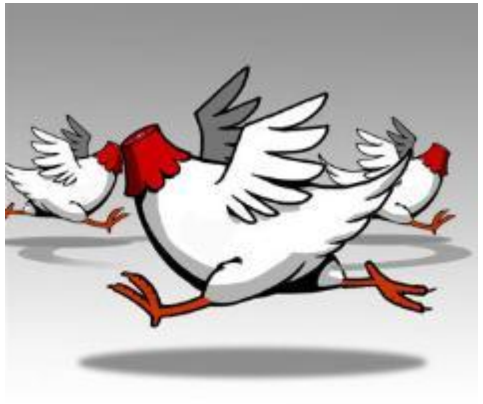




The Story of GNSS Shadow Matching



- 4 or 5 different research groups came up with the idea independently
- UCL came up with the name
- We got most of the credit for inventing the technique
- "Shadow matching" started appearing in corporate slide decks
  - *But with no indication of what it actually was*
- "Shadow matching" was mentioned in the introduction to research papers
  - *With a reference to a UCL paper that was NOT about shadow matching!*



The Story of GNSS Shadow Matching

What have we learnt today?

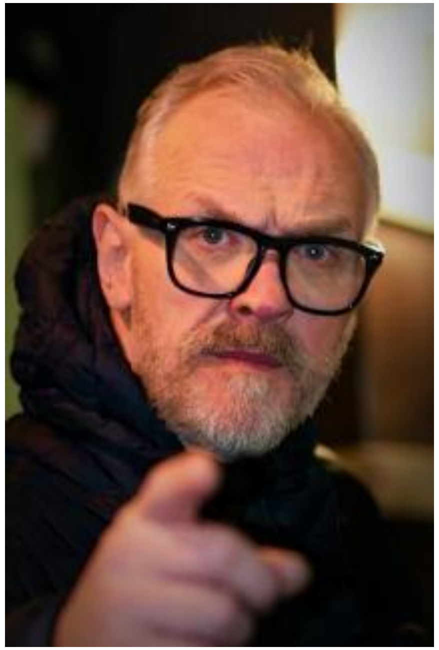


Image: Wikipedia

Buzzwords Rule!

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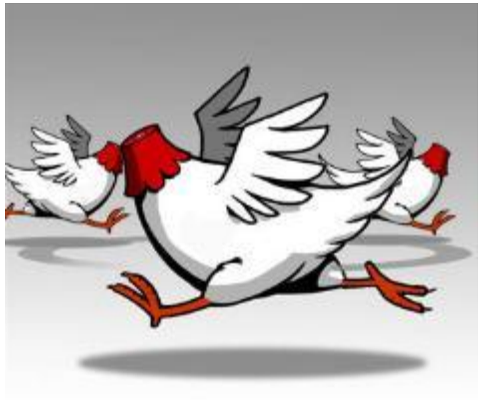

The Ultimate Buzzword

BUZZWORD BINGO				
action item	exit strategy	metrics	synergy	win-win
learnings	best practice	buy in	helicopter view	proactive
blue sky thinking	holistic	Free space	leadership	on the radar
low-hanging fruit	big picture	value added	strategic	elevator pitch
outside the box	can-do attitude	touch base with	alignment	incentivise

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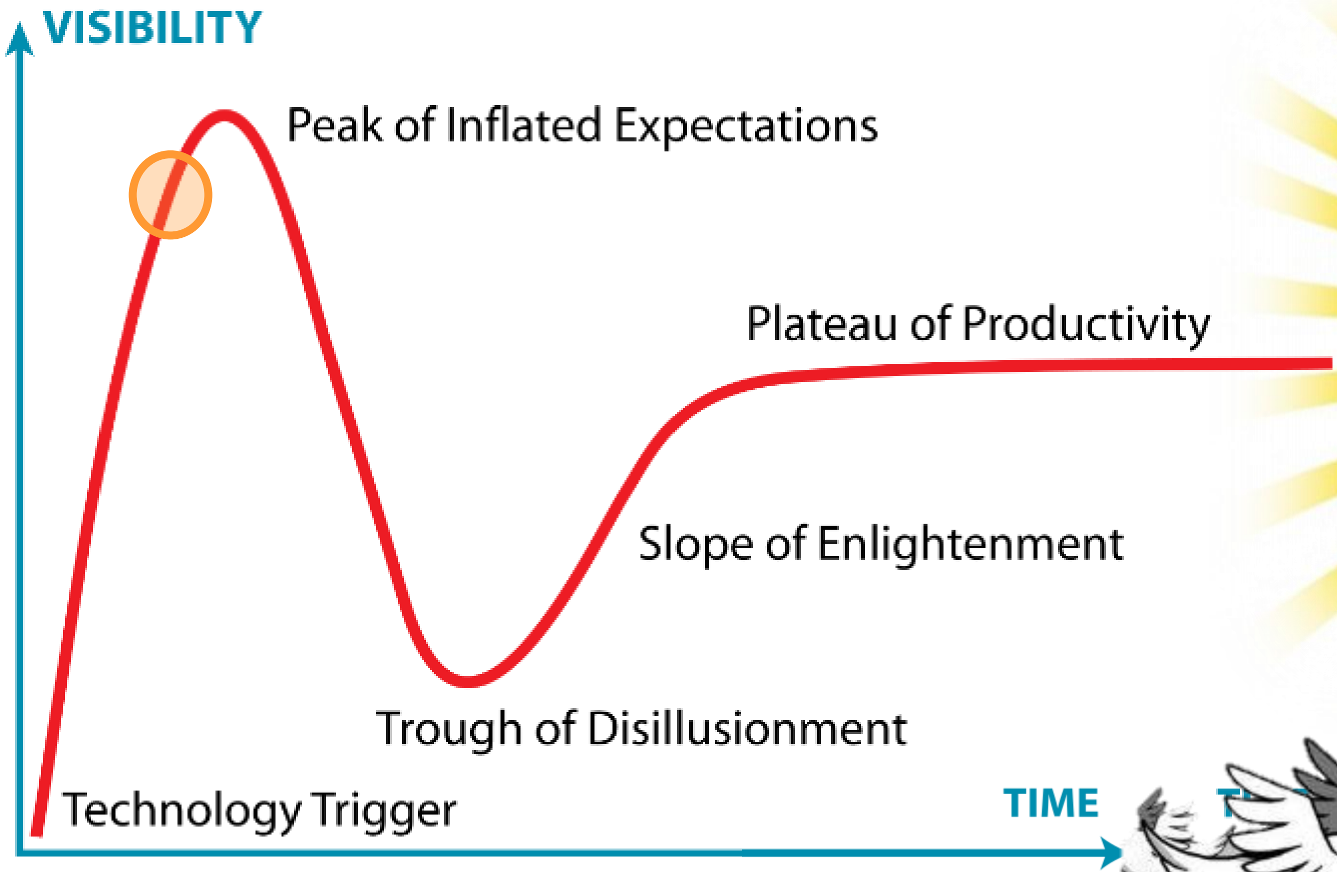
The Hype Cycle

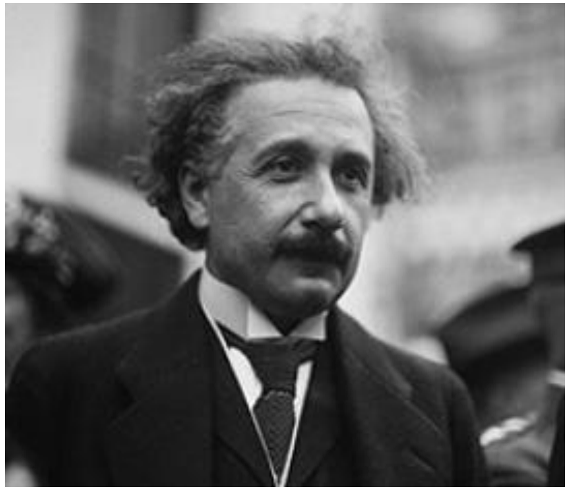


The “AI” Bulldozer

- Are you starting a business?
- Are you looking for investment?
- Do you want to keep selling your products?
- Do you want research funding?
- Are you recruiting students?
- If you’re not using “AI”, the Bulldozer is coming for you

But What Actually Is "AI"?

Is it Artificial Intelligence?



- Does it understand?
- Does it solve problems?
- Does it come up with new ideas?
- Not really!

Is it Artificial Incompetence?

- Does it tell you what you want to hear?
- Does it make things up?
- Does it disregard facts?
- Sometimes!

It is a Massive Statistical Model

- It matches inputs to massive training data sets
- This generates predictions

Image generated by Microsoft Copilot

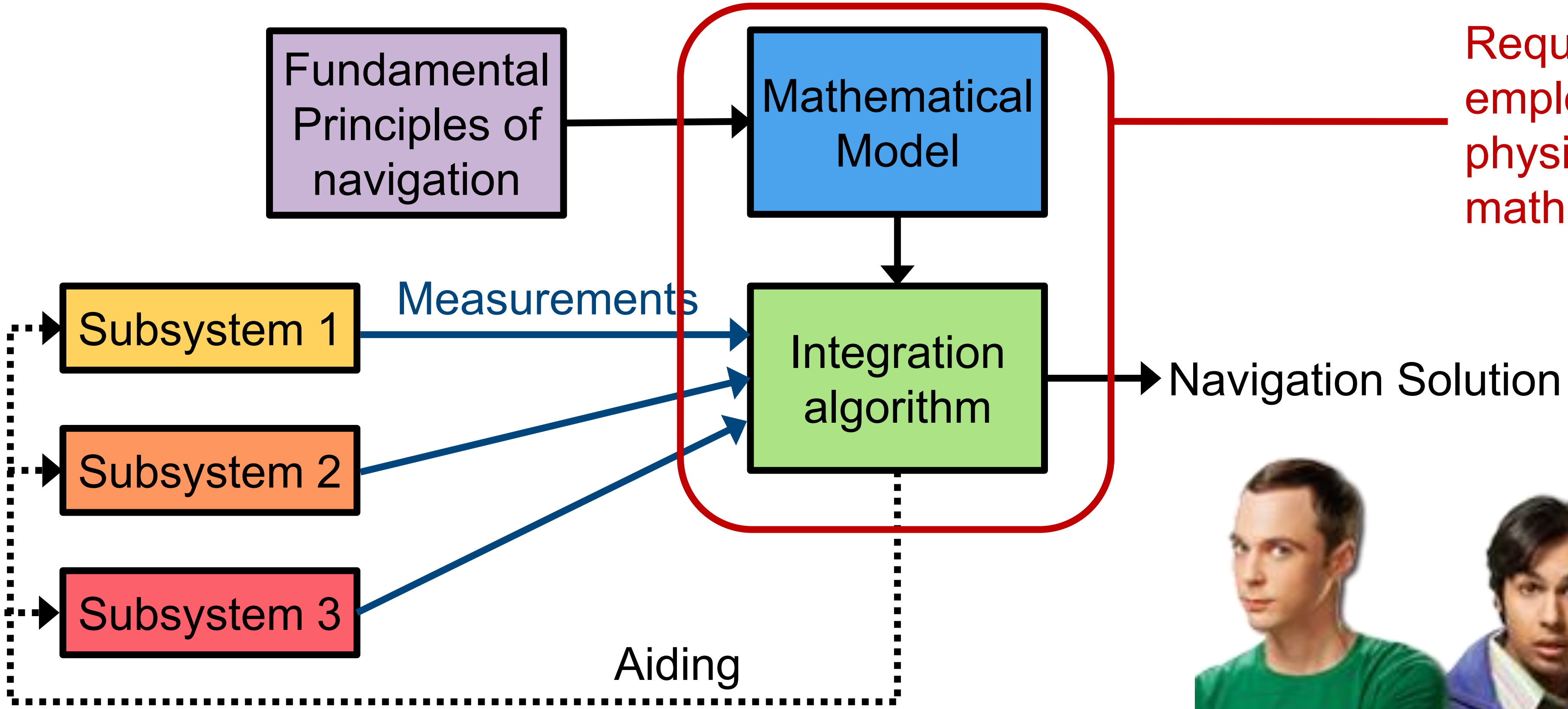
“AI” Coffee – A Quiz

How to Make a Cup of Coffee

Coffee has been a cornerstone of civilisation since before the foundation of Starbucks in 1971. A truly global phenomenon, its indispensability cannot be overstated as elucidated through its utilisation by prime ministers, presidents, monarchs and even vice chancellors. This is underscored by the plethora of coffee varieties from around the world, including the pivotal Americano, the foundational espresso, the quintessential latte, and the retro-futuristic "instant". The ubiquity of its availability is indisputable, encompassing bars, cafes, pseudo-nostalgic carts and even some supermarkets. Moreover, leveraging the reusable cup engenders a transformational respect for the environment. In conclusion, it can be ascertained that coffee is a truly transcendental phenomenon.

Which was generated by “AI”? The text or the picture?

Traditional Navigation System Design

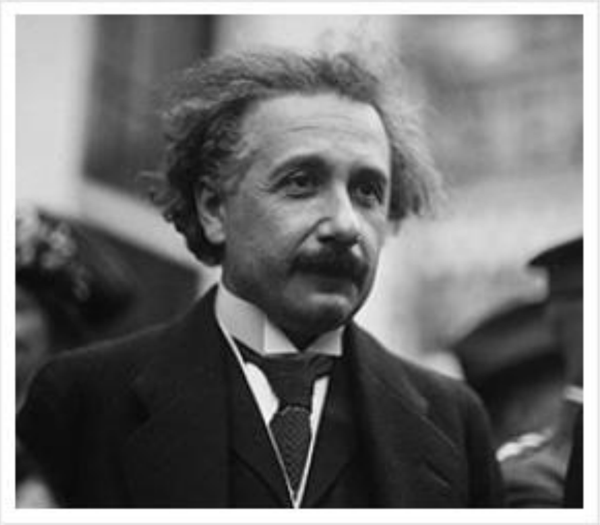


Requires employment of physicists or mathematicians

Thinking for Yourself is now Deeply Unfashionable

It's even classed as 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.

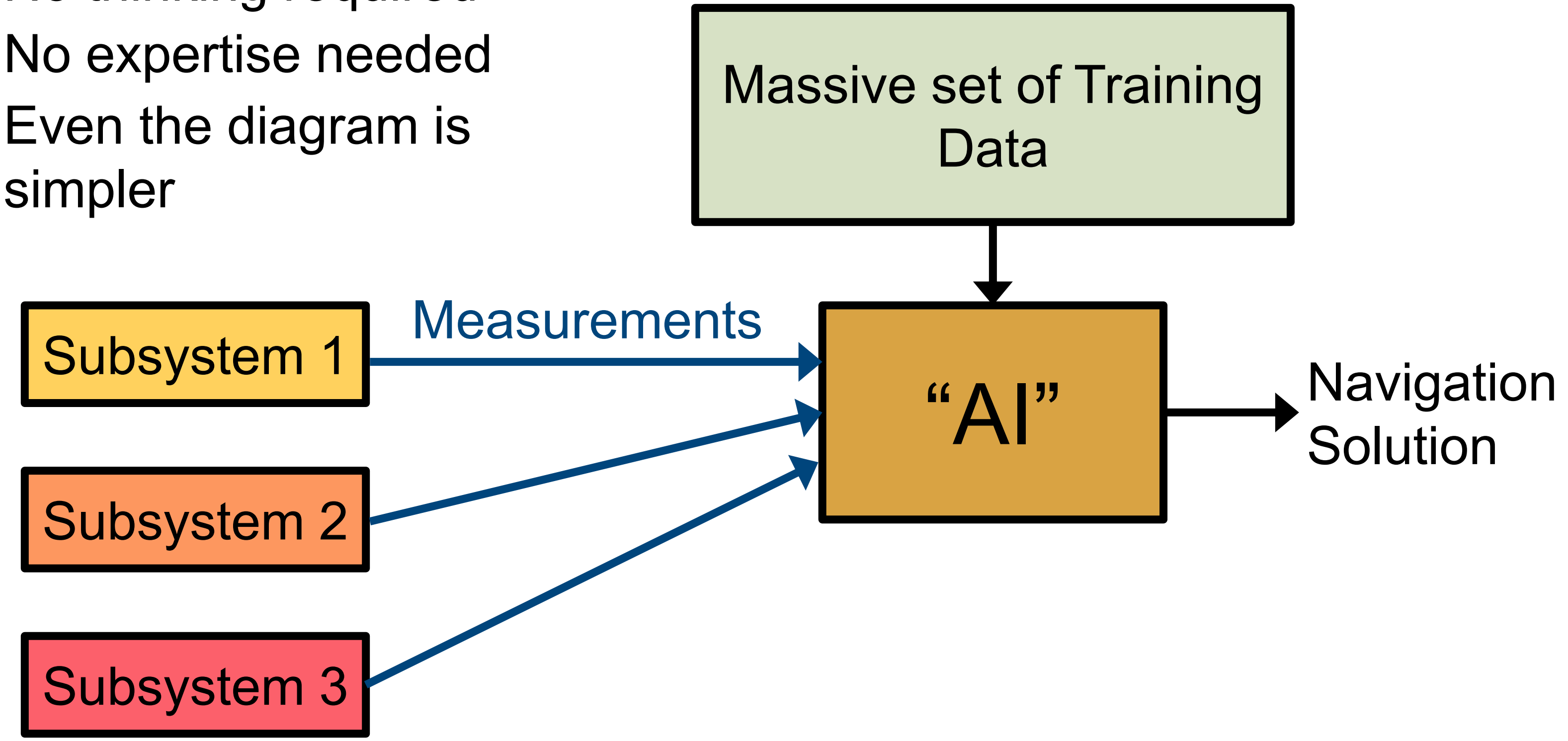
But then, as he grew older, he wouldn't speak!

