Distributed Algorithms Student Presentations

CDT Showcase 2023
The Spine

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UKRI Engineering and Physical Sciences Research Council

Gaussian Processes

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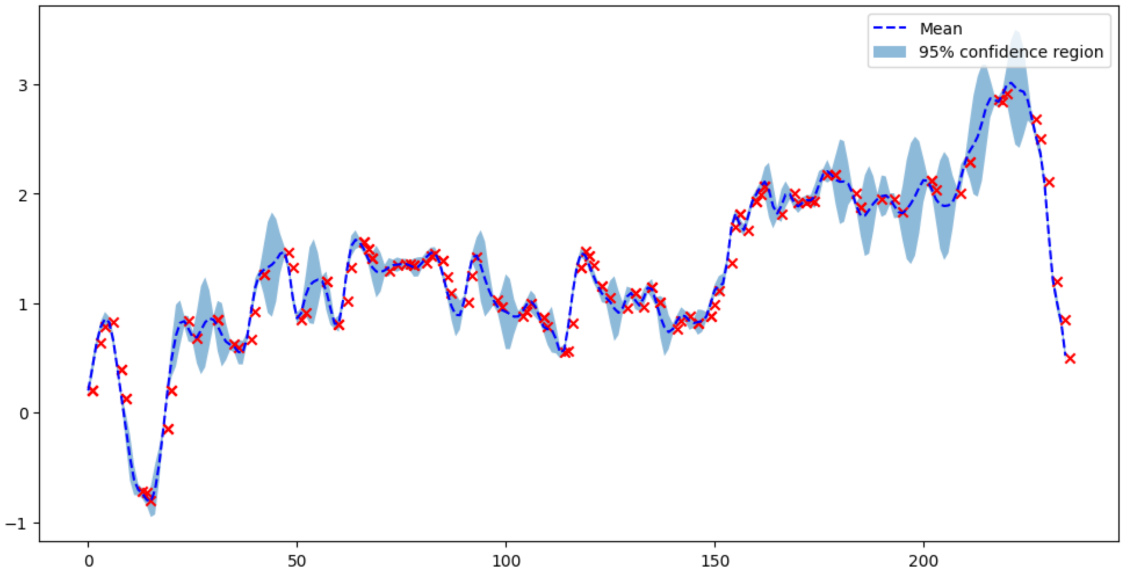
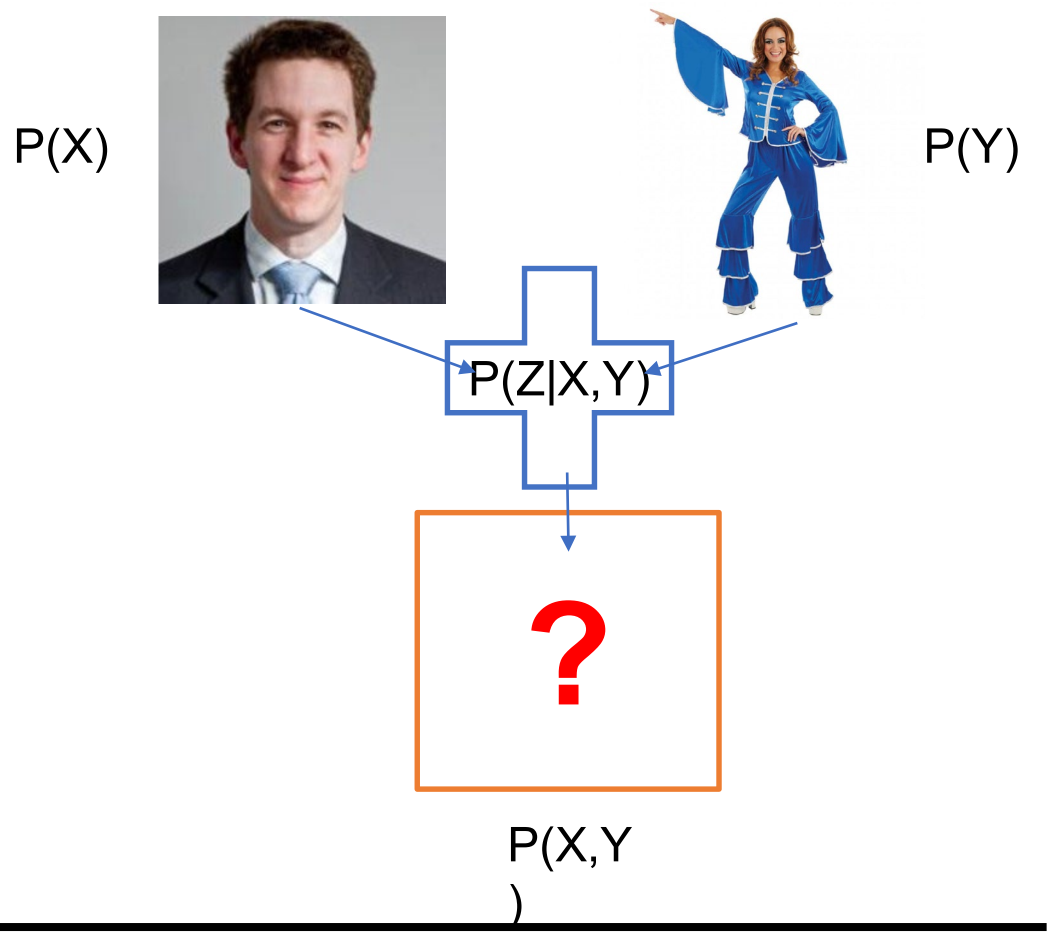
Engineering and Physical Sciences Research Council

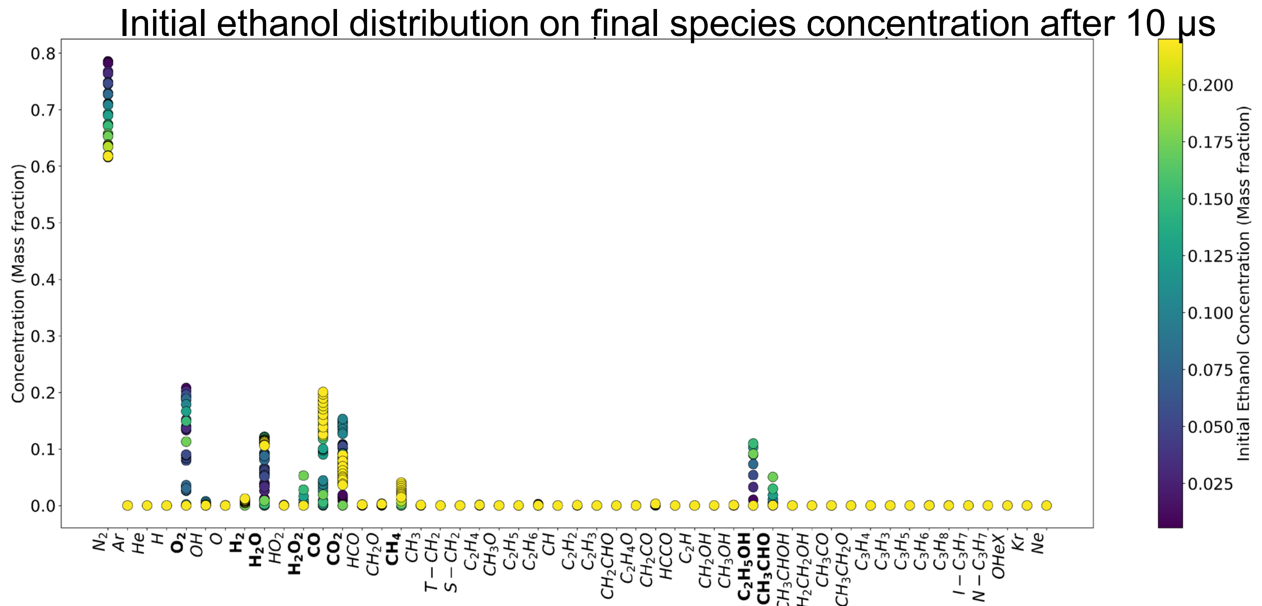
Uncertainty Quantification for Generative Modelling