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

The Cool People Follow the Crowd

“AI” Navigation System Design

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



Challenge: Can we trust the navigation solution?

Solution: If you don’t employ experts, no-one will ask the question

The “AI” Approach to GNSS Positioning (1)

Assuming no “experts” employed

Step 1: Collect training data

- Distribute GNSS receivers across entire area of operation
- Space them at the required position resolution
- Record data straight from the receivers’ analogue-to-digital converters (ADCs)
- Record data for 24 hours to capture GPS ground track repeat period (longer for other constellations)

The "AI" Approach to GNSS Positioning (2)

Step 2: Train your "AI"

- Input receiver ADC outputs & true positions
- 4 MB per second per receiver (2 bit sampling at 16 Msamples/s)
- 86,400 s of data
- 3500 petabytes of training data for 10 km^2 of service area at 1m resolution
- This is more data than CERN has

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

The “AI” Approach Inertial Navigation (1)

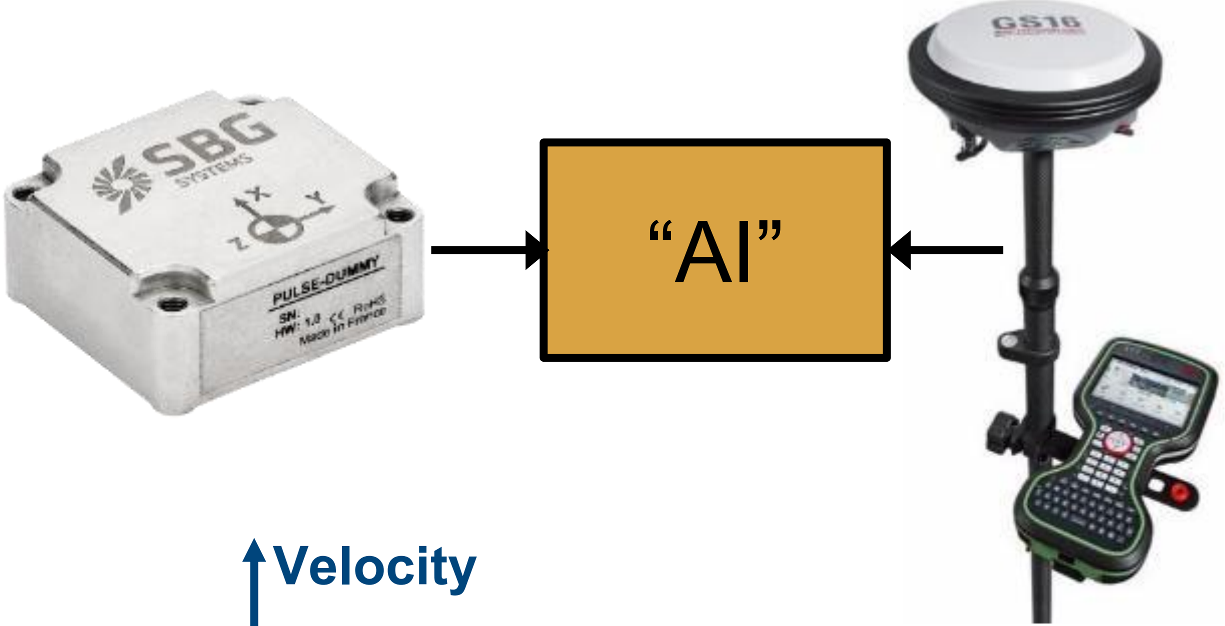
Assuming no “experts” employed

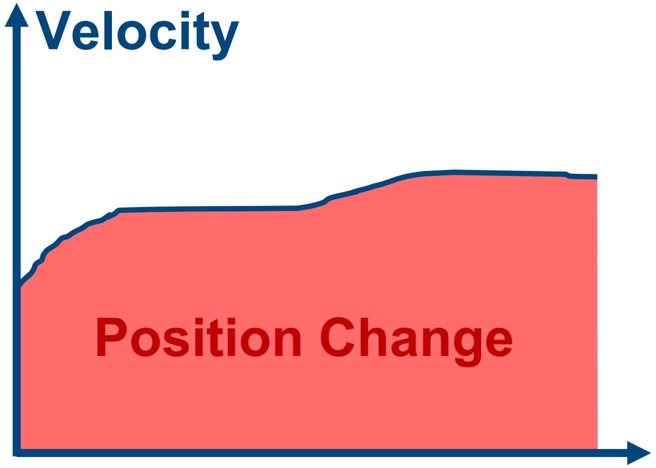
Train the “AI”: Using raw sensor measurements and a GNSS truth reference

With enough variation in the training data, it should learn the basics:

- Position is the integral of velocity
- Velocity is the integral of acceleration
- Attitude is the integral of angular rate
- Acceleration = Specific Force + Gravity

But still much more effort than simply coding up the maths





The “AI” Approach Inertial Navigation (2)

Assuming no “experts” employed

Train the “AI”: Using raw sensor measurements and a GNSS truth reference

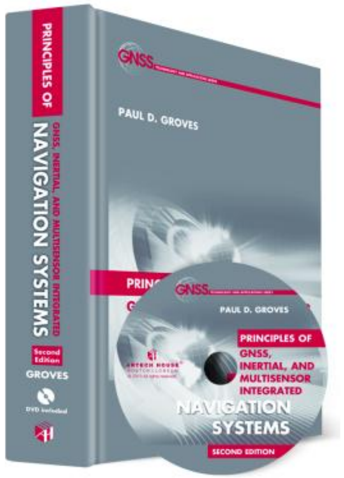
But what about….

- Variation of gravity with latitude and height
- Earth rotation
- Coordinate frame rotation
- Coriolis acceleration

Very large training sets would be needed for “AI” to learn these.

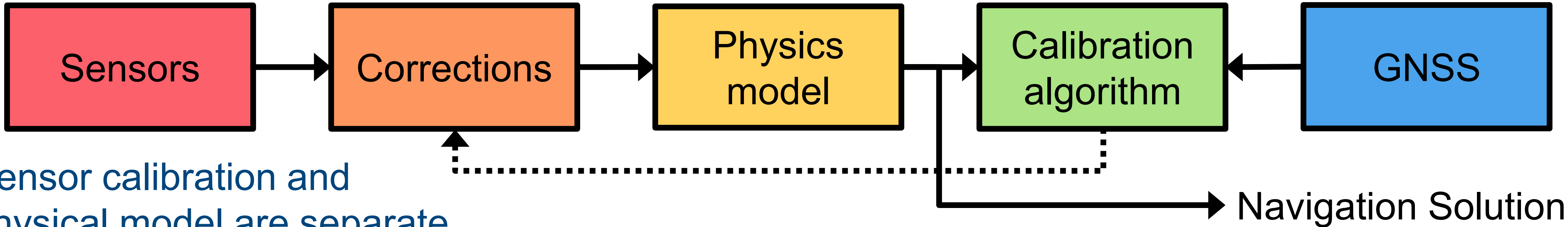
Errors would arise due to noise in the training data

We’ve had very precise mathematical models for 60 years!



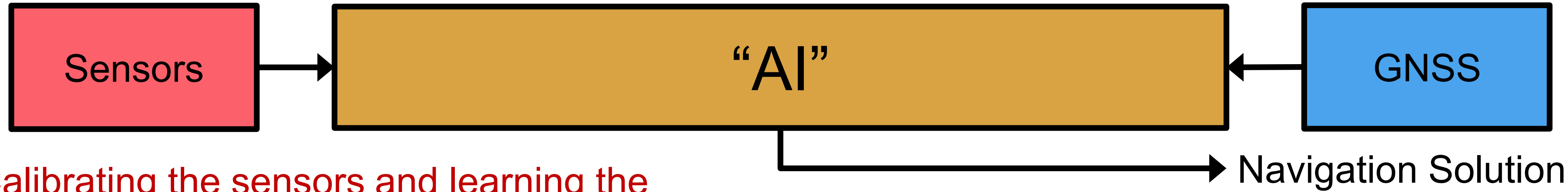
The “AI” Approach Inertial Navigation (3)

Conventional Approach



Sensor calibration and physical model are separate

Basic AI Approach

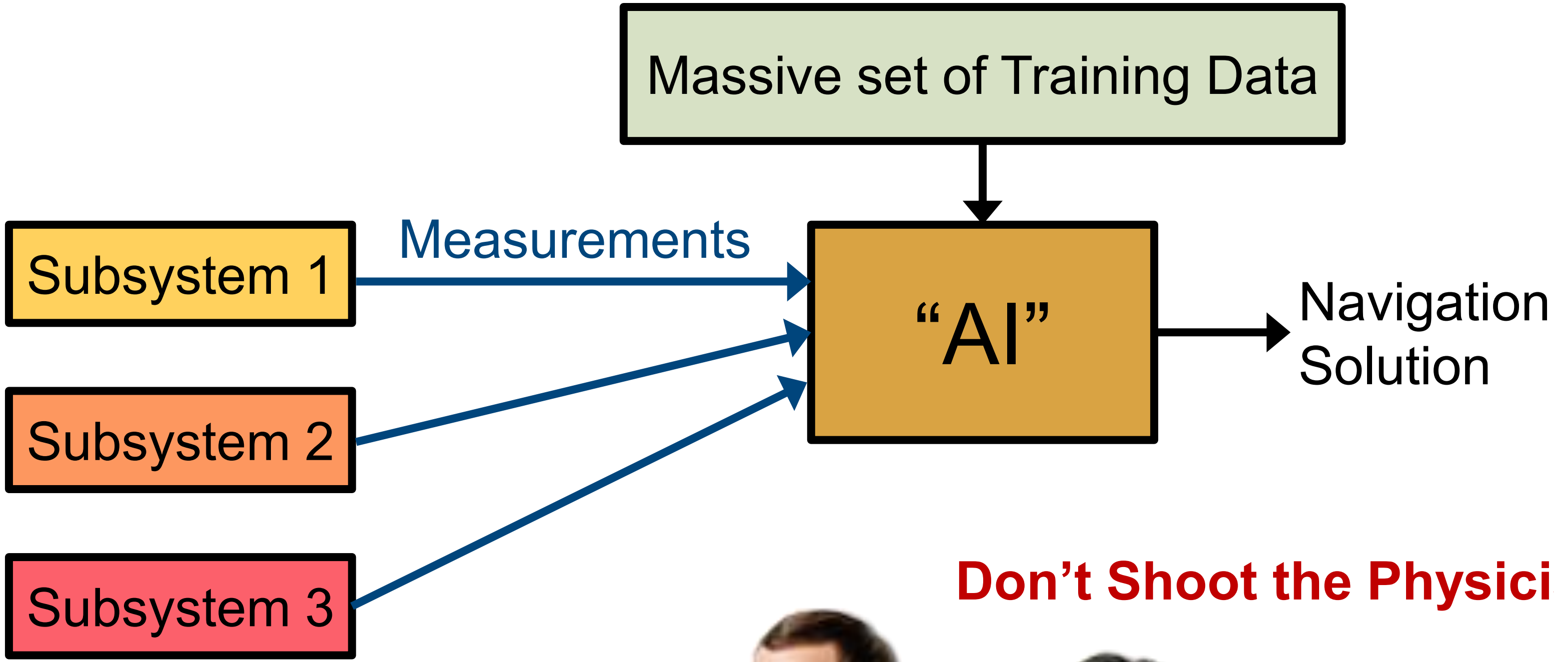


Calibrating the sensors and learning the physics are combined

- You have to train a separate AI for each inertial measurement unit (IMU)
- The IMU errors change over time – you have to keep retraining

So What Have We Learnt Today?

Image: Wikipedia



Replacing our physics-based navigation systems with AI is totally impractical

- Worse performance
- Vastly higher computational load

Don't Shoot the Physicists!

The “AI” Bulldozer is Still Coming for You!

If you don’t embrace AI

- Your business won’t attract investment
- Your products will be branded out of date
- You won’t attract research funding
- You won’t recruit staff or students?

So what do we, the PNT Community do?

We must find ways of using AI that do not make our technology perform worse!

The Limits of Physics-Based Models

1. Highly complex systems

- Difficult to analyse the physics to build the model
- Model development very time consuming

2. Missing model parameters

- Physics-based models can depend on parameters that are not practical to measure

Examples

- Radio propagation in cities
- Step-length determination
- Object Recognition
- Context determination

These problems may be easier to solve using data-driven "AI" approaches

Radio Propagation in Cities (1)

- Standard range-based positioning algorithms assume signals travel in straight lines
- Buildings block, reflect and diffract signals
- Leads to position errors of 10s of metres

3D Mapping Aiding offers a Partial Solution

- Predicts which direct signals are blocked where
- Can determine path delays of reflected signals
  - Computationally intensive for multiple positions
- Diffraction can also be modelled
- Buses and lorries are not on the maps
- Signals are modelled as rays, but real radio signals are fat
  - GNSS signals are ~1m wide at buildings

Multipath Errors Depend on

- Building reflectivities, which are unknown and higher when wet
- Receiver design, which is proprietary

Thus, we cannot predict them

Radio Propagation in Cities (2)

- Standard range-based positioning algorithms assume signals travel in straight lines
- Buildings block, reflect and diffract signals
- Leads to position errors of 10s of metres

"AI" Offers a Potential Solution

Conventional algorithms produce an initial position solution

"AI" techniques then estimate a correction based on

- Ranging measurement residuals
- Signal to noise ratios
- Satellite (or terrestrial transmitter) positions
- 3D mapping

Step Length Estimation

Pedestrian dead reckoning depends on the ability to accurately determine step length, which depends on

- Walking speed
- Height and leg length
- Age, physical fitness and tiredness level
- Gradient and roughness of terrain

We have an IMU measuring 3D specific force and angular rate at 100 Hz +.

This could be

- Hand-held
- In a pocket
- In a bag

And at any orientation

Building a mathematical model to accurately determine step length from the IMU measurements is very difficult

A data-driven “AI” approach is highly attractive

Object Recognition

Visual navigation, matching landmarks to a map, needs object recognition.

Traditional feature descriptors need a matched database

- Less flexible
- Higher cost

Image segmentation using "AI" enables recognition of

- Buildings
- Roads
- Foliage etc

These can be matched to any map or an aerial image

Context and Navigation

Different **environments** provide different information

GNSS works best in an open environment

Visual positioning works best with lots of features

Wi-Fi positioning works best in a cali-brated environment

Behaviour can contribute additional information

Land vehicle motion

- Sideways motion constraints
- Vertical constraints
- Cars normally travel on roads (map matching)

Pedestrian motion

- Pedestrian dead reckoning using step detection
- Pedestrian map matching

Machine learning and other "AI" techniques are an effective way of detecting context

Conclusions

What have we learnt today?