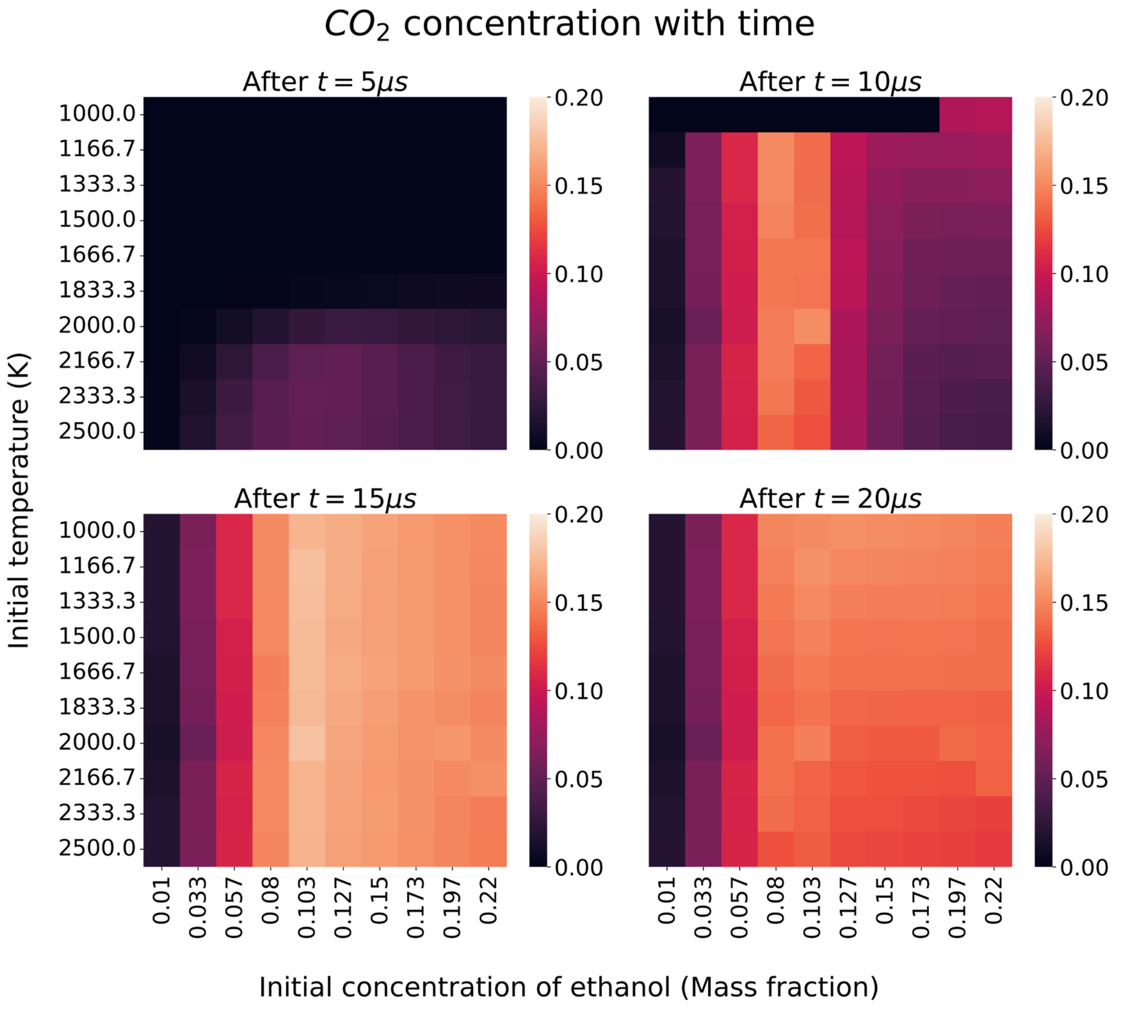




Adam Lee

Faster Uncertainty Quantification of Hydrocodes



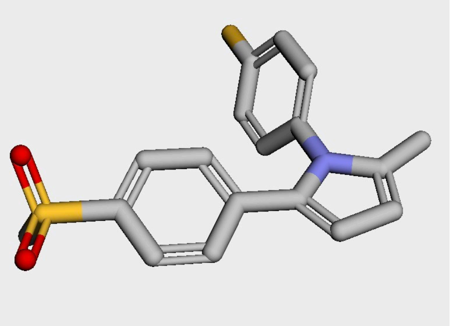


Sarah M. Askevold

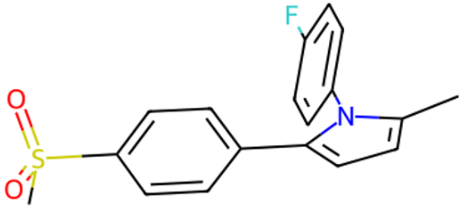
University of Liverpool

dstl — The Science Inside

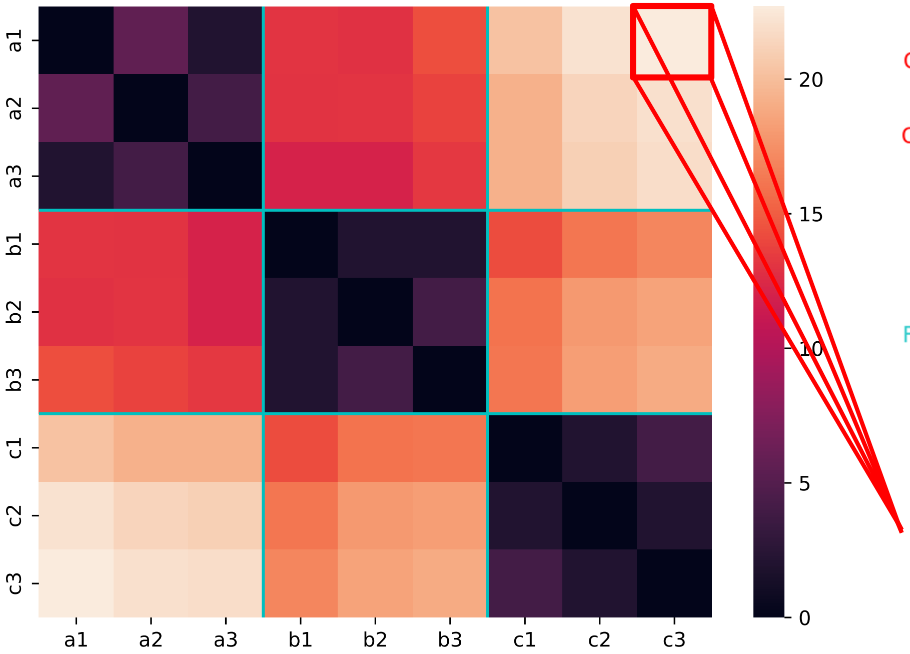
AI for Fast Discovery of Novel Materials for Healthcare



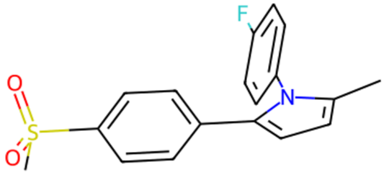
Molecule



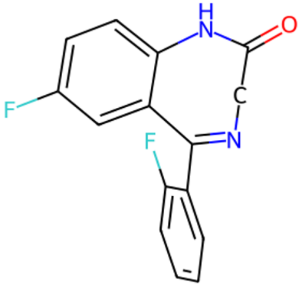
Molecular graph



Distance matrix of molecules



Mol 1



Mol 2

d(Mol1,Mol2)

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Jinhao Gu

Unilever

Towards Data Driven Aerodynamic Models

Experimental wind tunnel

Computational aerodynamics

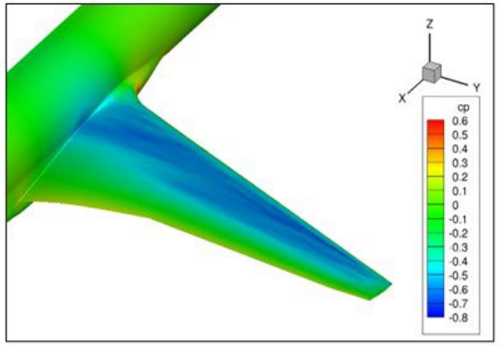

Image credit: ARA *(top left)*, DLR *(right)*.

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Mehdi Anhichem

ARA

Advanced Bayesian Algorithms

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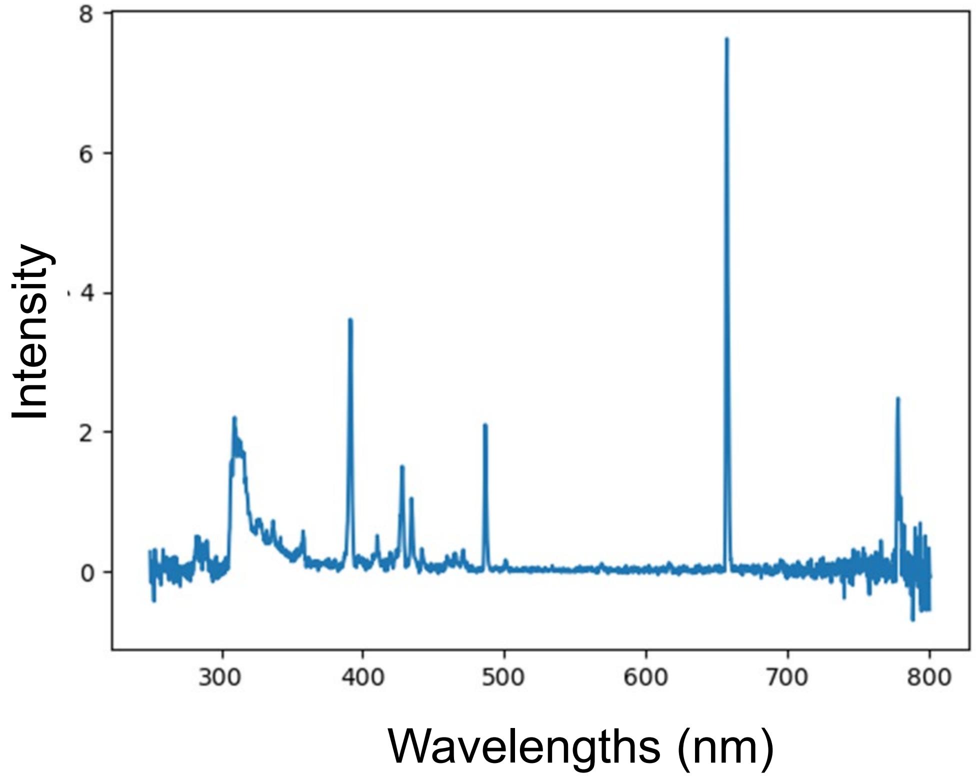
UKRI Engineering and Physical Sciences Research Council

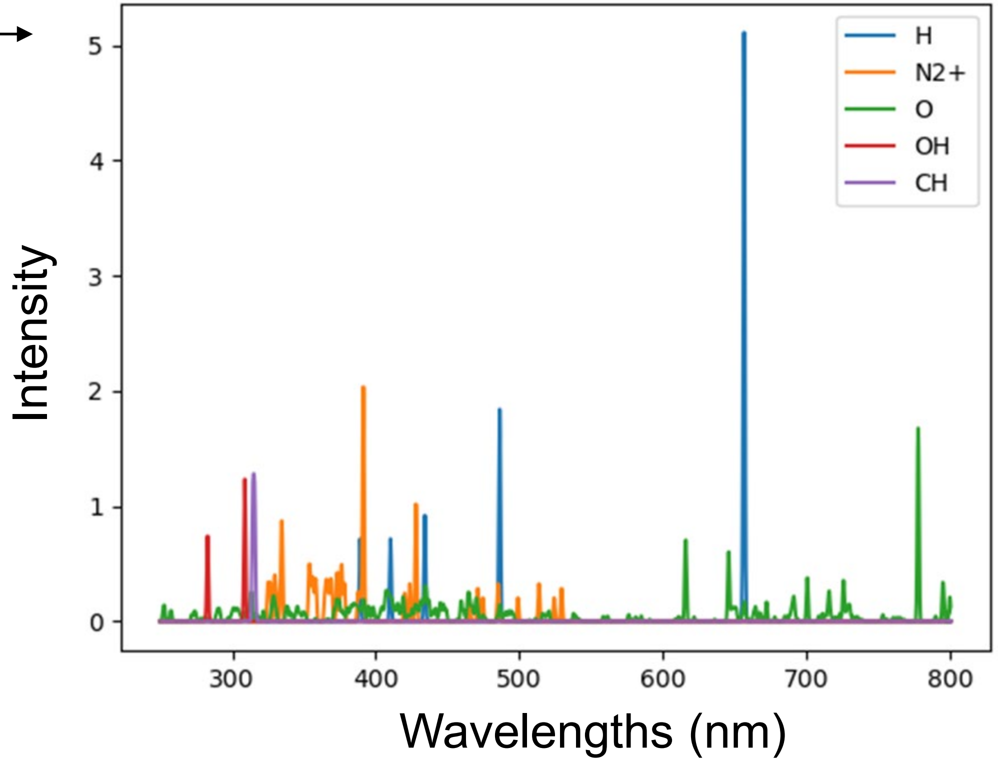
Bayesian Block Sparse Spectral Unmixing

Plasma Spectral Data



Dictionary Based Bayesian Learning

Spectral Unmixing



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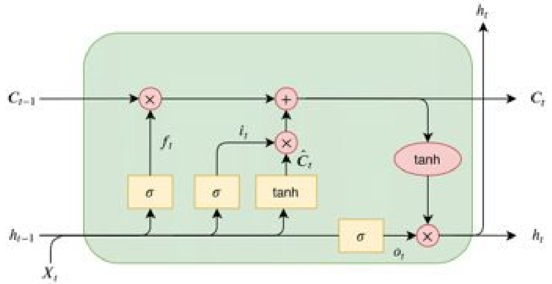
Oisín Boyle

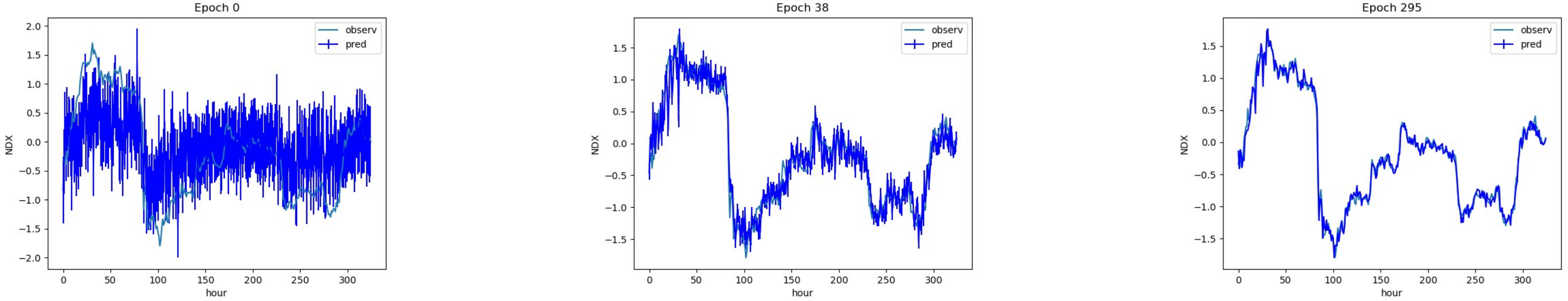
GENCOA

Capturing Uncertainty through Neural Networks

State: $$x_t = f(x_{t-1}) + w_t \quad w_t \sim N(0, Q)$$

Observation: $$y_t = h(x_t) + u_t \quad u_t \sim N(0, R)$$

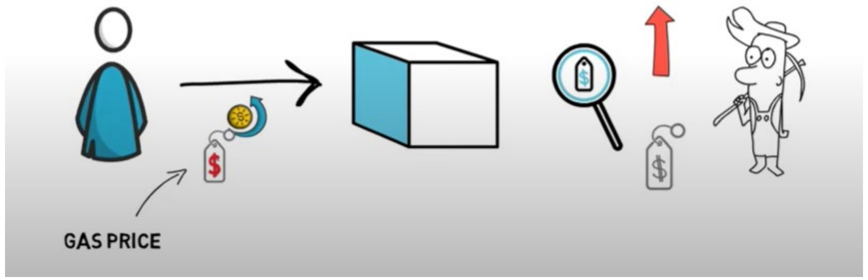




Algorithms and Mechanisms on Distributed Settings

Blockchain

- Users
- Miners (Validators)

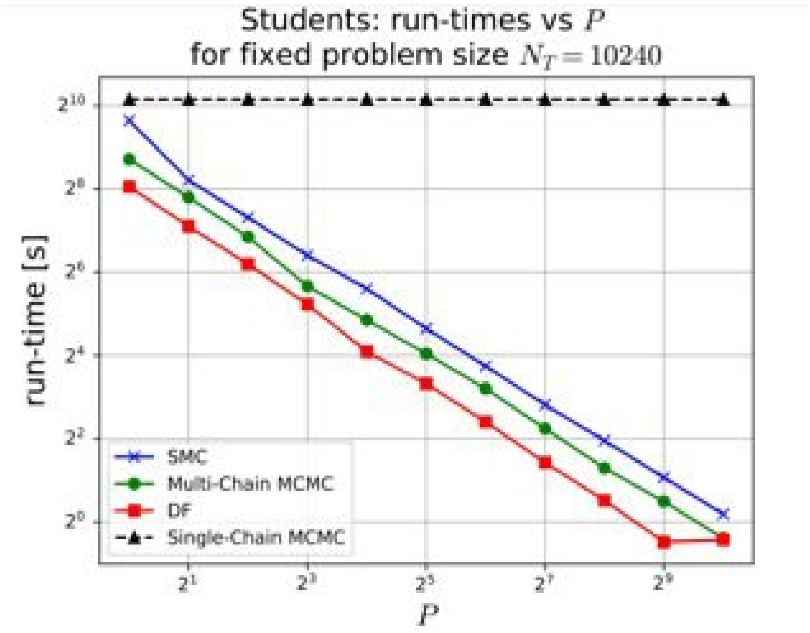


Mechanism Design (a.k.a. inverse Game Theory)

- Selfish agents
- Design rules that lead to desired outcomes

Examples: efficient allocation of blockspace, honest participation of protocol participants, etc

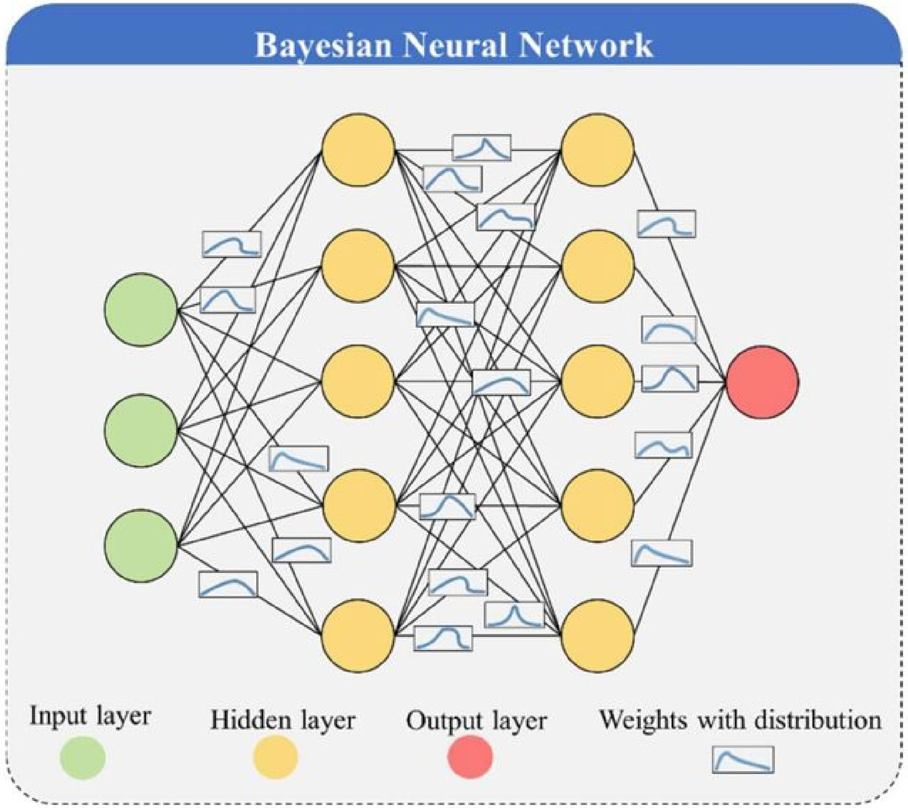
Sequential Monte Carlo Trees



Method	Students
SMC	71.48%
Single-Chain MCMC	71.64%
Multi-Chain MCMC	54.62%
Decision Forest	66.86%

Bayesian Learning for Sparse High-Dimensional Data

Using Sequential Monte Carlo samplers to estimate parameters in Bayesian Neural Networks to calculate uncertainty in classifications