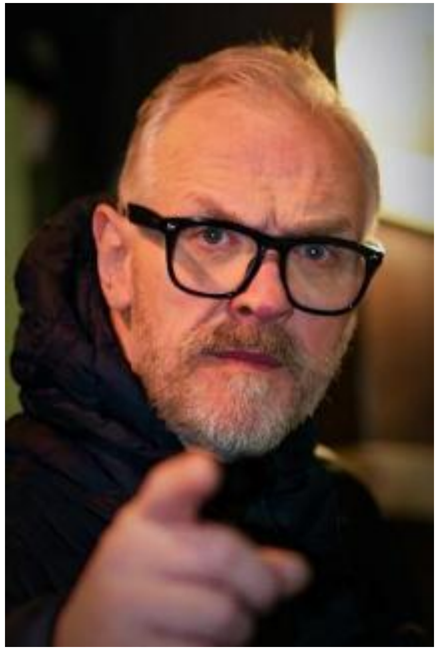


Image: Wikipedia

If we don't embrace "AI", we will be bulldozed out of the way

Replacing physics-based navigation algorithms with "AI" will

- Massively increase computational load
- Make performance worse

We need to focus "AI" on problems that are hard to model

- Radio propagation in cities
- Step-length determination
- Object Recognition
- Context determination

AI-Driven Resilient PNT: Enabling Trusted Navigation and Timing in Challenging Environments

Prof Ivan Petrunin
Professor of Signal Processing & Intelligent Systems,
Centre for Space Systems
Cranfield University

CAMBRIDGE WIRELESS

ROYAL INSTITUTE OF NAVIGATION

AI-Driven Resilient PNT:

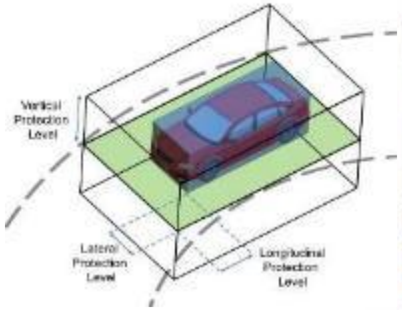
Enabling Trusted Navigation and Timing in Challenging Environments

Ivan Petrunin

June 30, 2026

www.cranfield.ac.uk

Applications and Requirements



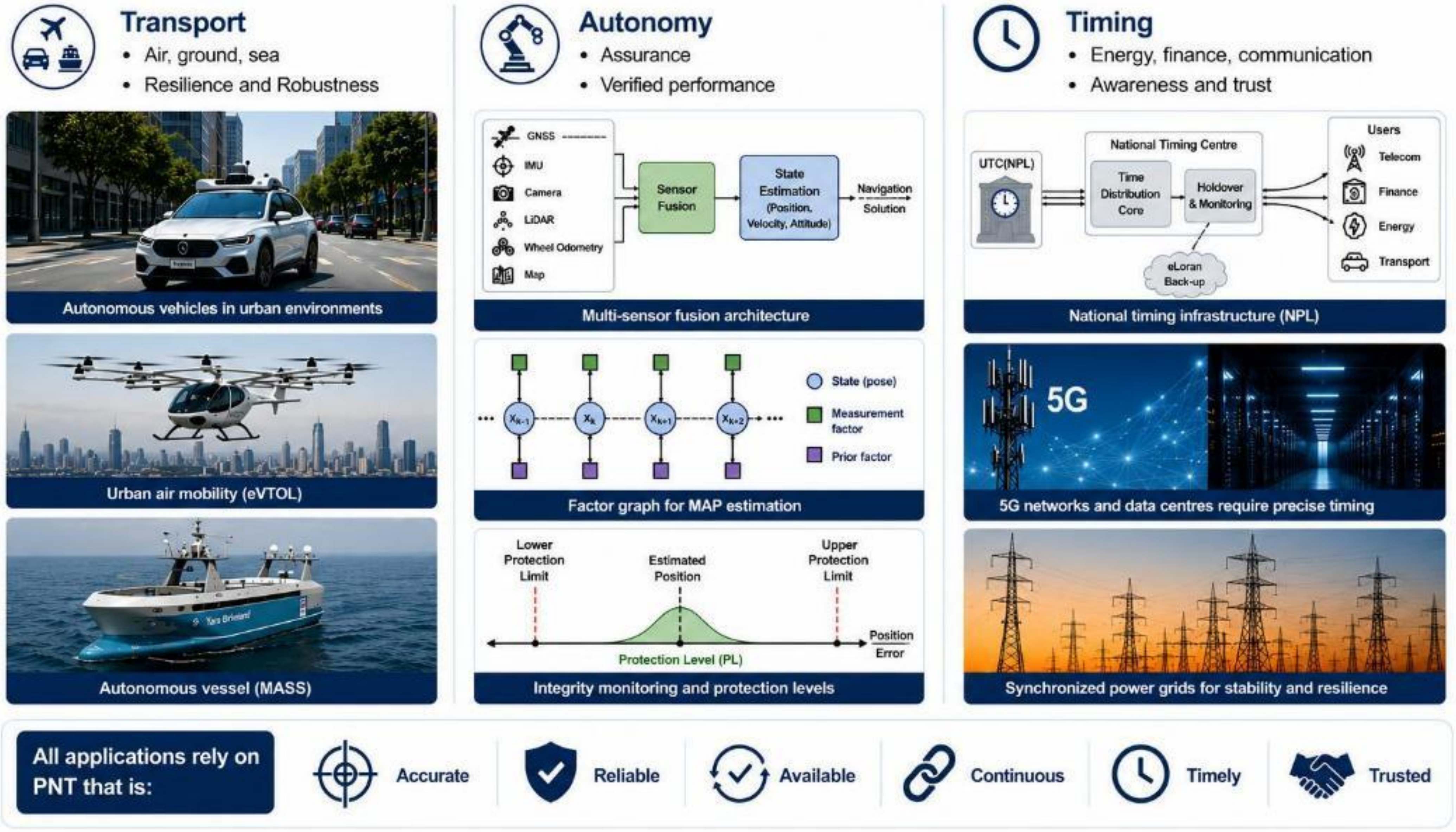


IMAGE CREDITS:

1. https://www.researchgate.net/publication/332464064_Localization_Requirements_for_Autonomous_Vehicles
2. https://waymo.com/safety/
3. https://ntrs.nasa.gov/citations/20200001786
4. https://www.yara.com/knowledge-grows/game-changer-for-the-environment/
4. https://ieeexplore.ieee.org/document/8714072
5. https://www.cs.cmu.edu/~kaess/pub/Dellaert17fnt.html
6. https://gssc.esa.int/navipedia/index.php?title=Integrity
7. https://www.npl.co.uk/national-timing-centre
8. https://www.etsi.org/images/files/ETSIWhitePapers/etsi_wp41.pdf
9. https://ieeexplore.ieee.org/document/8324181

Threats

- Space weather
- Complex environments
- Jamming (incl. space)
- Spoofing
- Other threats

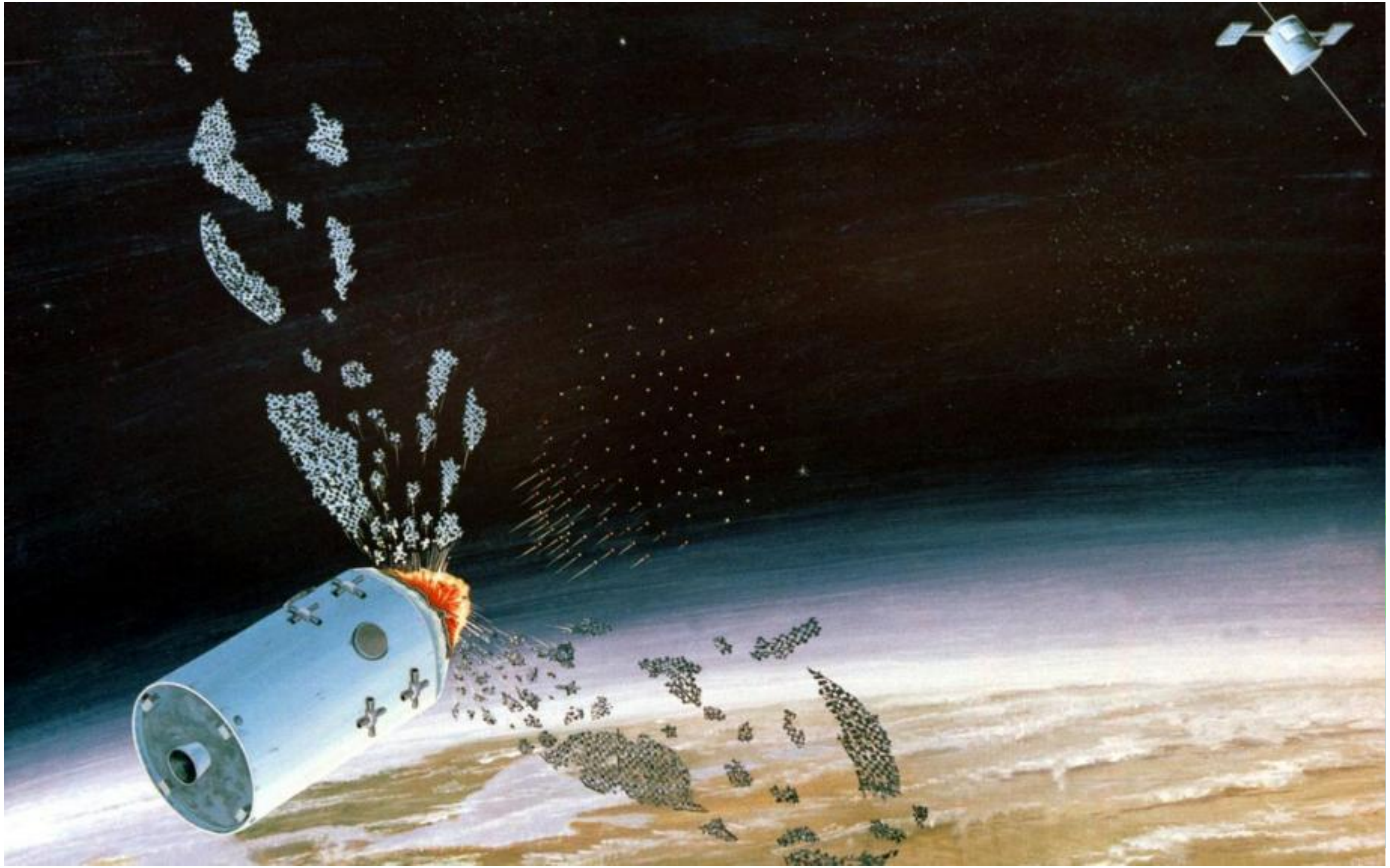
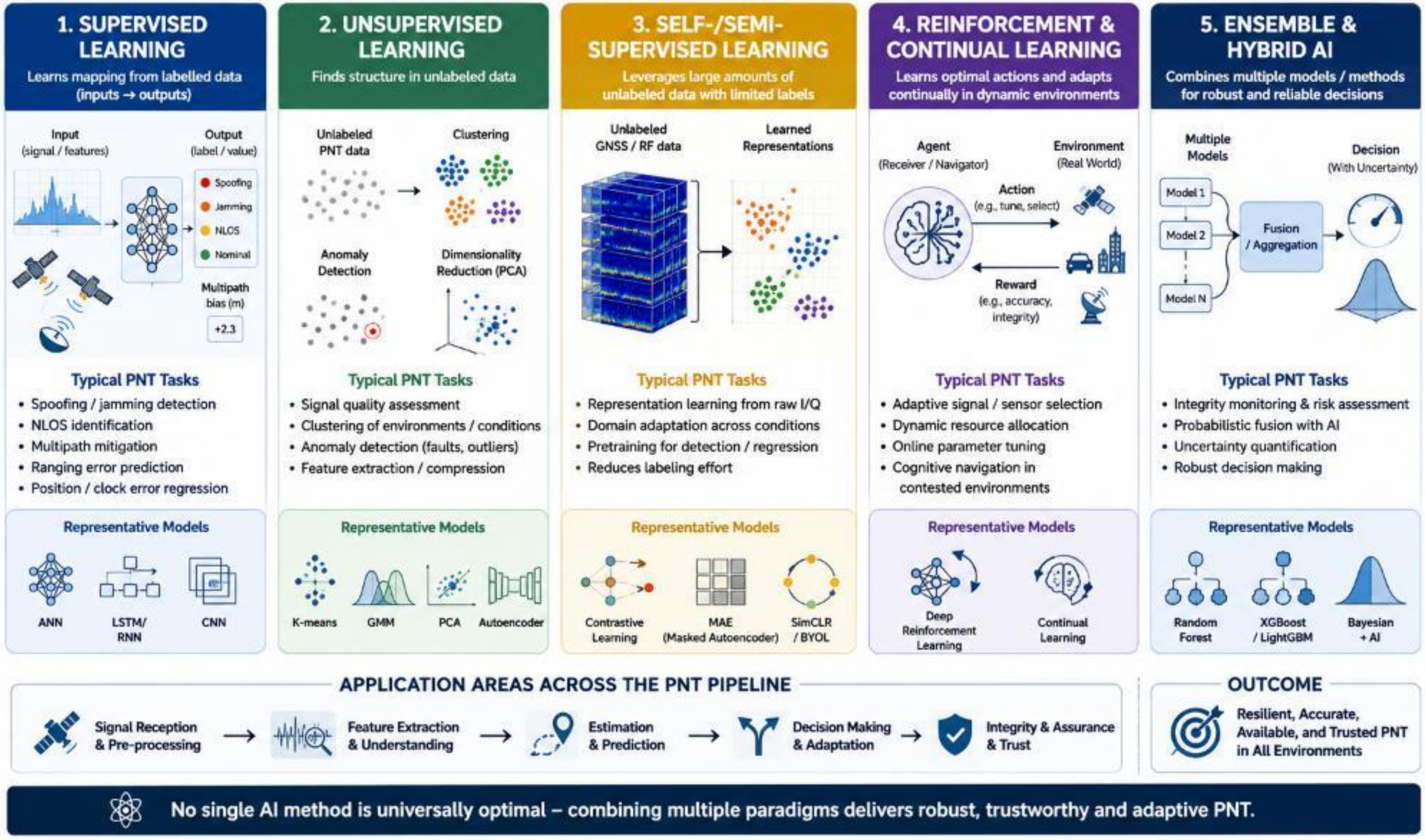
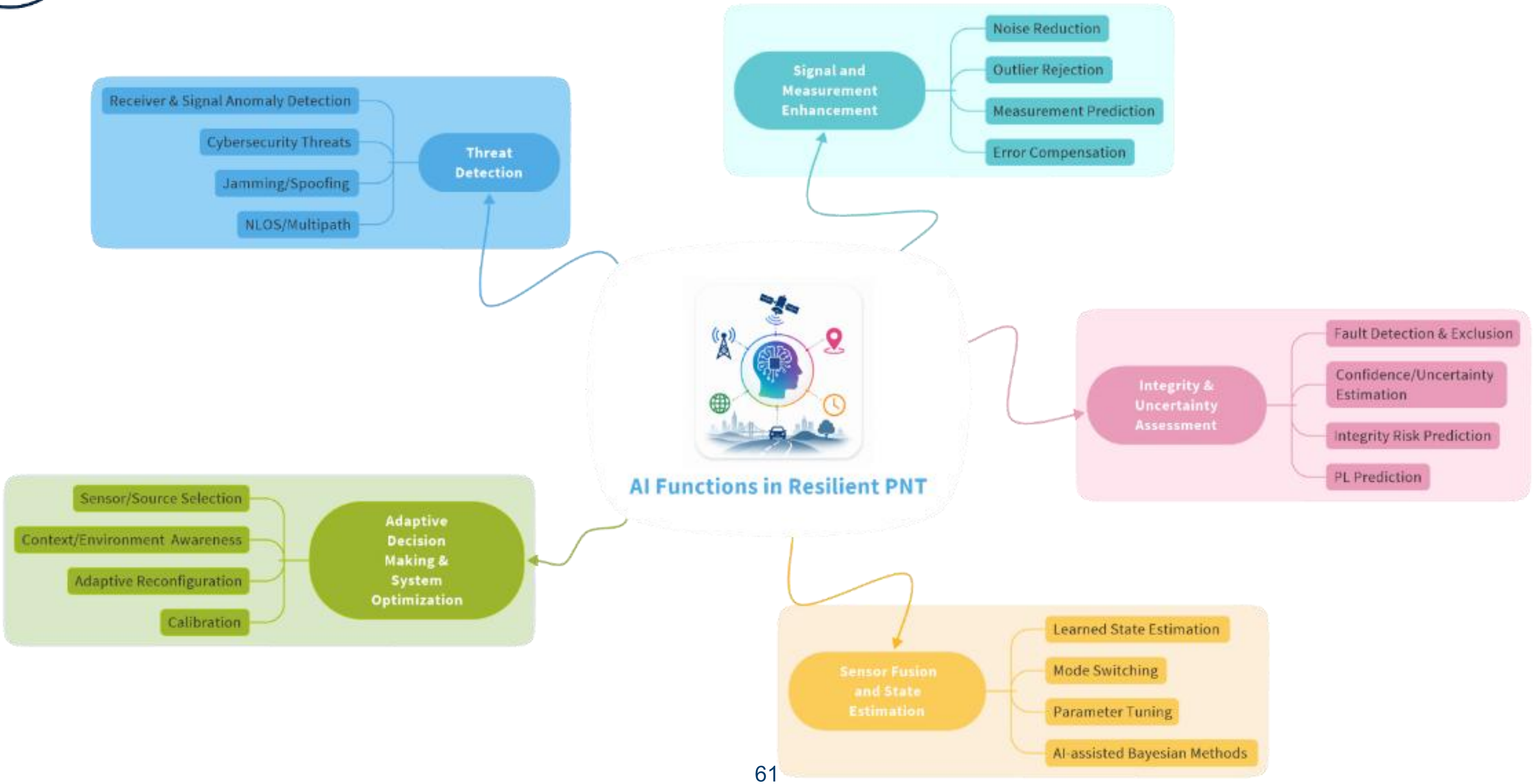