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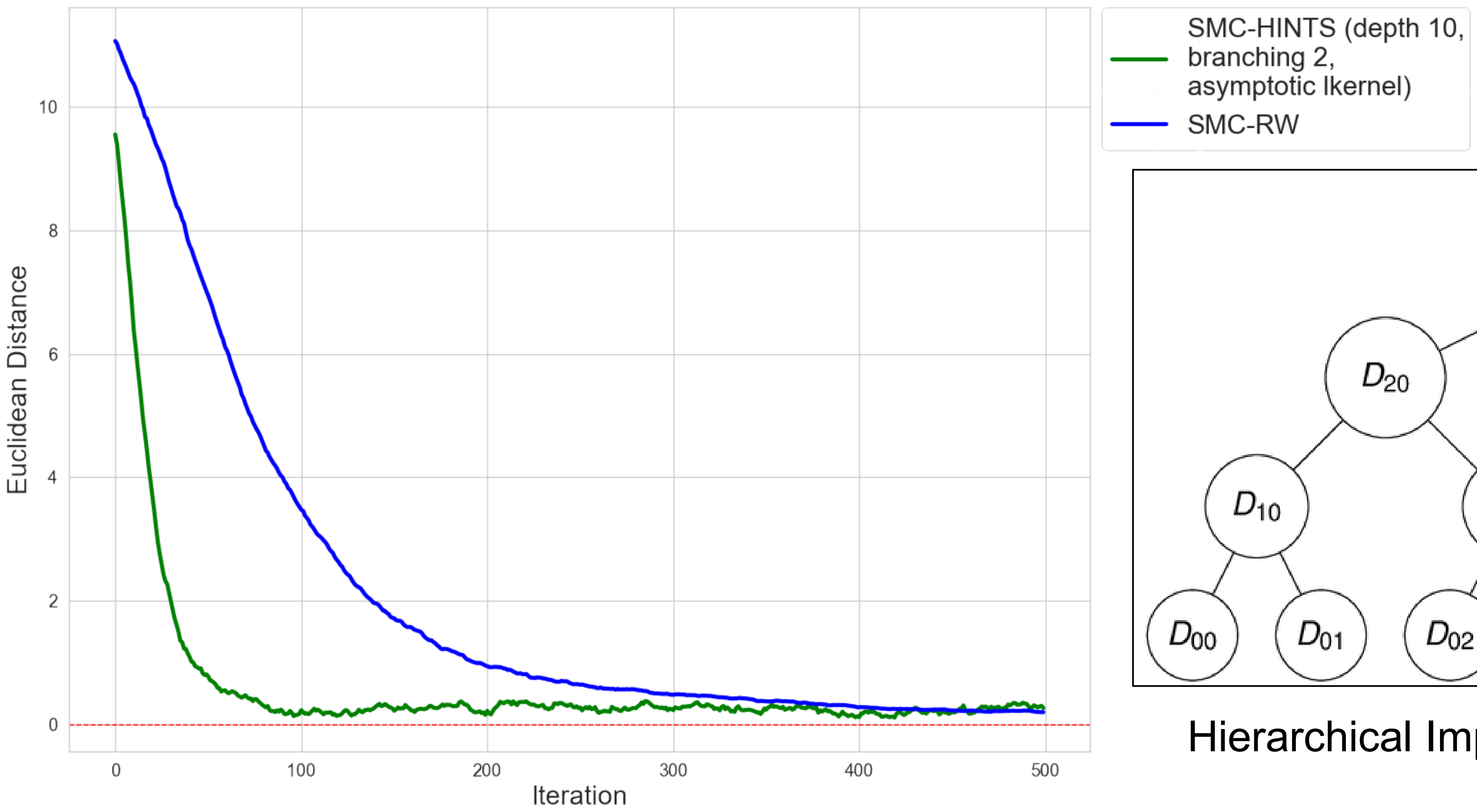
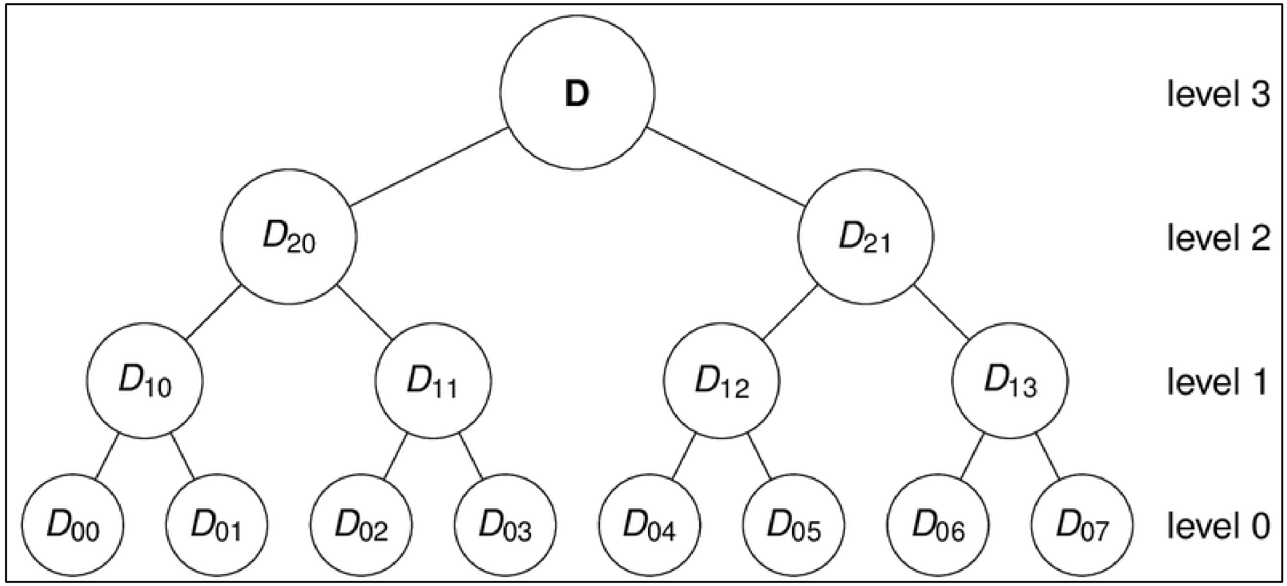
Daniel J. Sumler

QINETIQ

Developing Efficient Numerical Algorithms Using Fast Bayesian Random Forests

Euclidean Distance from the Target Mean of an 11-D Gaussian using 256 particles, 500 iterations and 1024 data points





Hierarchical Importance with Nested Training Samples (HINTS) Example

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Harvinder Lehal

GCHQ

Developing Novel Bayesian Track Before Detect Approaches for Maritime Big Data Challenges

Problem:

- Targets like USV, UUV, and divers use surface clutter to evade radar detection.

Project goal:

- Develop methods to separate targets from within surface cutter.
- Detect smaller signatures than existing trackers.
- Investigate various filters and develop algorithms to improve tracking performance.

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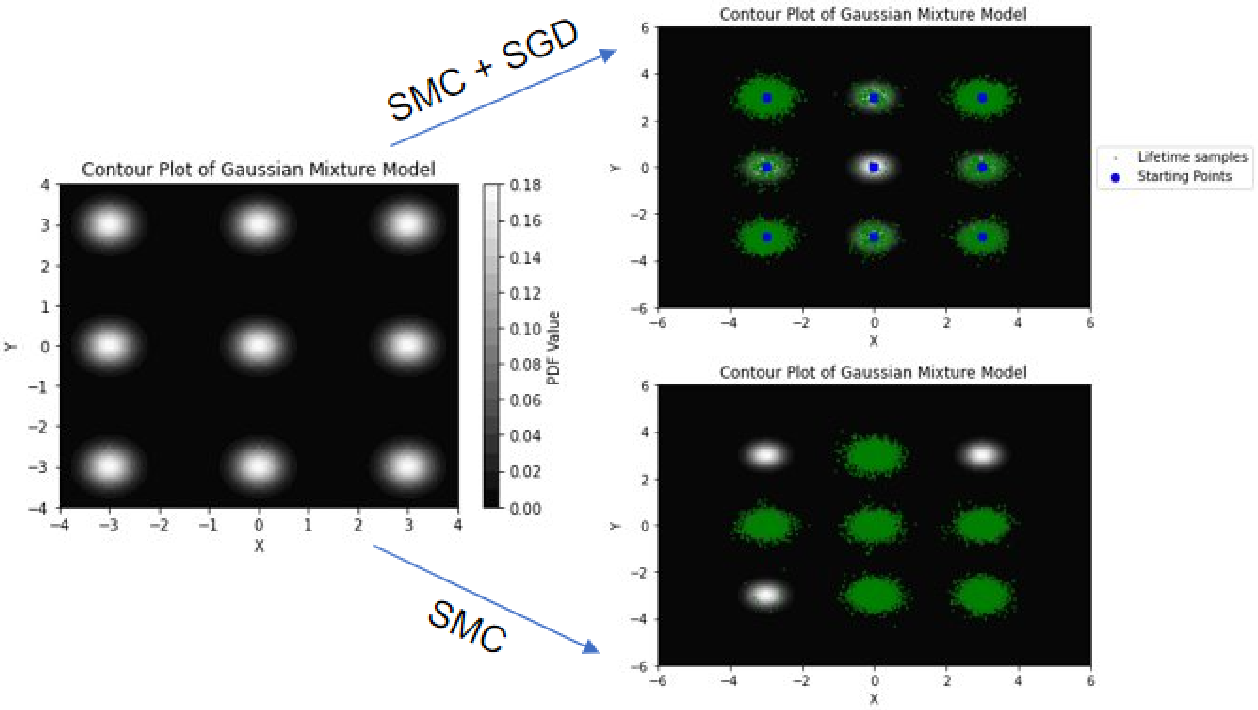
Omree K Naim

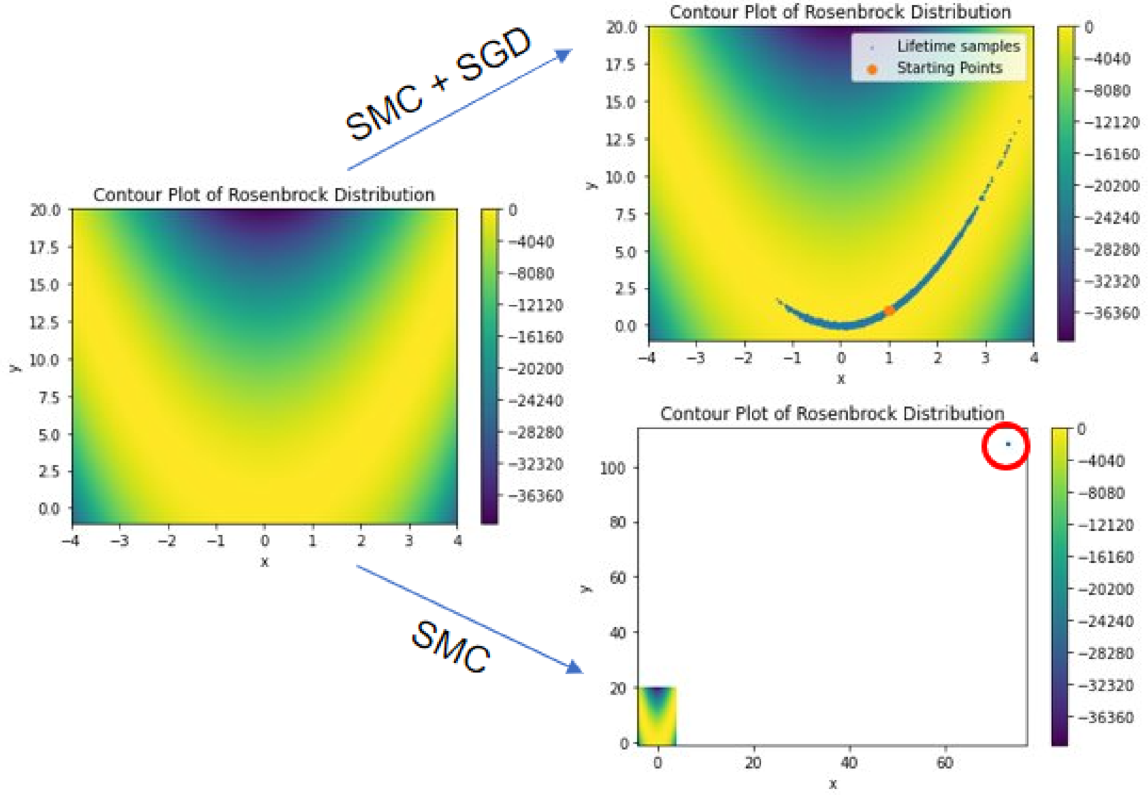
HENSOLDT Detect and Protect.