Image credits:
- https://gpsjam.org/?lat=54.29883&lon=43.37815&z=4.5&date=2025-10-12
- GPS Spoofing: Final Report published by WorkGroup – International Ops 2025 – OPSGROUP
- https://insidegnss.com/sww-2016-space-weather-workshop/
- New Space Threat Fact Sheet - US Space Force – RNTF
- (PDF) 3D LiDAR Aided GNSS NLOS Mitigation for Reliable GNSS-RTK Positioning in Urban Canyons

AI for PNT: What and How Can We Learn



AI-Driven PNT



Sensor Data Enhancement: Denoising

- Aiming to enhance low SNR recording of Starlink signal

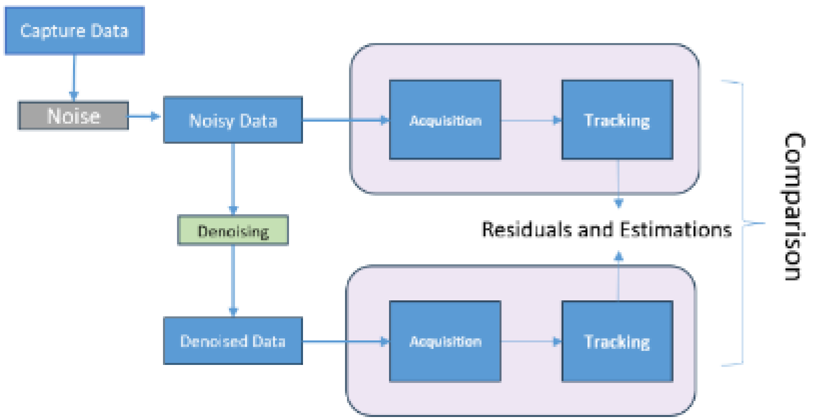
- **Denoising Autoencoder (1D U-Net)**
- Starlink I/Q signals
- Trained with MSE + STFT loss to retain structure and phase.

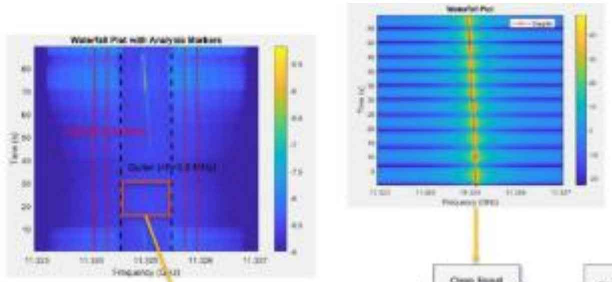
- **Training**
- **Dataset:** Training uses 20% real Starlink snapshots and 80% synthetic PSS–SSS OFDM signals, with Doppler variations generated and validated from TLE simulations.

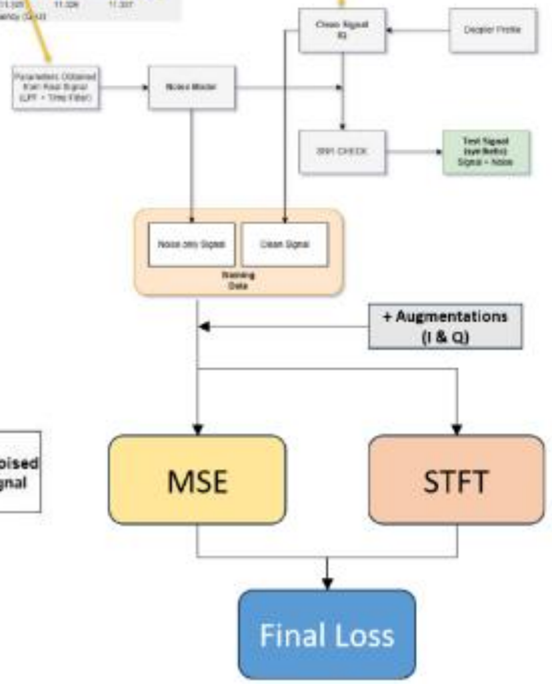
- **Added Augmentations**: Varying noise range, doppler shifts

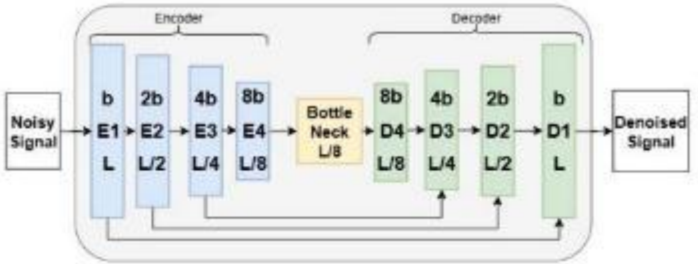
- **Dataset Split**: 70% train, 15% and 15 % for test and Valid

- **Loss Functions:**
- Hybrid Loss = Time MSE (50%)+ Spectral L1 (50%) with Adam optimizer







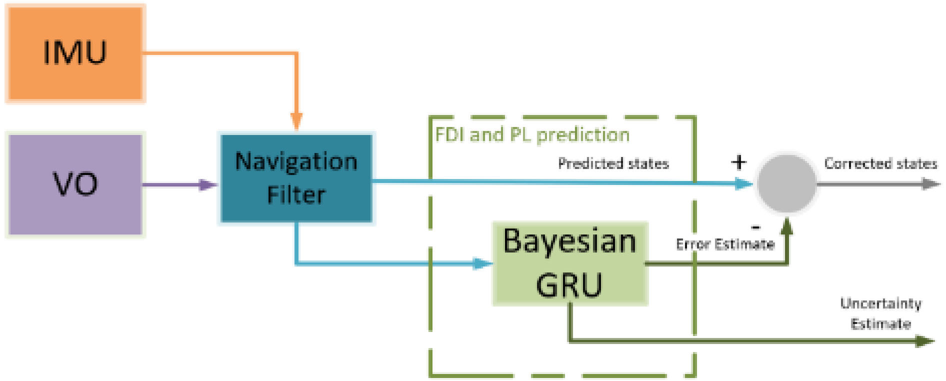


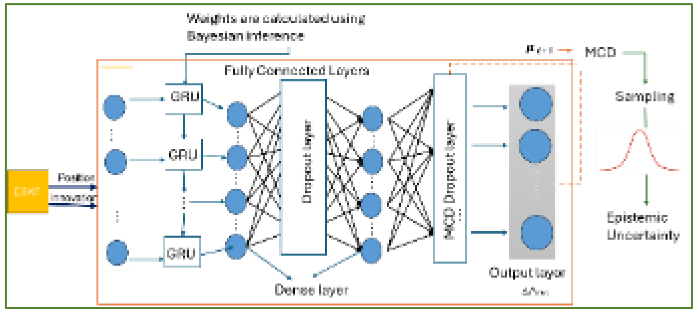
Signal	Acquisition Doppler RMSE (Hz)	Tracking Doppler RMSE (Hz)	Position Estimation – 3D RMSE (m)
Full BW, Unprocessed	339.8	140.1	26.2
5x Reduced BW, Denoised	**409.2**	**110.7**	**20.4**

S. Syamal, I. Petrunin, T. Witworth, P. Peltola. *Machine Learning-based Denoising of Starlink Signals for Opportunistic Navigation*, in Proceedings of the European Navigation Conference (ENC) 2026, Vienna, Austria, 28-30 April 2026

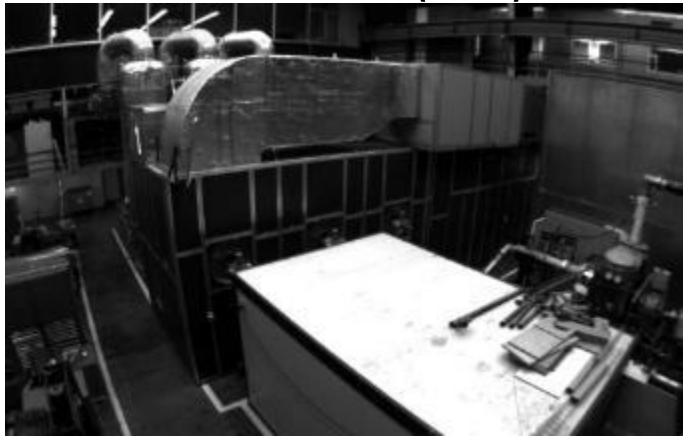
Error Correction in Multi-Sensor Systems

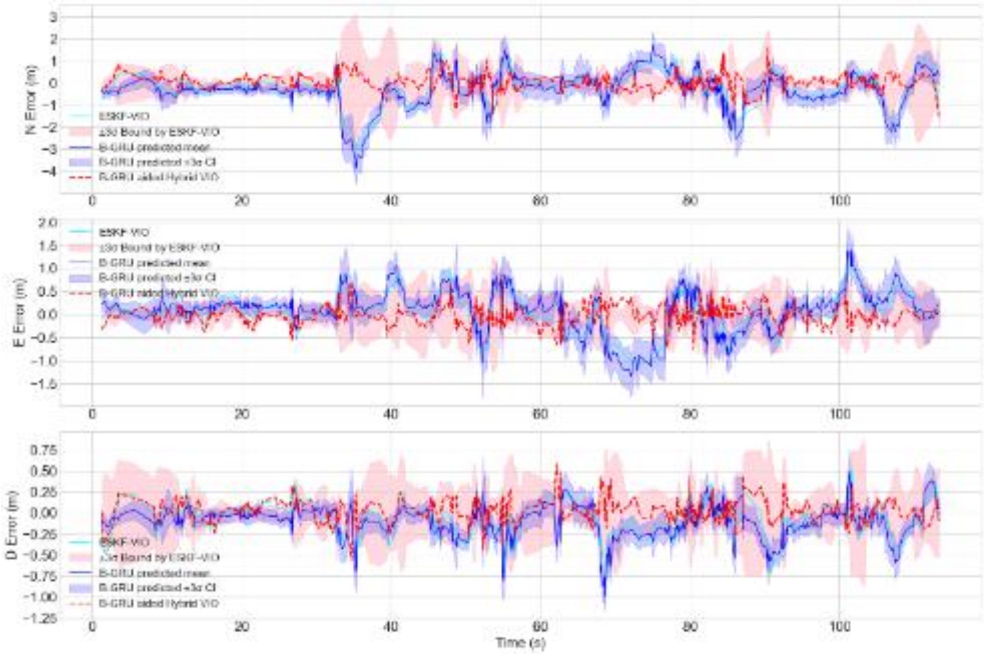
- State estimate error correction and uncertainty estimate





EuRoC Dataset (UAV)



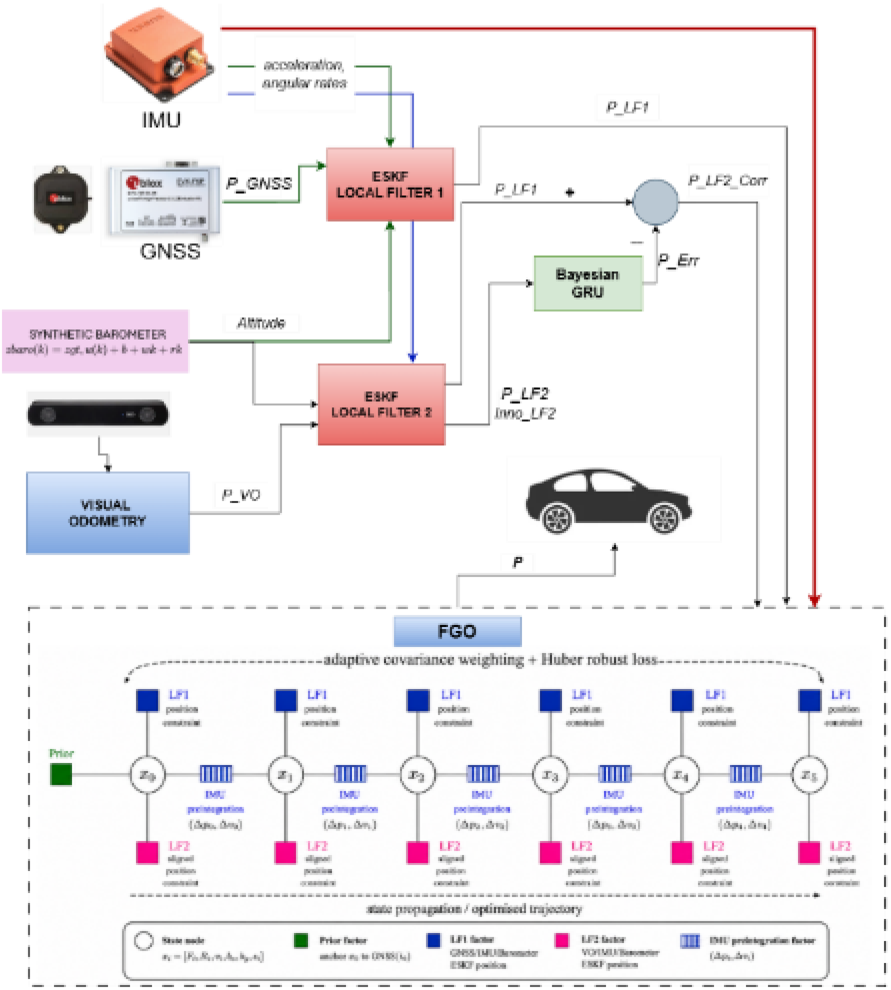


Error and uncertainty estimation in EuRoc MH05- difficult dataset

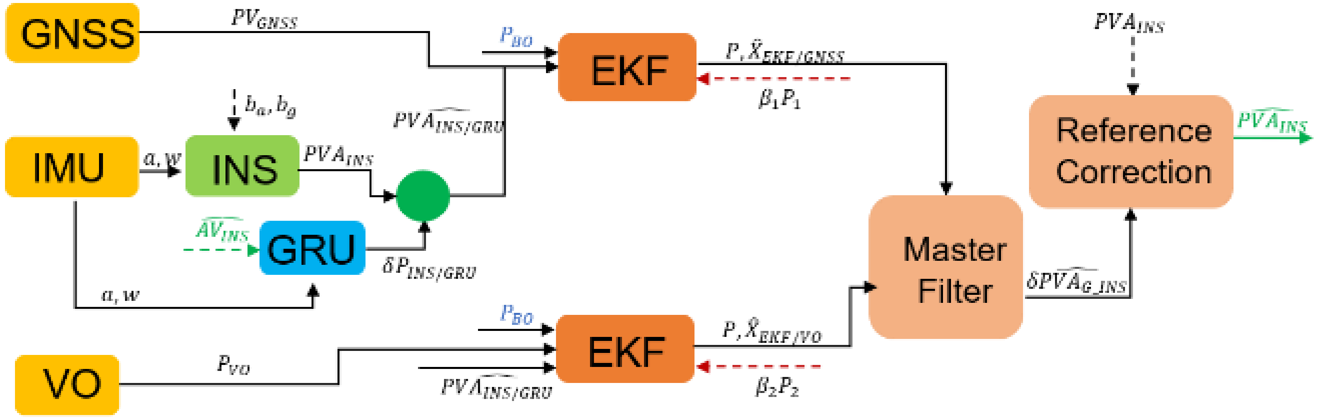
Techniques	RMSE (m)				Horizontal RMSE (m)	3D 95th Percentile (m)
	N	E	V	3D	3D	
End-to-End VIO [4]	-	-	-	1.96	-	-
DeepVIO [14]	-	-	-	0.52	-	-
Self-VIO[3]	-	-	-	0.29*	-	-
GRU-aided Hybrid VIO [11]	0.40	0.65	0.16	0.65	0.56	0.71
B-GRU-aided Hybrid VIO	**0.29**	**0.44**	**0.10**	**0.43**	**0.37**	**0.56**