Combining GD and SMC for Complex Distributions

Multimodal



Bad Prior



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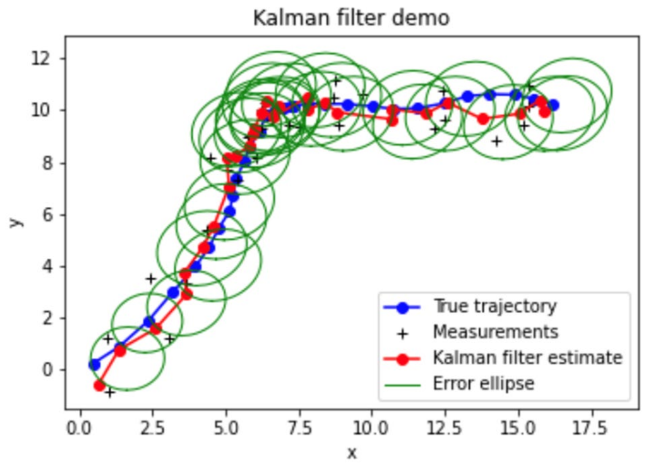
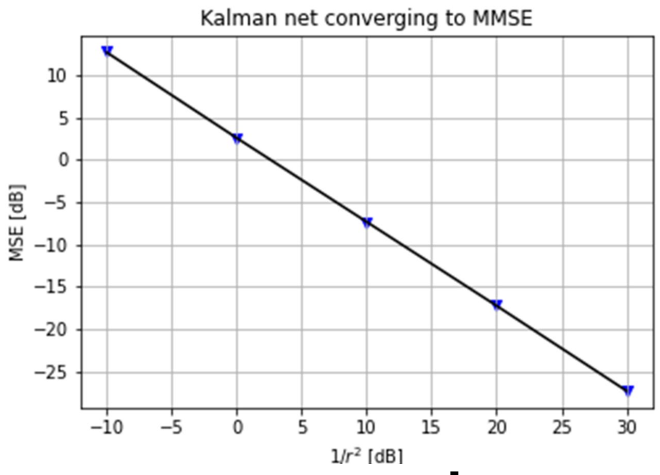
Andy Millard

HM Government

Learning transparent models from DD algorithms for streaming data analysis





$$\hat{Q} = \frac{1}{MT}\sum_{i=1}^{M}\sum_{k=1}^{T}\left(x_k^i - f\left(x_{k-1}^i\right)\right)\left(x_k^i - f\left(x_{k-1}^i\right)\right)^T$$

$$\hat{R} = \frac{1}{MT}\sum_{i=1}^{M}\sum_{k=1}^{T}\left(z_k^i - h\left(x_k^i\right)\right)\left(z_k^i - h\left(x_k^i\right)\right)^T$$

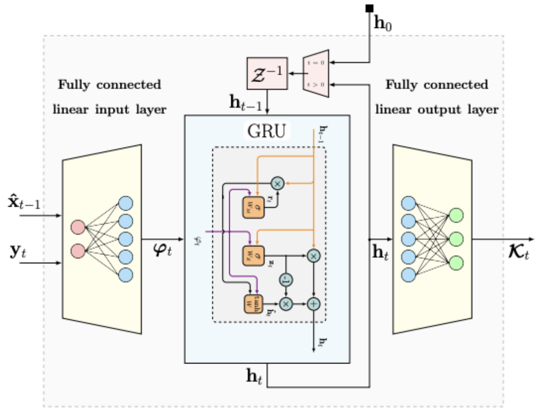
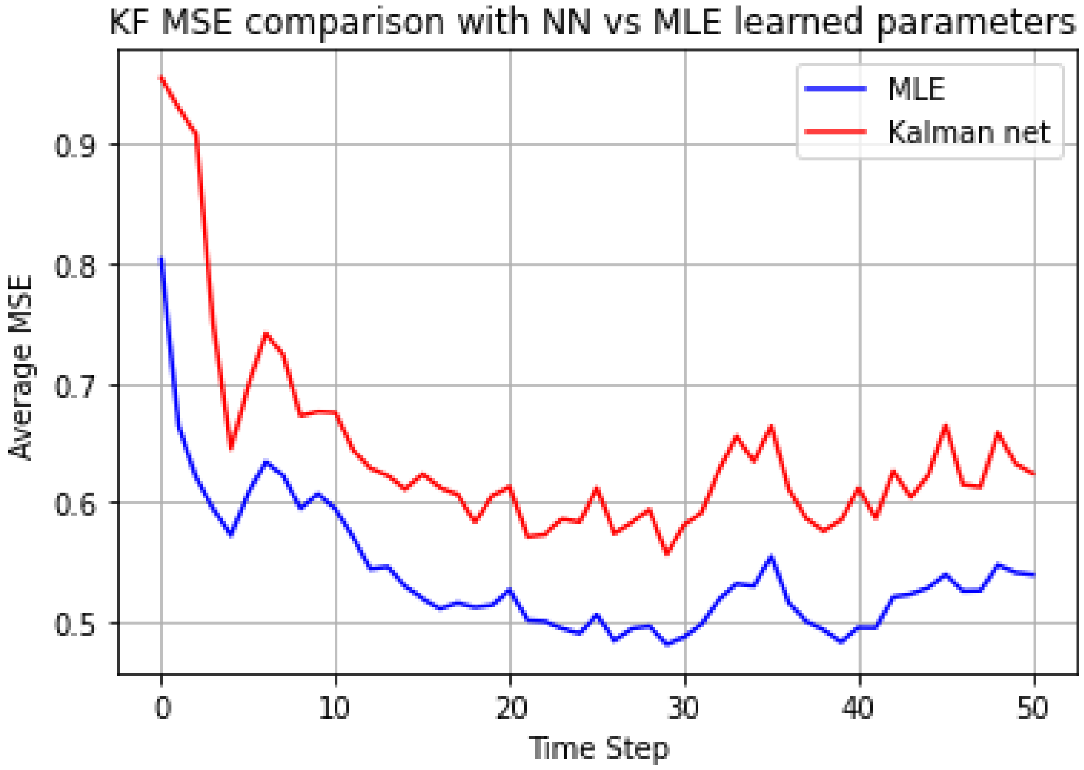


Fig. 3. Kalman gain neural network block diagram.



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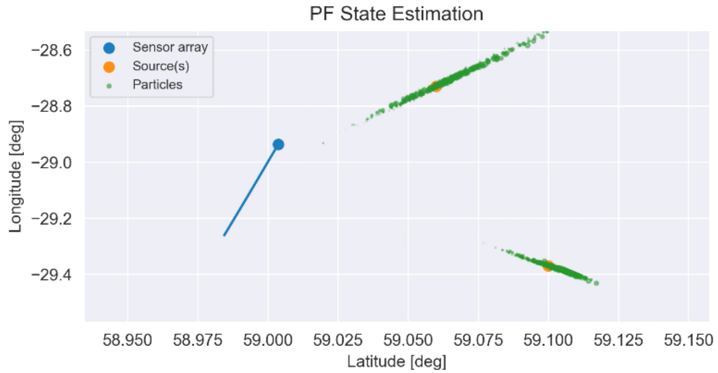
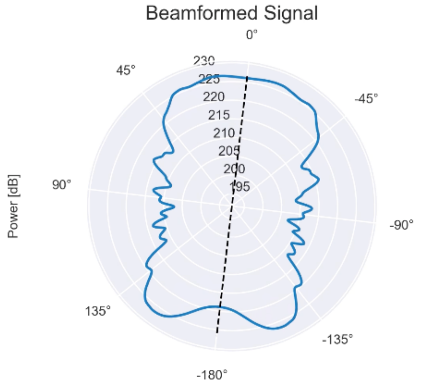
Bettina Hanlon

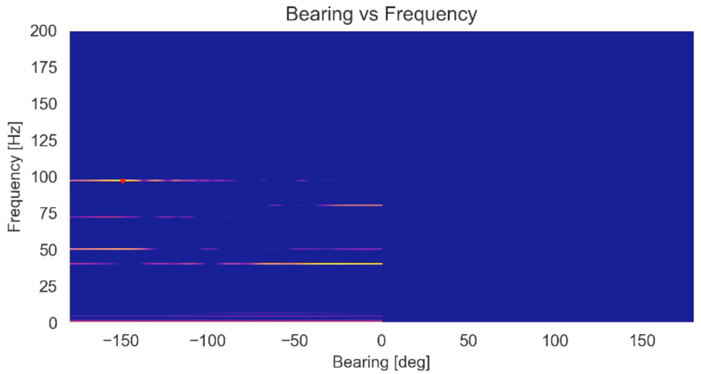
GCHQ

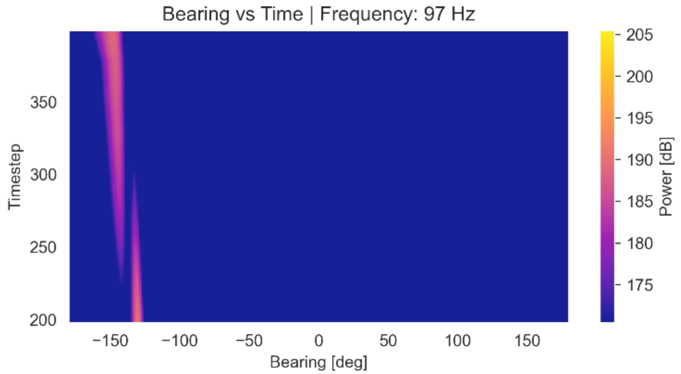
Dynamics

Maximising Detection Using High-Performance Processing of Multi-Sensor Data









Ray Traced Acoustic Propagation Modelling

This work utilises ray tracing techniques to simulate sound propagation in complex underwater environments, enabling the accurate prediction of acoustic signal paths.

Conventional Beamforming

Conventional array beamforming techniques are then employed to process the received signals and extract directional information for target localisation.

Particle Filtering for Bearing-Only Measurements

A particle filter tracking algorithm is implemented to estimate the trajectory of underwater objects based on bearing-only measurements.

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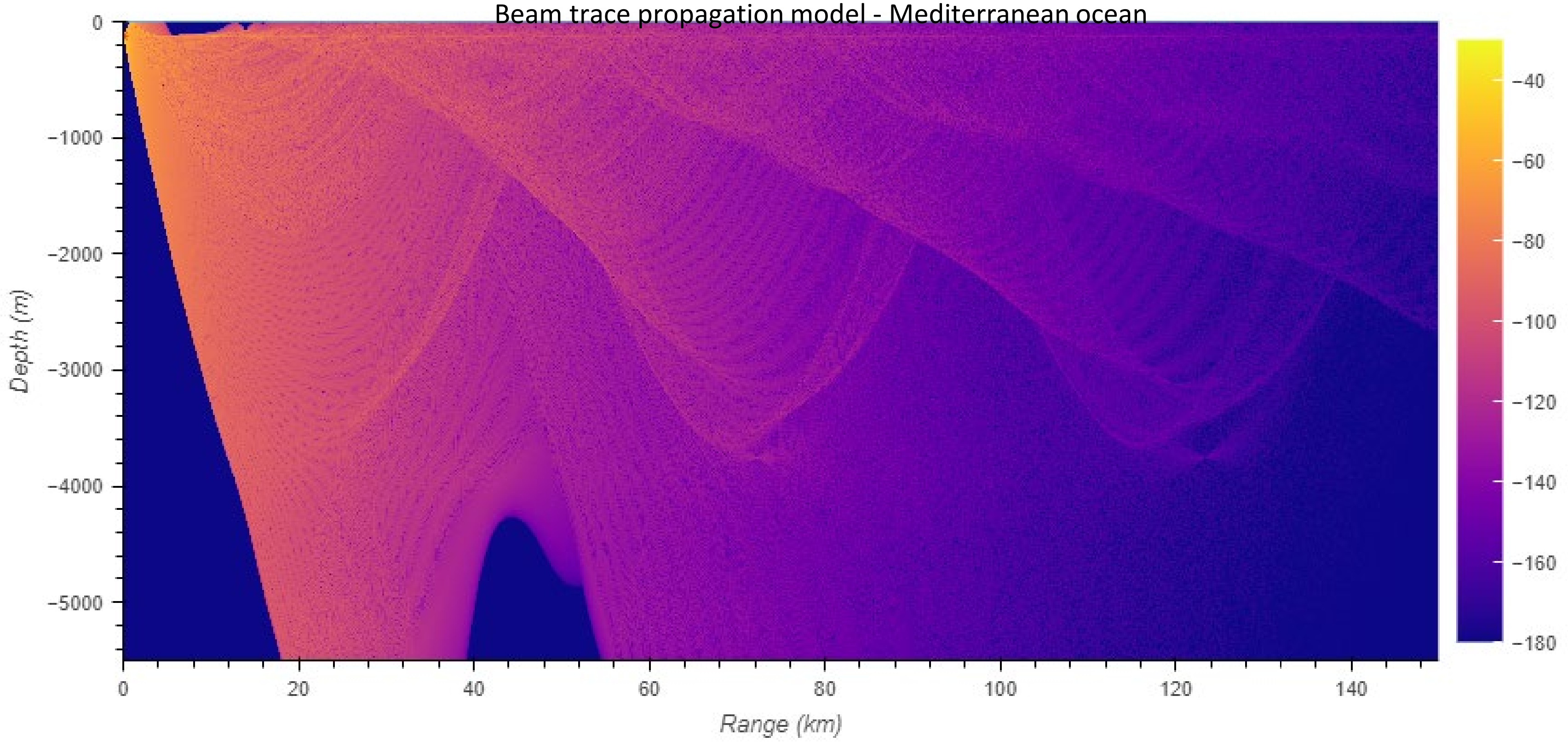
Joshua J. Wakefield

THALES

Machine Learning for Data Driven Sound Propagation Modelling



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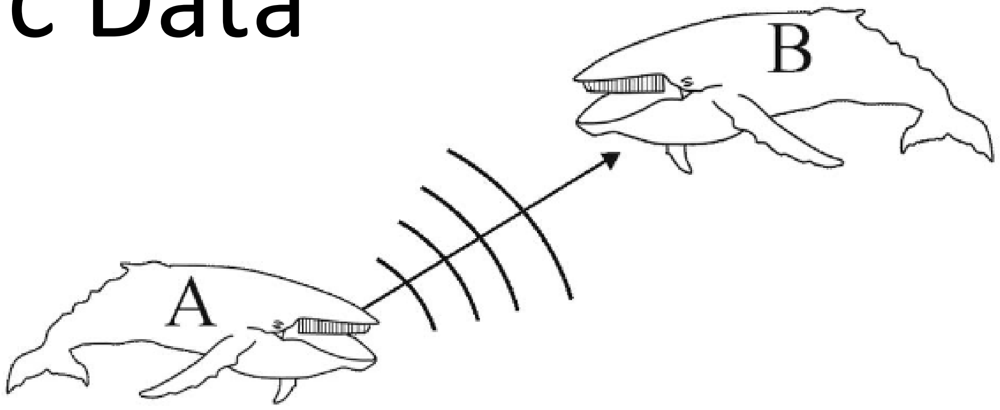
Finley Boulton

[dstl] The Science Inside

Machine Learning Inference of the Ocean Environment from Acoustic Data

- The ocean acoustic environment is complex.
- Getting an accurate reading on the position of an object and determining if it is of interest is difficult
- Machine learning methods can be utilised to build a library of acoustic profiles



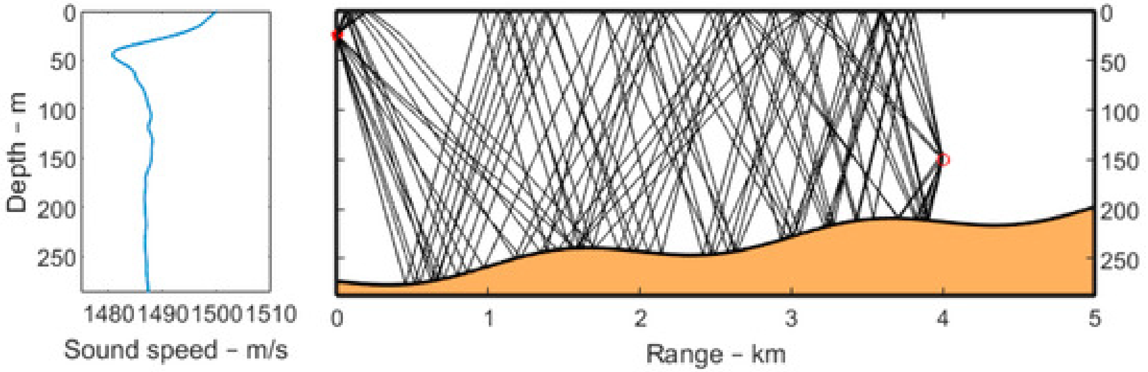


Image references: "*J. M. Hoven and H. Dong, "Understanding Ocean Acoustics by Eigenray Analysis," Journal of Marine Science and Engineering, vol. 7, no. 4, Apr. 2019.*", "*M. A. Ainslie, in Principles of Sonar Performance Modelling, Springer, p. 56*"

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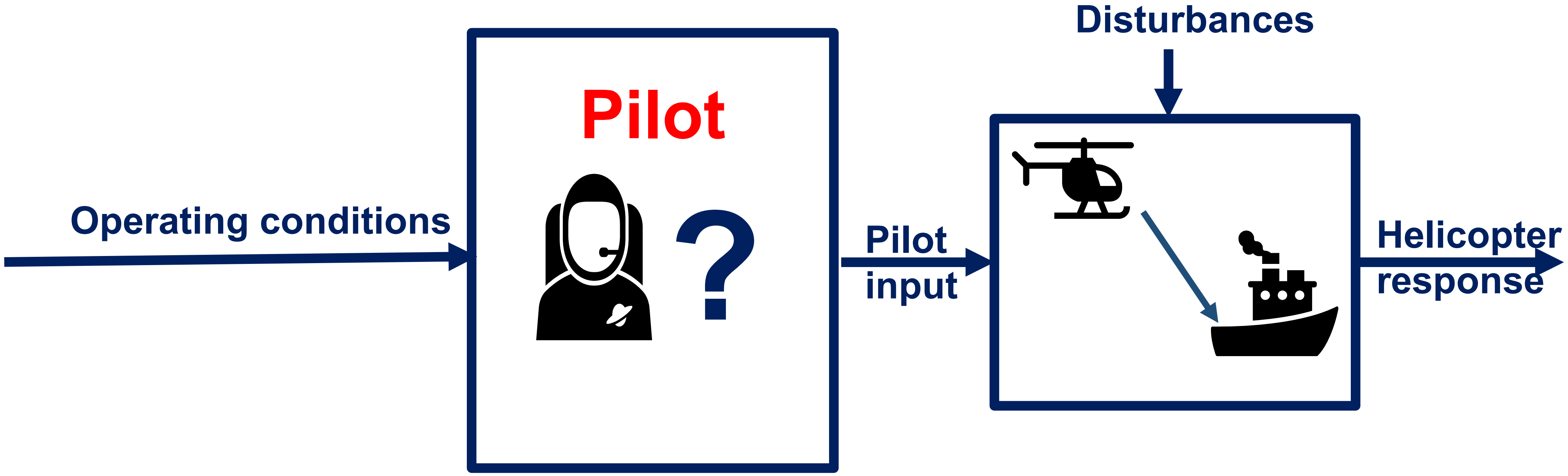
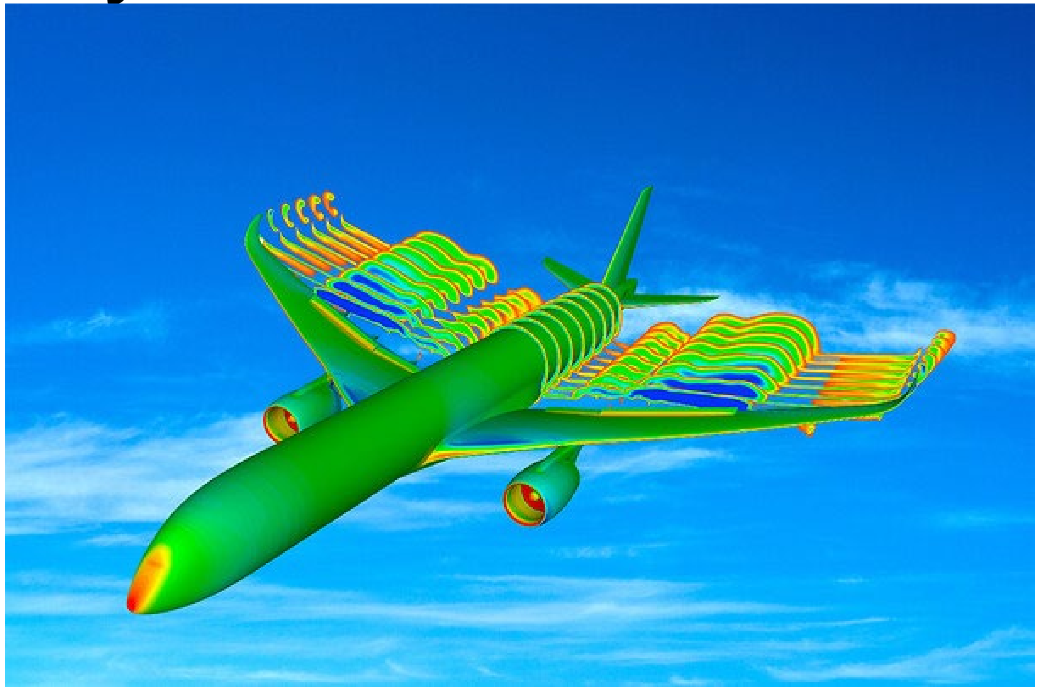
Finn Henman

[dstl]