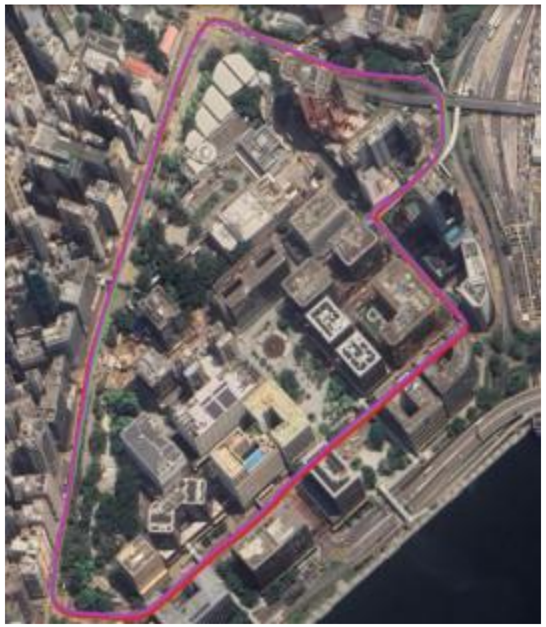
Tabassum TE, Negru SA, Petrunin I, Rana Z. Error Correction Using Bayesian GRU Network in Hybrid Visual Inertial Navigation System. *Engineering Proceedings*. 2026; 126(1):52. https://doi.org/10.3390/engproc2026126052

Error Correction in Multi-Sensor Systems: Concepts



vs





Chandni Saha ,Tarafder Elmi Tabassum, Ivan Petrunin. An FGO-based Federated Multi-Sensor Navigation System for Automotive Applications, in Proceedings of the European Navigation Conference (ENC) 2026, Vienna, Austria, 28-30 April 2026

Error Correction in Multi-Sensor Systems: Comparison

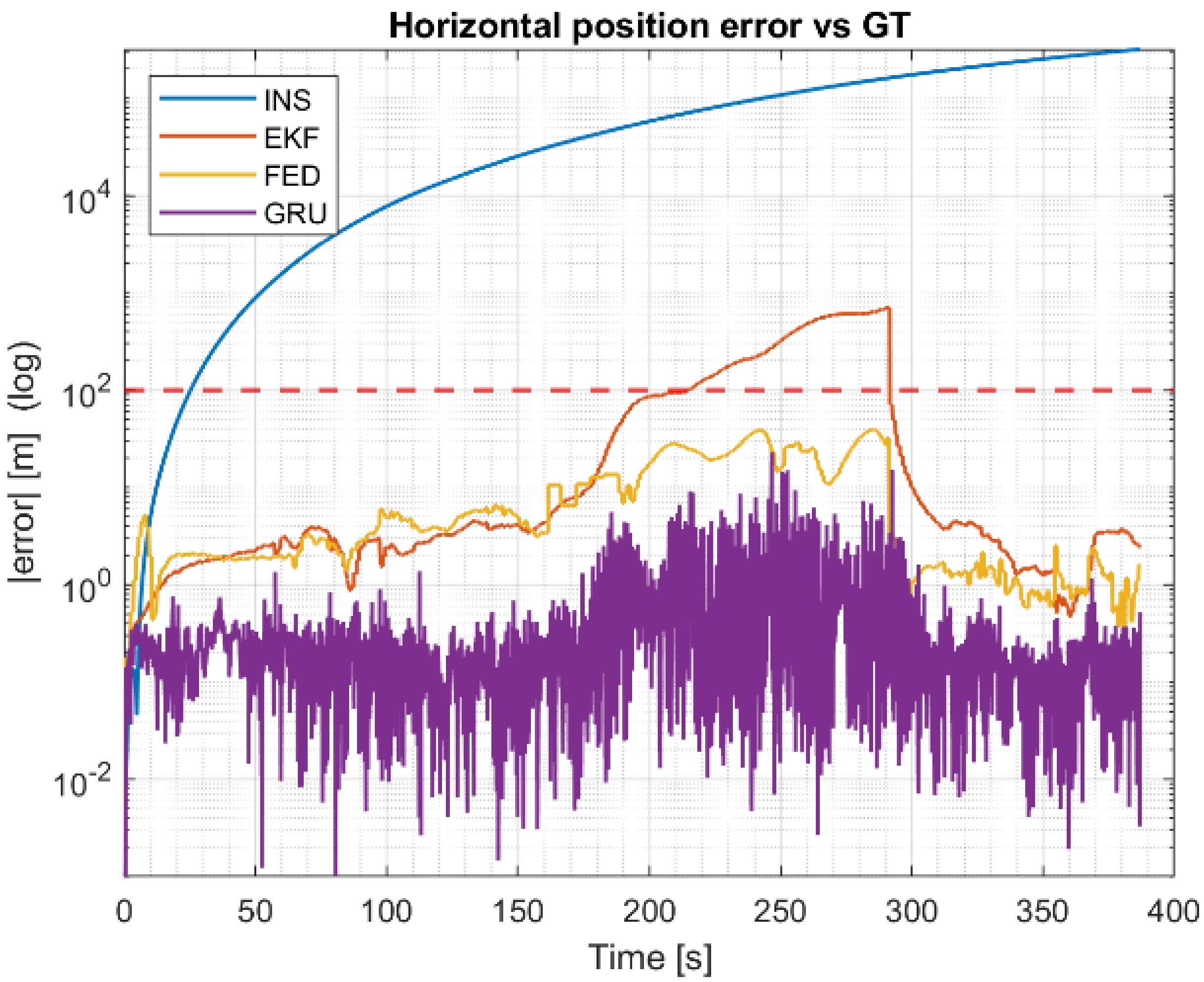
- Effects of the different types of error correction

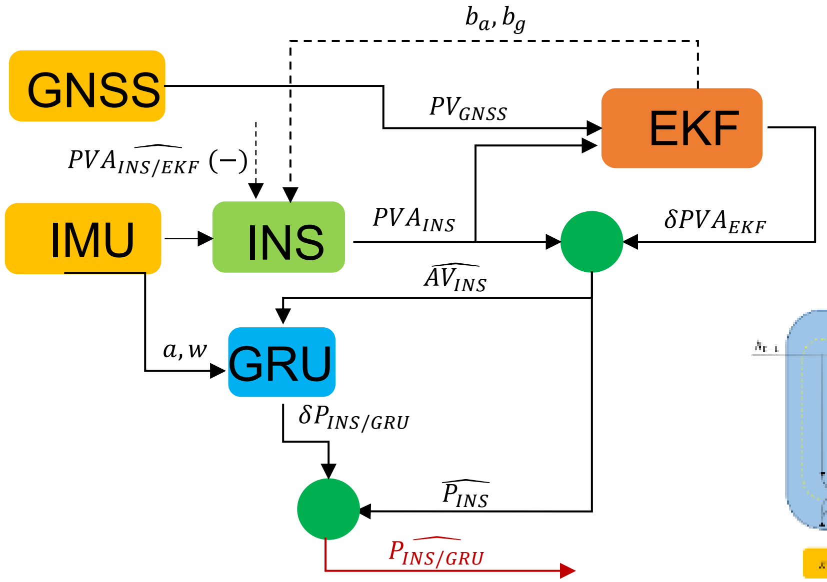
Techniques	Loop 1		Loop 2					
	RMSE / 95th percentile		RMSE / 95th percentile					
			Before Outage		During Outage		After Outage	
	2D	3D	2D	3D	2D	3D	2D	3D
GNSS	2.96 / 4.52	7.25 / 10.77	3.26 / 5.85	5.46 / 8.16	-	-	1.70 / 2.14	3.86 / 4.88
LF1	2.78 / 4.70	3.24 / 5.14	3.19 / 5.39	6.29 / 10.24	527.21 / 1048.46	527.48 / 1049.14	107.63 / 4.62	107.80 / 6.58
VO	28.67 / 48.01	26.68 / 48.02	18.62 / 37.48	32.77 / 39.78	23.86 / 35.69	25.42 / 35.99	26.58 / 37.82	57.42 / 101.59
LF2	27.44 / 43.82	28.41 / 45.45	19.95 / 39.53	21.43 / 40.32	22.74 / 34.60	24.06 / 35.46	25.94 / 35.99	27.13 / 36.85
LF2 (IMU_Corr)	2.96 / 4.59	4.59 / 7.29	3.47 / 5.95	5.13 / 7.63	22.78 / 37.20	23.14 / 37.39	1.884 / 2.705	2.64 / 3.39
LF2 (VIO_Corr)	5.84 / 14.02	6.20 / 14.36	0.44 / 0.86	0.47 / 0.88	0.55 / 1.06	0.57 / 1.07	0.60 / 1.14	0.62 / 1.15
FGO MF	**3.18 / 5.40**	**3.83 / 6.48**	**3.84 / 5.88**	**11.29 / 12.22**	**27.11 / 42.74**	**29.18 / 42.74**	**26.57 / 32.02**	**28.64 / 34.68**
EKF MF	2.96 / 4.59	4.59 / 7.29	3.47 / 5.87	5.13 / 7.63	22.76 / 37.19	23.11 / 37.12	1.88 / 2.71	2.64 / 3.39
FGO MF (Corr)	**1.68 / 2.83**	**1.82 / 2.93**	**0.44 / 0.83**	**0.53 / 0.85**	**0.53 / 1.03**	**0.56 / 1.045**	**0.59 / 1.14**	**0.62 / 1.16**
EKF MF (Corr)	**0.62/1.27**	**0.69/1.23**	**0.21 / 0.37**	**0.32 / 0.57**	**0.80 / 1.17**	**0.85 / 1.22**	**0.30 / 0.43**	**0.38 / 0.55**
GS-GVINS [5]	-	27.91	-	-	-	-	-	-
RTFGO [3]	-	27.91	-	-	-	9.33	-	-
RTFGO-TC [4]	6.44	29.60	7.17	22.88	-	-	-	-

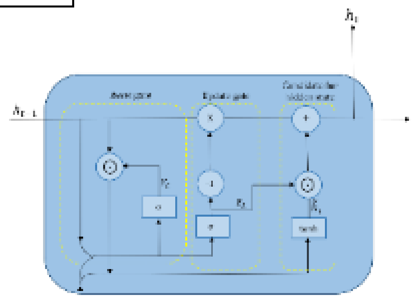
Chandni Saha ,Tarafder Elmi Tabassum, Ivan Petrunin. An FGO-based Federated Multi-Sensor Navigation System for Automotive Applications, in Proceedings of the European Navigation Conference (ENC) 2026, Vienna, Austria, 28-30 April 2026

Error Correction in Multi-Sensor Systems

- IMU error correction (work in progress)

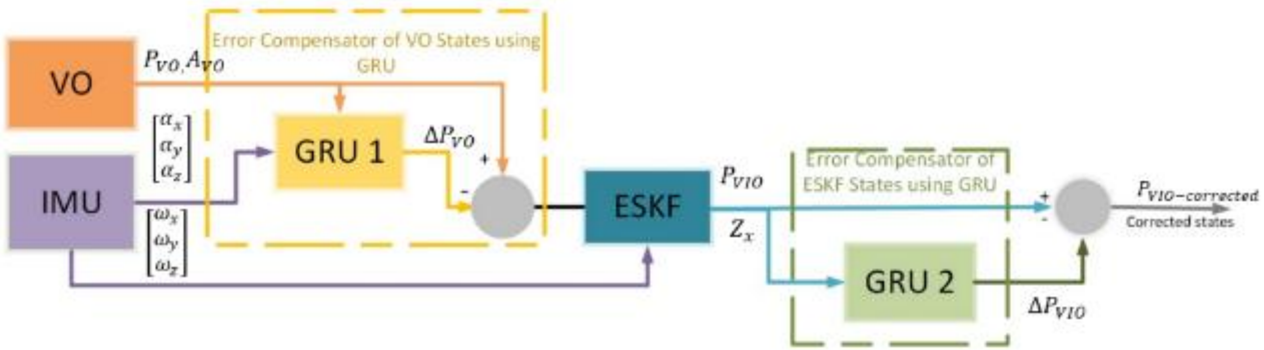




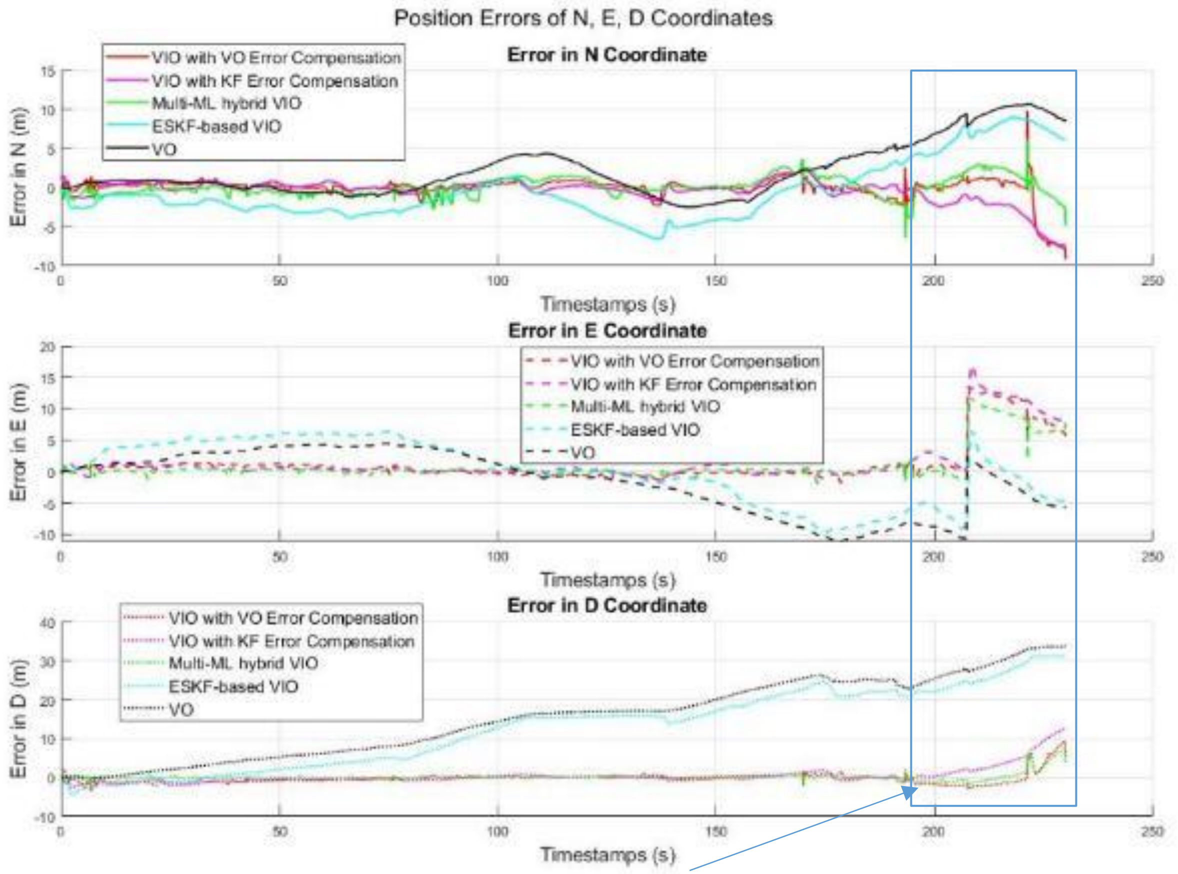


Error Correction in Multi-Sensor Systems: Integration Benefits (1)