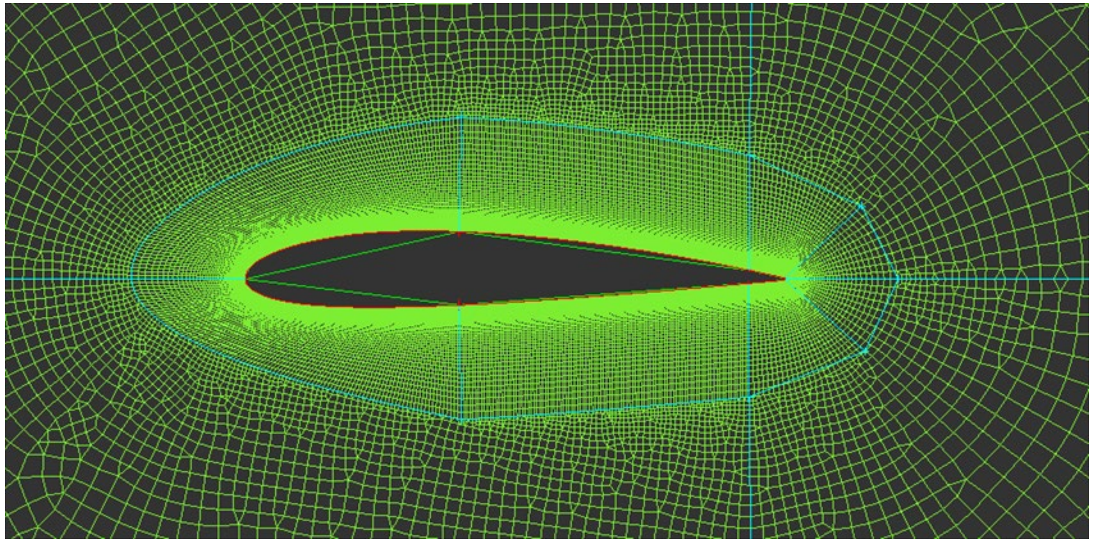
Digital test pilot model



Data Models for Large Aircraft Aerodynamics using Next Generation Computational Fluid Dynamics



Airbus, 2017 - https://www.airbus.com/en/asset-preview/88111



Supervisors: Dr Sebastian Timme, Dr Jony Castanga (STFC Hartree), Dr John Pattinson (Airbus)

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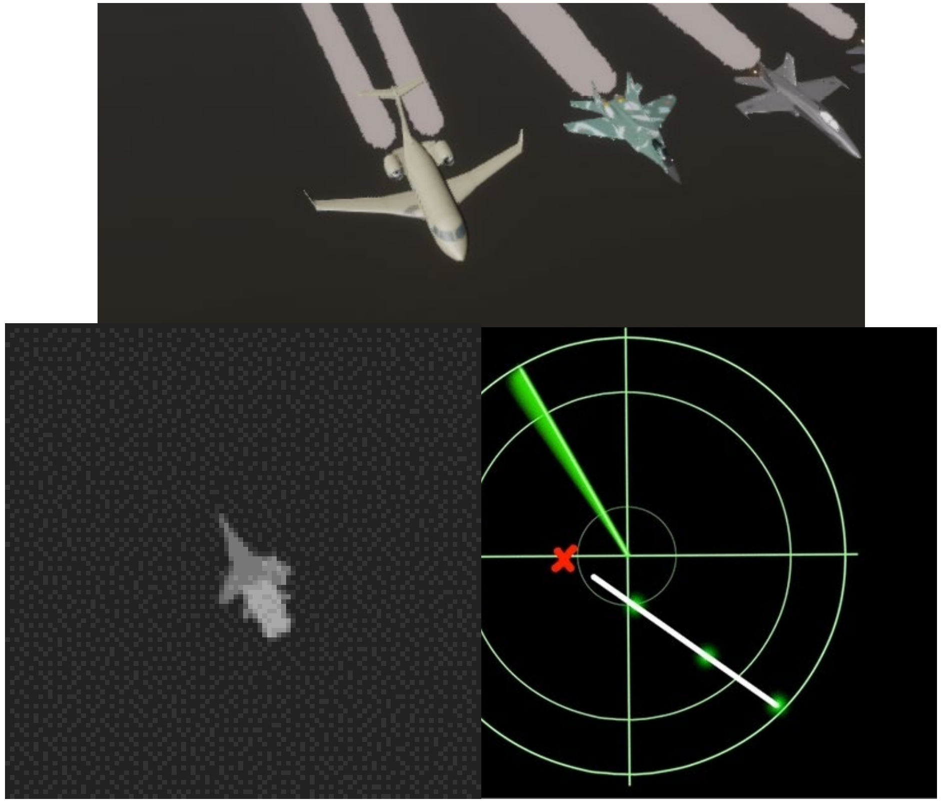
Daniel Nash

AIRBUS

Machine Learning of Behavioural Models for Improved Sensor Fusion

- Combining data from **multiple sources** to aid **quick decision-making.**
- Existing behavioural models are simplistic
- Methods need to be flexible to cover:
  - **Wide range of target behaviours**
  - **Target-generated phenomena**
- **Extreme Machine Learning (XML)**



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Christian Pollitt

Dr. Murat Uney, Dr. Mario Gianni, Dr. David Greig

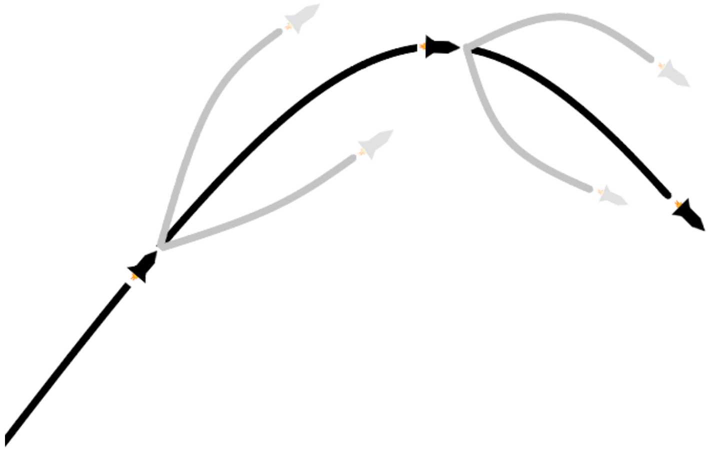
LEONARDO

Parallel Processing For Novel Navigation

Dead reckoning is significantly impacted by the accumulation of small errors.

Particle filters can be used to estimate and correct for these errors delaying the inevitable drift associated with dead reckoning.

Currently: Producing a simulation to be used for testing sensor fusion methods and possible sensors. Literature review.



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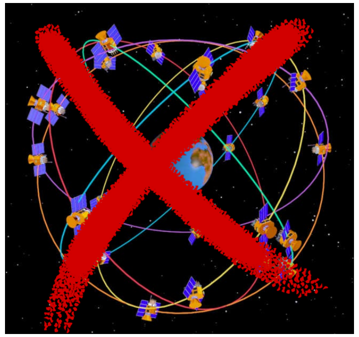
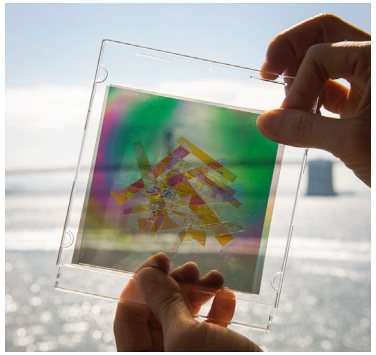
Daniel Chadwick

Prof. Jason F. Ralph, Dr Kirsty McKay, Grant McClean

Raytheon Technologies

Machine Learning for Bio-Inspired Navigation





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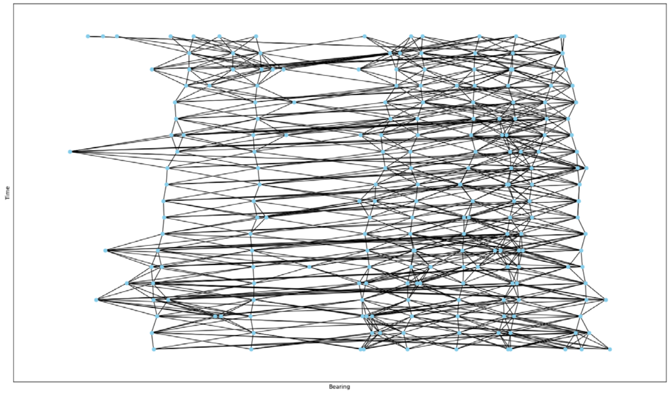
Teodor-Avram Ciochirca

Prof. Jason F. Ralph, Dr. Ian Sandall, Dr. Grant McClean

Raytheon Technologies

Improving Passive SONAR Detection & Tracking Using Machine Learning

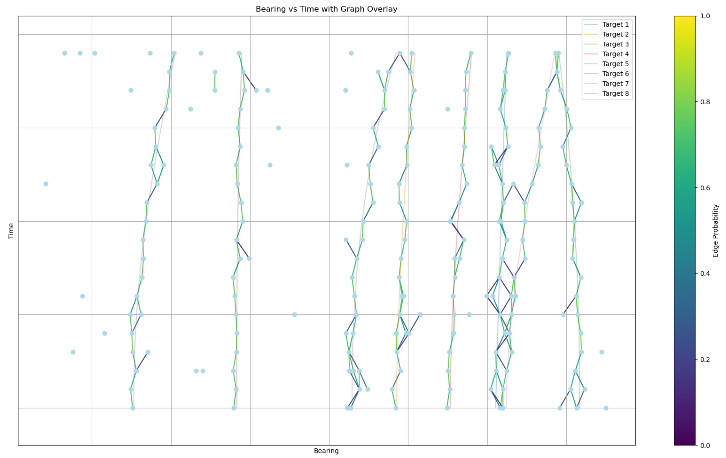
Tracking in passive SONAR is difficult due to various noise sources, non linear target movement and false alarms.



GNN edge classifier

Aim of the project is to utilise advanced machine learning algorithms like Bayesian and graph neural networks.

Detections are converted into a graph, and graph neural networks are employed for edge classification, identifying detections from the same target. This approach offers a data-driven methodology.