- VIO scenario



Techniques	RMSE (m)					95th Percentile (m)			
	N	E	V	3D	Horizontal	3D	Improvement	Horizontal	Improvement
VO	4.04	5.13	18.11	27.56	6.53	33.20	-	11.36	-
ESKF-based VIO	3.7	4.83	16.00	24.19	6.15	29.63	40%	9.01	21%
VIO with VO error compensation	1.37	3.43	1.25	3.9	3.70	11.85	64%	11.32	0.4%
VIO with KF error compensation	1.76	3.46	1.96	4.31	4.16	11.34	66%	12.12	-
Multi-ML Hybrid VIO (proposed)	**1.19**	**2.74**	**1.01**	**3.13**	**2.81**	**9.33**	**72%**	**8.88**	**22%**

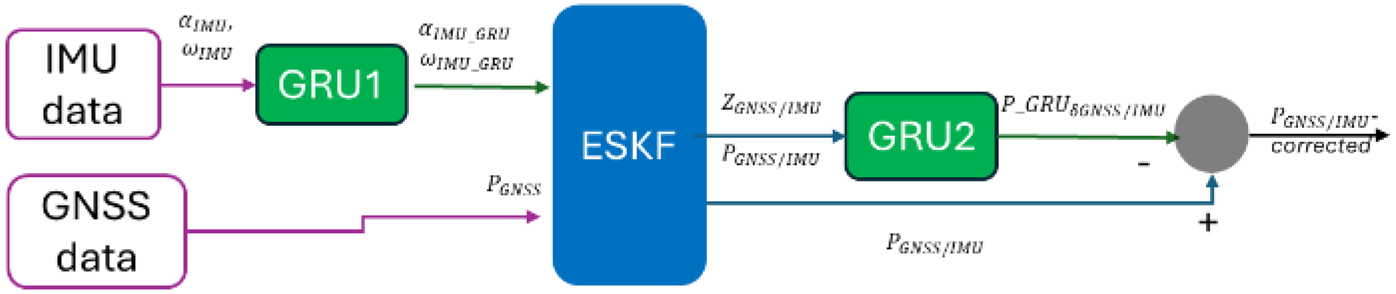


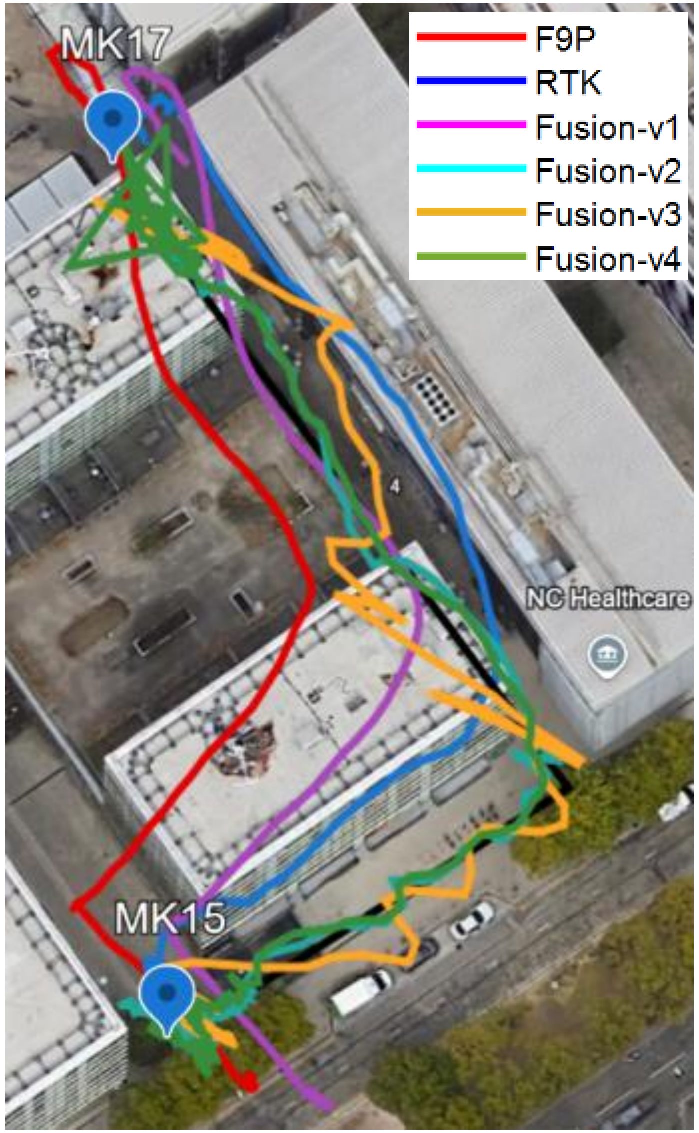
Source of aleatoric and epistemic uncertainty arises due to poor information present in data

Tabassum, Tarafder Elmi, Petrunin, Ivan, Rana, Zeeshan A., "Position Uncertainty Reduction in Visual-Inertial Navigation Systems Using Multi-ML Error Compensation," *Proceedings of the 37th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2024)*, Baltimore, Maryland, September 2024, pp. 1741-1755. https://doi.org/10.33012/2024.19790

Error Correction in Multi-Sensor Systems: Integration Benefits (2)

- Micromobility scenarios

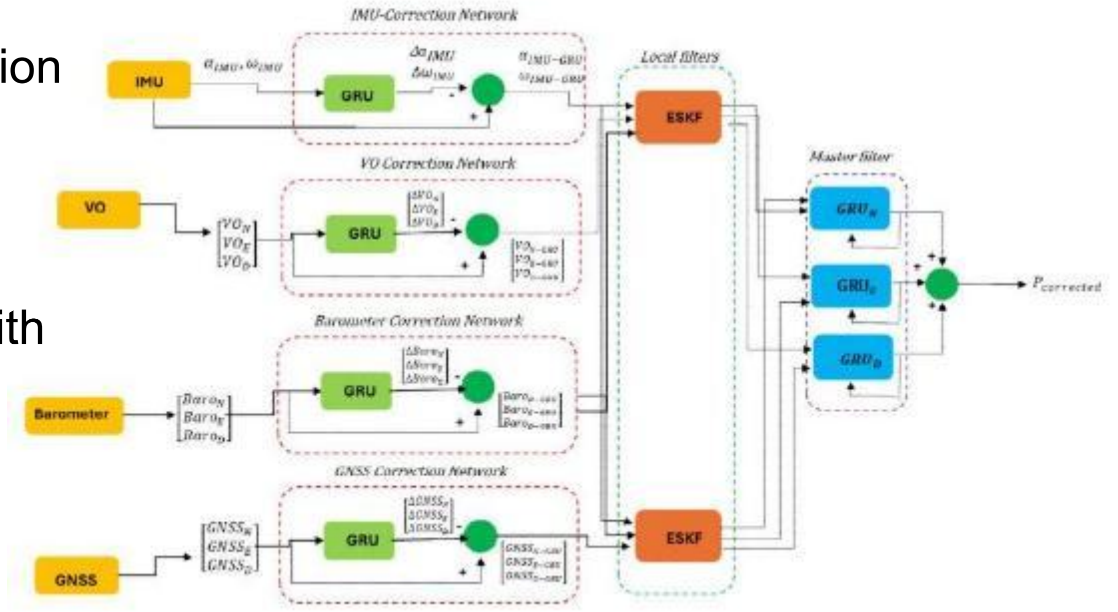


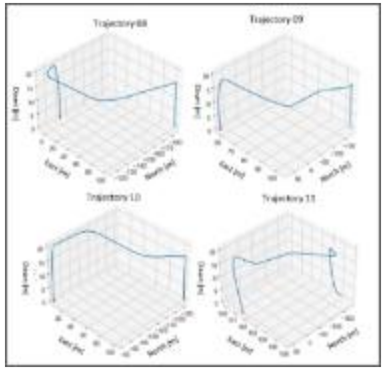


Fusion Version	Model	Training Trajectories	Scenarios Included / Notes	Duration, (min)	Trajectory 1	Trajectories 2-4	
					HPE, (m)	HPE, (m)	Improvement
	F9P	—	Raw GNSS F9P	—	15.11	—	
	RTK	—	RTK GNSS solution	—	10.26	—	
Fusion-v1	IMU-GRU-v1	1, 2	Pedestrian and rover dynamic	35	12.14	1.09, 0.67, 1.02	—
	ESKF-GRU-v1	1–3	OS + mild MP/NLOS	39			
Fusion-v2	IMU-GRU-v1	1, 2	Pedestrian and rover dynamic	35	2.16	0.82, 0.61, 0.94	14%
	ESKF-GRU-v2	1–8	OS, mild MP/NLOS, severe MP/NLOS	86.8			
Fusion-v3	IMU-GRU-v2	1, 2, 7, 8	Pedestrian, rover dynamic and scooter dynamics	64.7	4.01	0.67, 0.55, **0.69**	30%
	ESKF-GRU-v2	1–8	OS, mild MP/NLOS, severe MP/NLOS	86.8			
Fusion-v4	IMU-GRU-v3	1, 2, 9–17	Pedestrian, rover dynamic and scooter dynamics	96.4	**2.08**	**0.67**, **0.54**, 0.73	31%
	ESKF-GRU-v3	1–8	OS, mild MP/NLOS, severe MP/NLOS	86.8			

Error Correction in Multi-Sensor Systems: Integration Benefits (3)

- Hybrid multi-sensor navigation system with uncertainty correction
  - Multiple sources and architecture are contributing to:
    - Performance improvement
    - Integrity enhancement
  - Resilience to spoofing requires evaluation, not possible with a current setup





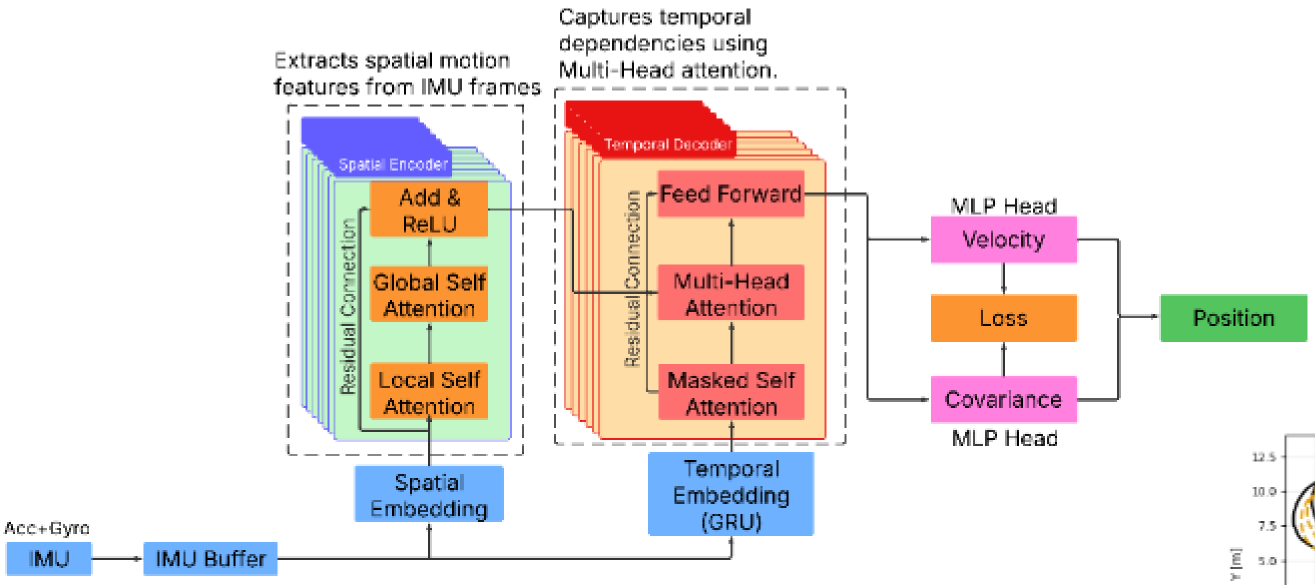
Techniques	RMSE (m) N	RMSE (m) E	RMSE (m) V	RMSE (m) 3D	Horizontal RMSE (m)	3D 95th Percentile (m)
GNSS	2.76	3.91	3.51	5.36	4.91	9.75
GNSS/IMU/Barometer (local filter 2)	1.04	1.13	0.89	1.02	1.17	1.64
VO/IMU/Baro fusion (local filter 1)	0.12	0.10	0.8	0.17	0.16	0.15
Multi-sensor navigation system (proposed)	**0.49**	**0.34**	**0.21**	**0.51**	**0.58**	**0.45**

Techniques	RMSE (m) N	RMSE (m) E	RMSE (m) V	RMSE (m) 3D	Horizontal RMSE (m)	3D 95th Percentile (m)
End-to-End VIO [4]	-	-	-	1.96	-	-
DeepVIO [14]	-	-	-	0.52	-	-
Self-VIO[3]	-	-	-	0.29*	-	-
GRU-aided Hybrid VIO [11]	0.40	0.65	0.16	0.65	0.56	0.71
B-GRU-aided Hybrid VIO	0.29	0.44	0.10	0.43	0.37	0.56
VO/IMU/Baro local filter (GNSS-denied)	**0.20**	**0.32**	**0.06**	**0.37**	**0.29**	**0.35**

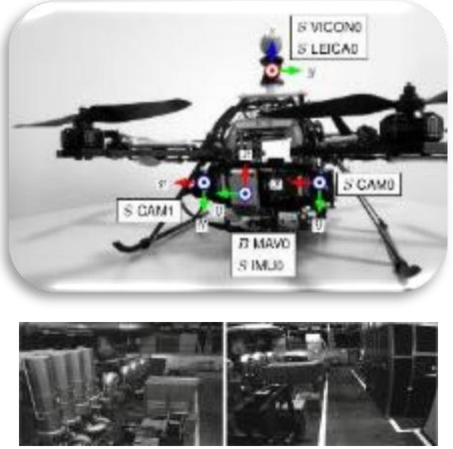
Tarafder Elmi Tabassum, Sorin Andrei Negru, Ivan Petrunin [Aleatoric Uncertainty Reduction in a Multisensor Navigation System Using Gated Recurrent Unit](), ION GNSS+ 2025, Baltimore, USA

End-to-End Systems with Transformers

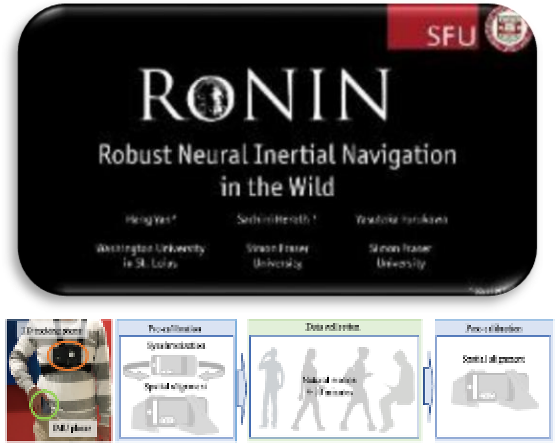
- Dead Reckoning Example



EuRoC (UAV)

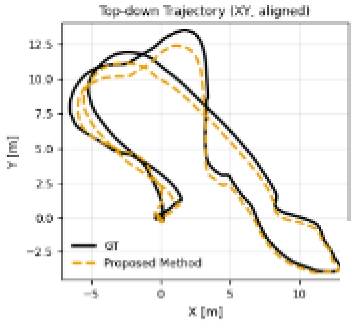


RoNIN (Pedestrian Dead Reckoning)



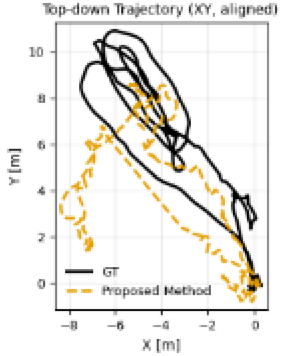
Dataset	Test Data	Metrics(m)	Proposed
EuRoC	Seen	ATE	**2.25**
		RMSE	**2.53**
	Unseen	ATE	**3.98**
		RMSE	**4.44**

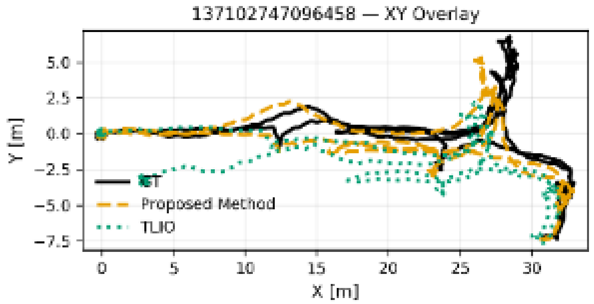
Dataset	Test Data	Metric	Error, m		TLIO
			CTIN	Proposed	
RoNIN	Seen	ATE	4.62	**1.59**	2.702
		RMSE	N/A	**1.823**	3.003
	Unseen	ATE	5.61	**2.74**	3.315
		RMSE	N/A	**3.046**	3.695

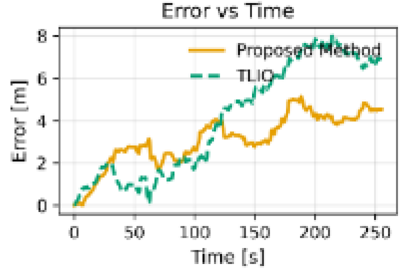


Seen sequence (MH_04)

Unseen sequence (MH_01)



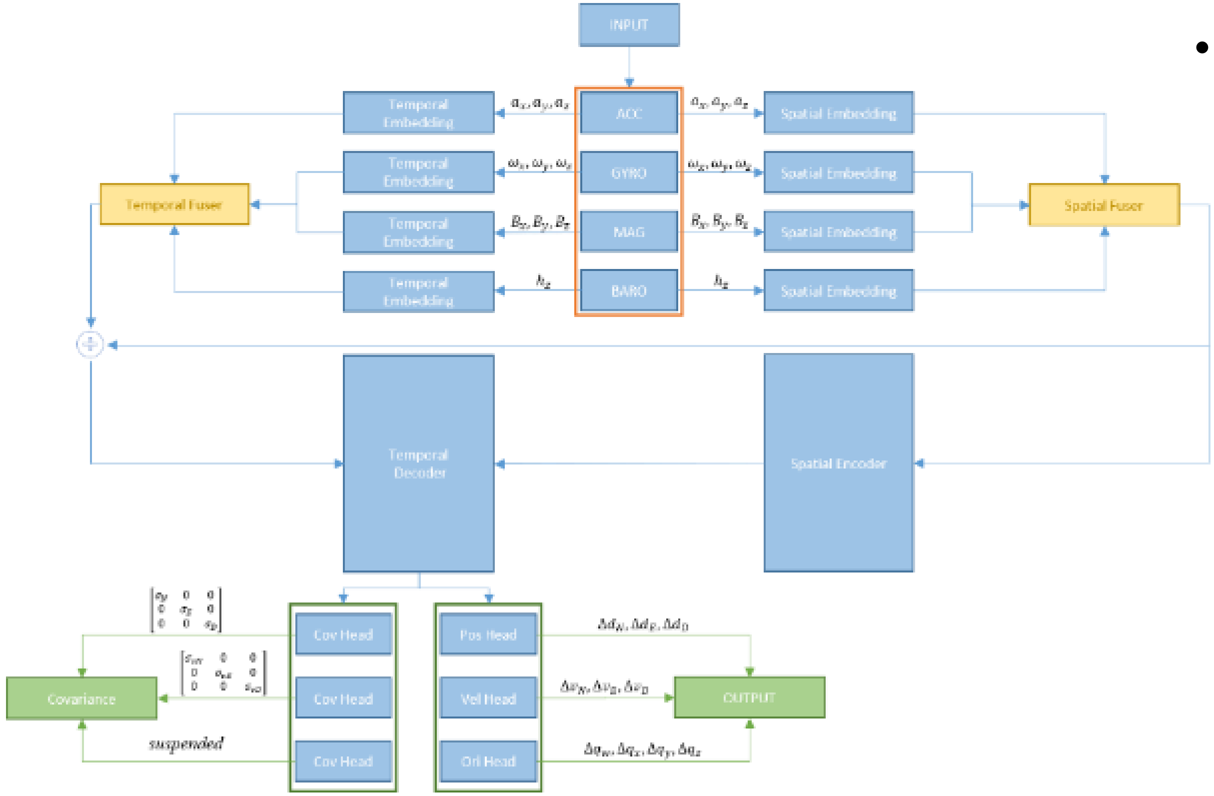




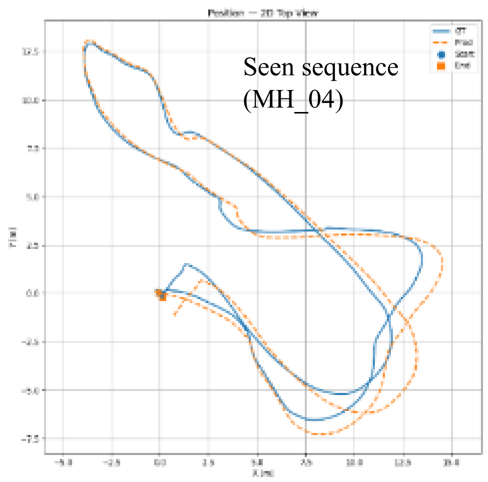
"INS Dead Reckoning Using an Enhanced Transformer-Based Solution," in the Proc. of RiTA Conference, 17–19 December, 2025, London

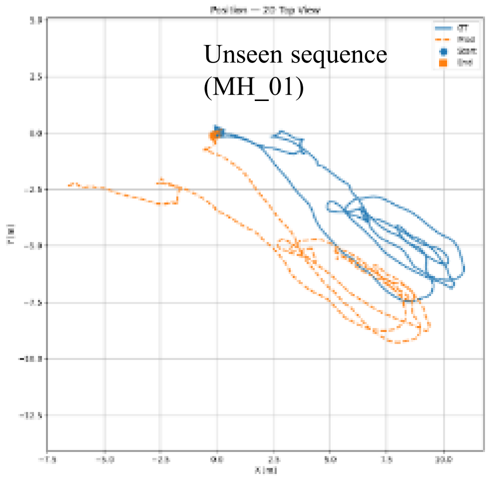
End-to-End Systems with Transformers

- Multi-sensor dead reckoning (work in progress)



- Significantly more complex
  - 2-part loss function: state part (MSE, NLL), physics part (residual-based)
  - Inference time 30 ms at a high-performance PC
    - Training is significantly slower
  - Complex convergence – loss function is the critical element





Test data (EuRoC)	Metric	TIN	Extended TIN
Seen (MH_04)	ATE [m]	2.25	0.61
Seen (MH_04)	RMSE [m]	2.53	0.89
Unseen (MH_01)	ATE [m]	3.98	1.92
Unseen (MH_01)	RMSE [m]	4.44	3.44

Opportunities and Open Research Challenges

Opportunities

- AI enhances signal quality and robustness
- AI improves multi-sensor fusion and state estimation
- AI enables uncertainty-aware navigation
- AI supports integrity monitoring and adaptive decision making
- End-to-end learning simplifies complex processing pipelines
- Foundation models may enable transferable navigation knowledge

Challenges

- Limited labelled data in challenging environments
- Generalisation across sensors, platforms and environments
- Trustworthy uncertainty calibration
- Explainability and certification
- Maintaining physical consistency and interpretability
- Computational efficiency and real-time deployment

➢ **The future of resilient PNT is likely to combine data-driven AI with probabilistic estimation, physical models and integrity frameworks rather than replacing them.**

Conclusion

- **AI is becoming an important component of resilient PNT**
- AI contributes across the complete PNT pipeline—from signal enhancement to integrity assessment and adaptive decision making.
- Hybrid AI-Bayesian architectures demonstrate more balanced performance vs purely model-based or purely data-driven approaches in challenging environments.
- Uncertainty-aware learning enables trusted navigation by providing confidence estimates alongside state estimates.
- Physics-informed learning and probabilistic loss functions are essential for robust convergence and trustworthy predictions.
- Future research should focus on foundation models for PNT, trustworthy AI, integrity-aware learning, and scalable datasets supported by simulation and generative AI.
- **The next generation of resilient PNT will bring an integration of AI, probabilistic estimation, physical models and integrity assurance - not AI alone.**

Thank you!

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Machine Learning Challenges in Navigation: Technical and Business

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ML Challenges: Navigation

Technical and Business Barriers

Dr Robert Schoonmaker

Introduction

<u>Motivating definition.</u>

With machine learning computers learn from data, rather than following pre-set rules.

It is useful when the underlying behaviours to model are too complex for a rules-based system to be effectively programmed.

Parameter Number: ~100 ~10^7

Potentially Interpretable | approachable, ~ancillary | Infrastructural challenges.

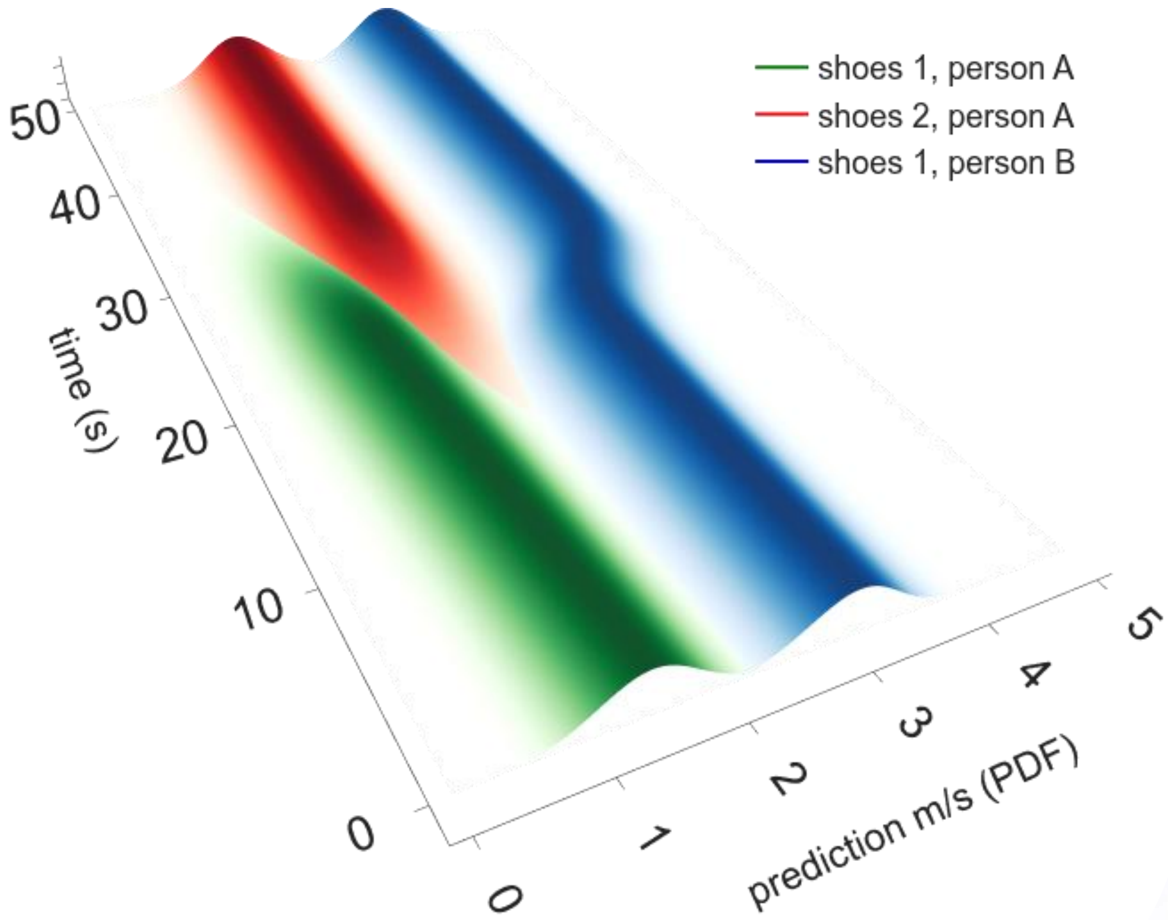
Structure: Story of the Existential Problems

- Where problems come from
  - Data and distributions
  - Model aging
- Managing problems (Case studies)
  - Facilitative environment
  - Cheap failure
- Conclude: ML Strategy summary,
  - Also a bit of AGI conjecture

Data Coverage – Mixture Models

An idealised pedestrian motion model example

- Multiple *plausible* interpretations of IMU data using short-term inference.
- Long-term inference makes better prediction.



Data Coverage – Mixture Models

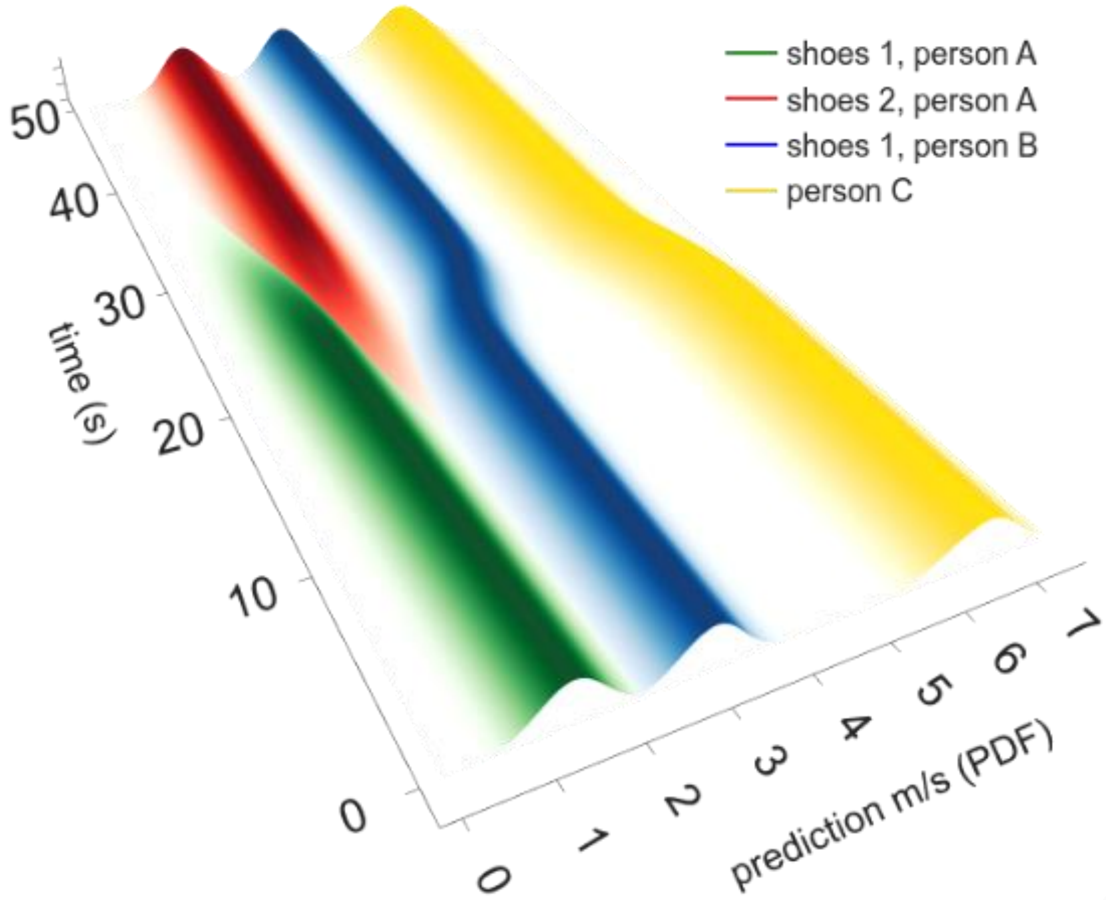
Possible alternative:

person C was the true user, but not represented in training data. **Wrong prediction with high confidence.**

Difficult to have confidence when blind testing with customer.

“let’s collect more data”

Example: the 4th Waymo recall from 2 weeks ago.



Model Aging

Two types of aging, literature has many names for these.

Model drift

- Underlying distribution changes

Online Aging

- A (usually) self-learning model learns/forgets incorrectly and gets stuck.

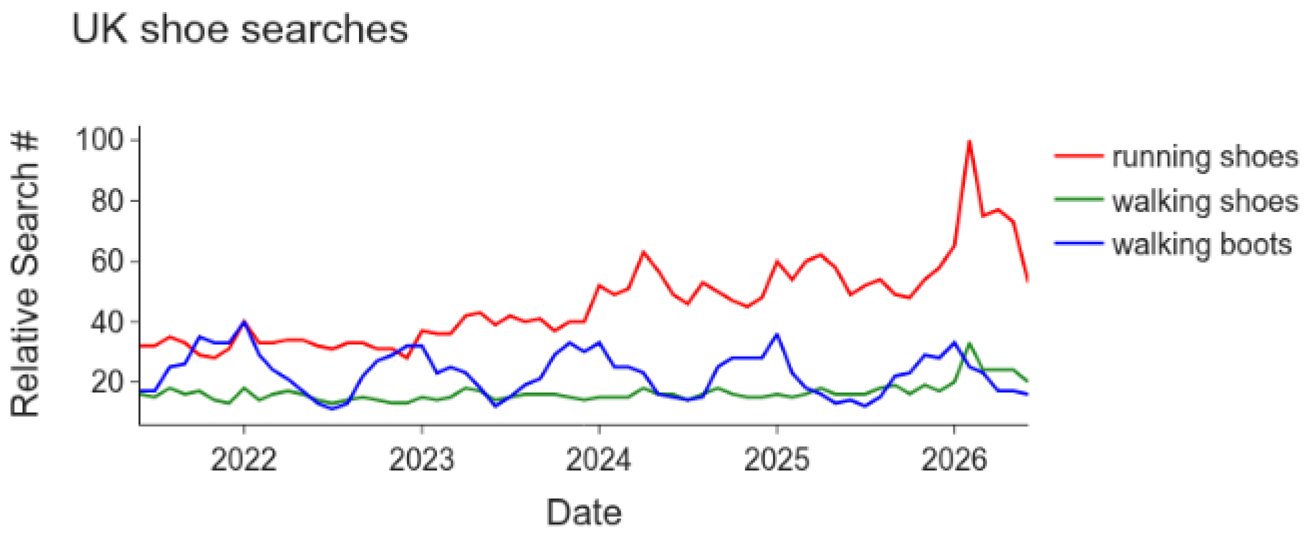
Consequences: Continuous monitoring/data collection/training, ongoing assistance required for top performance

Model Drift

Human behaviour, built environment, device construction all change over time.

Models will degrade due to these changes.

Google trends data shows that how people interact with footwear has changed.



Online Aging

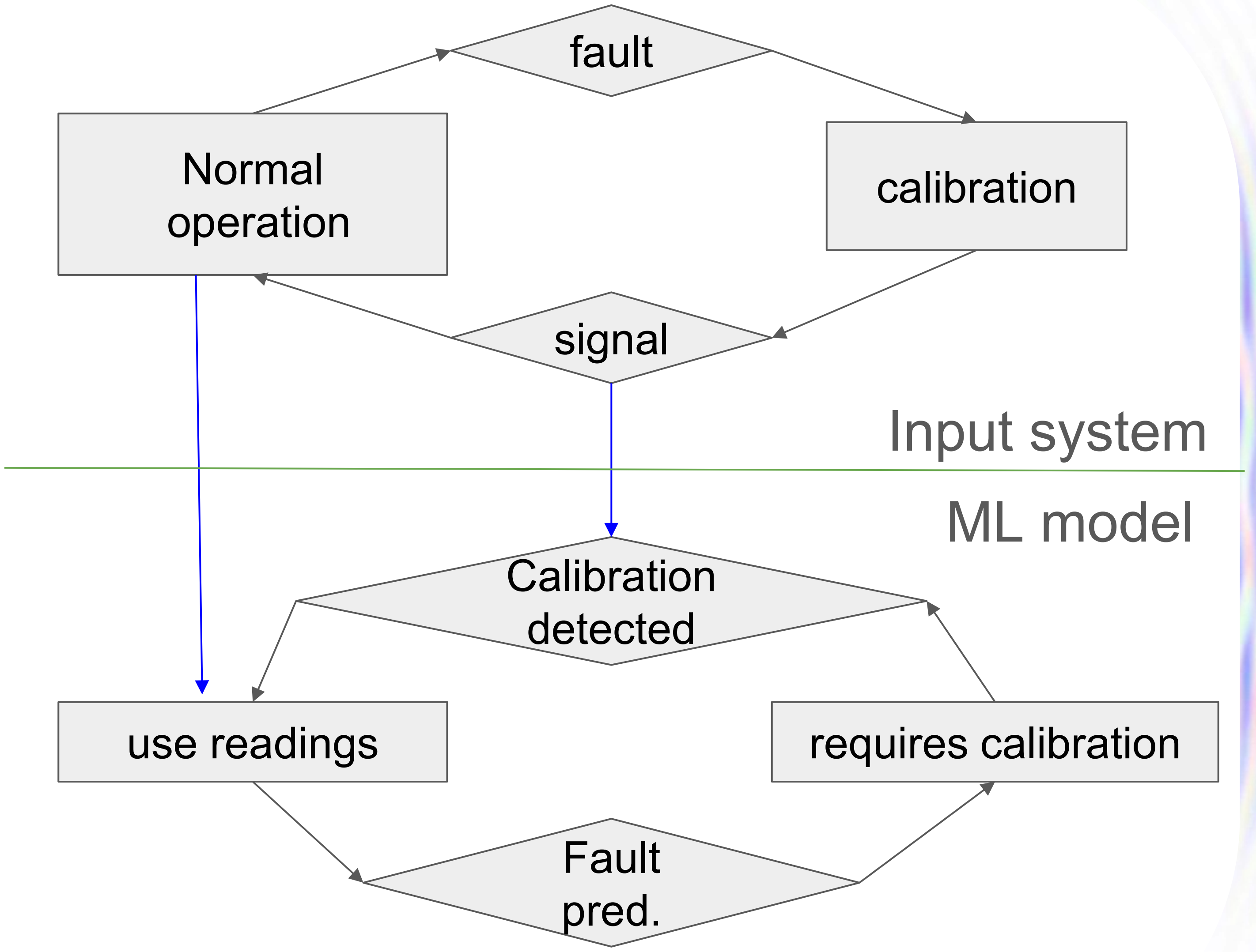
Follows the same mathematical model as biological aging.

Can use a Markov chain trap/leak to model.

Other terms:

- distraction (LSTM)
- memory corruption
- context loss
- error accumulation

(Not a retraining error)



Online Aging - examples

Amazon WH drone (real world state)

Roomba SLAM map corruption

Online Aging

Property of any complex system.

- Unpredictable degradation over time, requiring reset.
- Prevent with long time series data, or model biasing.

Online Aging

Property of any complex system.

- Unpredictable degradation over time, requiring reset.
- Prevent with long time series data, or model biasing.

Particularly a concern for products/ML models that (unpredictably) modify their environment.

Data - conclusions

Costs of an ML/AI method are ongoing, and not simple to determine.

- Customer need identification is ideally data-driven.
- Ongoing data collection required to monitor.
- Complex long-term models are more risky.
- Some errors/mistakes are emergent, focus on mitigation.

However there is significant opportunity to build robust utilities or businesses.

Managing Emergent Problems – Case studies

Business-relevant strategies:

- Facilitative environment - model does not work alone
- Cheap failure
- [Proactive updating]

Also other well-known strategies:

- Output fencing
- Input fencing (i.e. do not use outside of ‘x’ environment)

Business Opportunities Case studies:

- CashWalk
- Zainar

Facilitative environment

In a facilitative environment, the ML model works alongside collaborators.

- responsibility for failures can be relieved from the ML model.
- continuous feedback and monitoring is available, actionable.

Important requirements for user are that points of decision are clearly communicable.

Facilitative environment example – Waze

Performs navigation and route updates (traffic cameras, road closures), encourages collaborative responsible driving.

- map, icons, communicate points of decision
- responsibility always lies with driver
- anomaly detection prompts info requests
- speak-to-report on navigation issues.
- reporter community ranking
- active location tracking
- satisfying UI/experience
- integration with smart vehicles
- displays nearby community members

Non-facilitative example: Starship Cherry Hinton

Started in November 2022, delivery robots allowed home delivery of groceries from Coop at Adkins Corner.

- Robots frequently stuck on pavements or at traffic lights
- Complaints that items not delivered had limited follow-up.
- No recourse except to cancel delivery.
- Discontinued indefinitely
- Possibly still in Cambourne

Cheap failures – Domestic SLAM

ML technologies: SLAM, computer vision. Use

Roomba – self-driving robot vacuum

- Nav failure interrupts session, req. rescue.
- Users determine if Roomba cleans OK
- Still cheaper than a human cleaner

VR headset

- Location failure leads to short-term loss of coherence
- No lasting harm and recovery occurs fairly quickly

Not So Cheap Failure – Tesla

August 2019 crash in Florida.

Tesla found liable by jury, $240m damages bill.

Marketing gave false expectations of self-driving capability, directly leading to dangerous product usage.

‘Tesla's lies turned our roads into test tracks for their fundamentally flawed technology,’
-Brett Schreiber, plaintiff’s attorney

Case Study – CashWalk

Korean company, pays people to walk, inertial and location data is collected. Multiple B2B revenue streams:

- Health and events platform for customers.
- Contract with LG (data)
- Special events for government/business groups to encourage in person activity.
- Partnership with many charities to raise their awareness.
- Data tie ins: Insurance, public markets, tourism providers, test online marketing spend -> in person attendance.

Case study – Zainar

Multi-frequency coherent signal processing in 5G base-stations – device triangulation.

- “The Foundation Layer for Physical AI”
- B2B focus
- Uses 5G sounding signal (SRS)
- Touts ability to find first-arrival signal
- $1Bn Company value mostly IP and relationships

Conclusion

ML models experience unpredictable and potentially severe errors. (long tails)

ML products may need ongoing data as a key business expense (unlike many utilities).

Many emergent risks when embarking on an ML project. Visibility over usage key.

Many creative and interesting business approaches/opportunities as a result.

Thank you!

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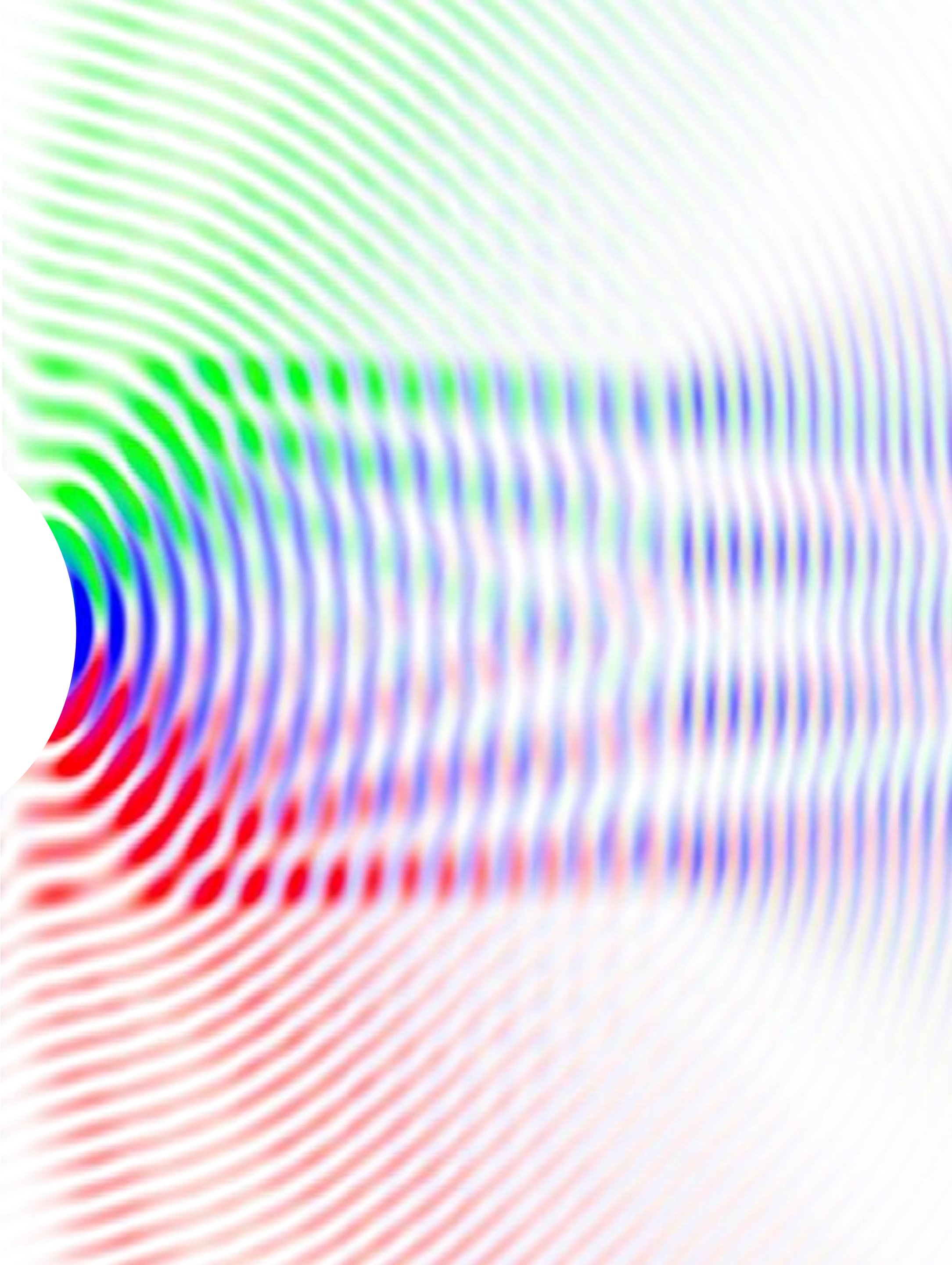
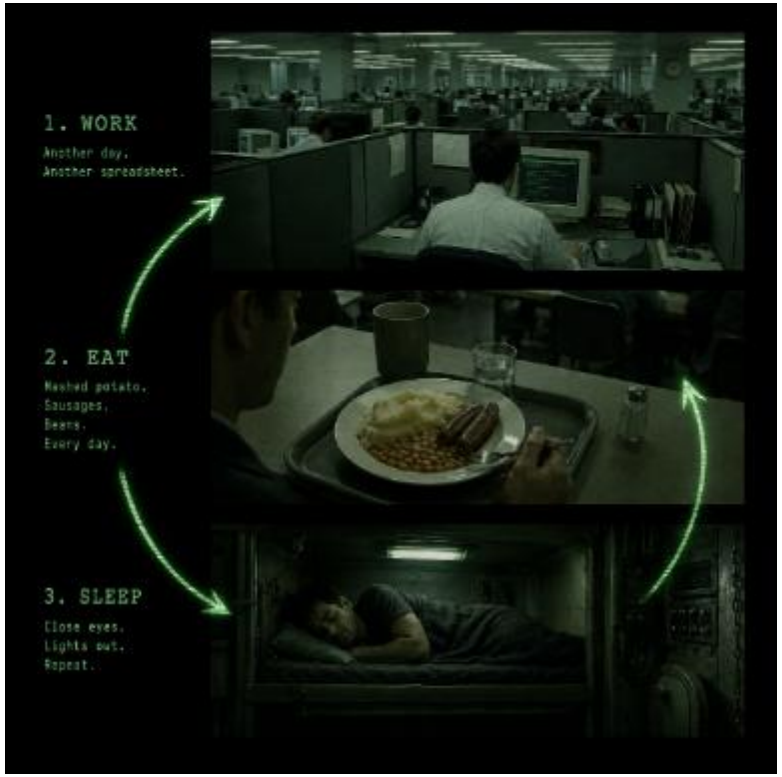


A bit of conjecture (with GPT+Transformer pictures)

Dependent;
performant



Interdependent;
responsibility

Independent;
sensitive and reactive

Responsibility/Stakeholder shifts:

Starship AGI

- raise tickets to modify pavements for better vehicle/disabled access
- Comparative testing across locations for different interactions
    - (telco call/siren/environmental awareness)

GNSS AGI:

- Active monitoring/identification of challenging sites
- Raise tickets to perform surveying of new construction/building shift.
- Recommendations for local pseudolite/rtk station deployment.

Refreshment Break

Please return at **15:45**