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William Shaw

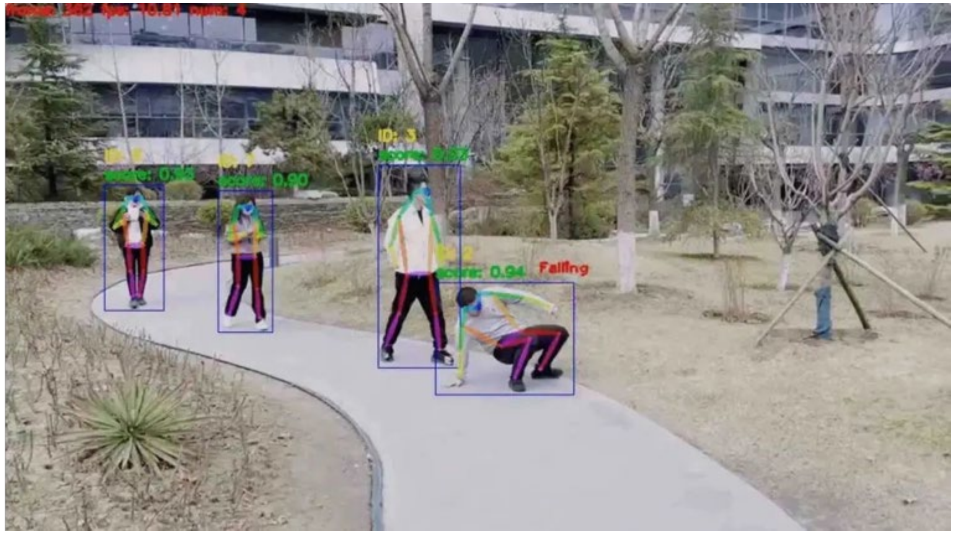
ULTRA MARITIME

Image Processing

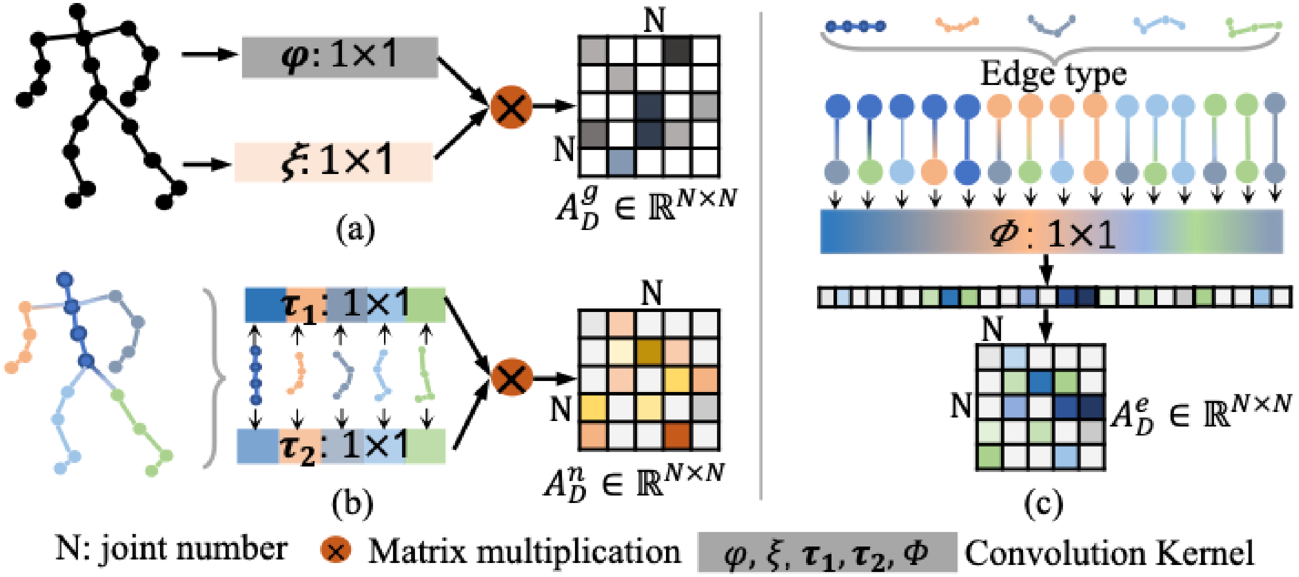
Video-based Human Action Recognition Via Deep Learning Algorithm

Main Supervisor: Yalin Zheng, Second Supervisor: Anh Nguyen, Industry Supervisor: Xiaoyun Yang (Remark AI)

Skeleton-based method



Encoding type of joints and edges in graph



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Jianyang Xie

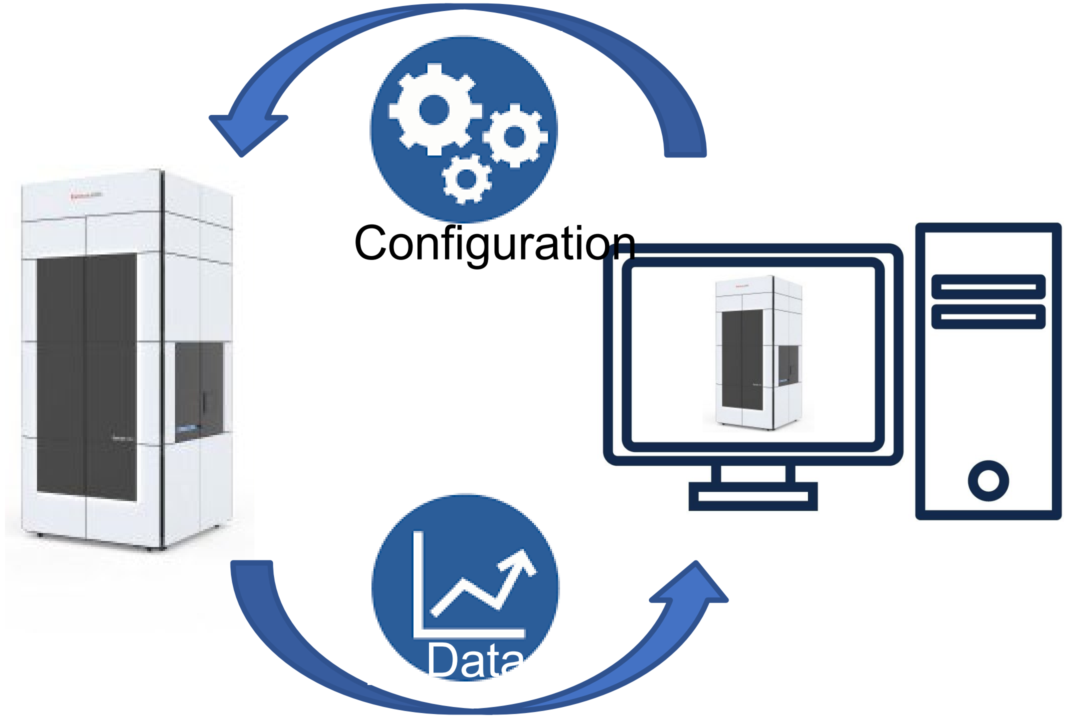
REMARK

Constructing a Digital Twin for a self-correcting Scanning Transmission Electron Microscope using Machine Learning Approaches

Problem: Optimising data acquisition from an electron microscope

Solution: Using Machine learning to perfect alignment and real time corrections during experiments

Advisors: Yaochun Shen, Mario Gianni & Nigel Browning



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Richard Jinschek

senseai

Transfer learning in airborne imagery

BigEarthNet

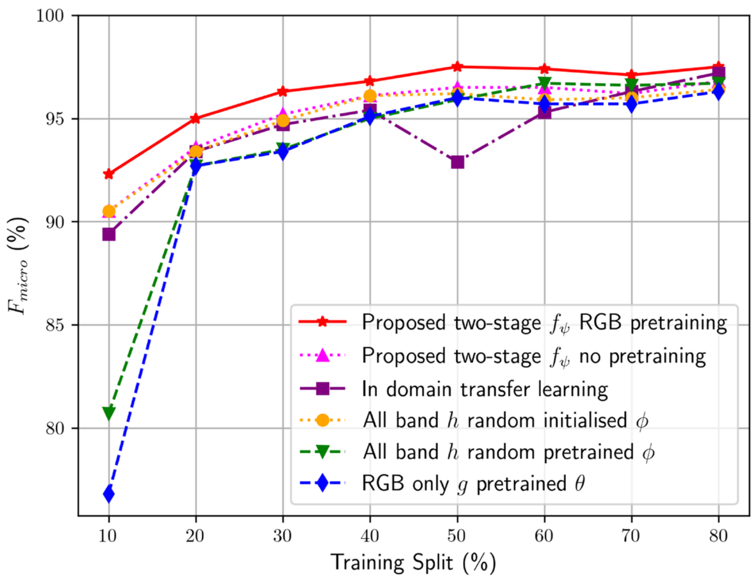
EuroSat

Transfer learning: $\min_{\theta} \mathbb{E}_{p(\mathbf{x})} \left[\ell \left(g \left(\mathbf{x}; \theta \mid \mathcal{T}_1^S, \mathcal{T}_2^S, \ldots \right) \right) \right]$

Supervised fine-tuning: $\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \ell \left(g(\mathbf{x}_i; \theta_{\mathrm{PT}}), \mathbf{y}_i \right)$

(θ_{PT} are parameters "pretrained" on a source dataset $D_s = \{\{\mathbf{x}_j, \mathbf{y}_j\}\}$

Modified fine-tuning approach results on EuroSAT dataset:



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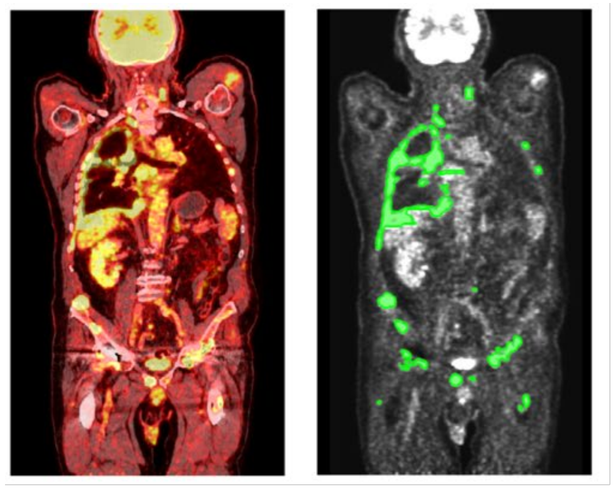
Benjamin Rise

Collins Aerospace

Using Artificial Intelligence to Help Predict Treatment Response in Patients

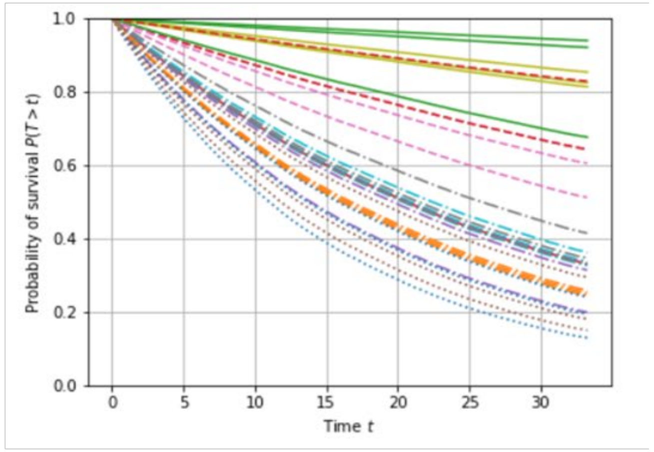
Problem: Designing personalized treatment plans for lymphoma patients.

Solution: Leveraging multi-modal data including PET, CT, health record and deep learning to develop and evaluate AI for accurate prediction of treatment outcomes.



Health record (Age, Sex...)
Treatment plans

Deep learning



Survival prediction

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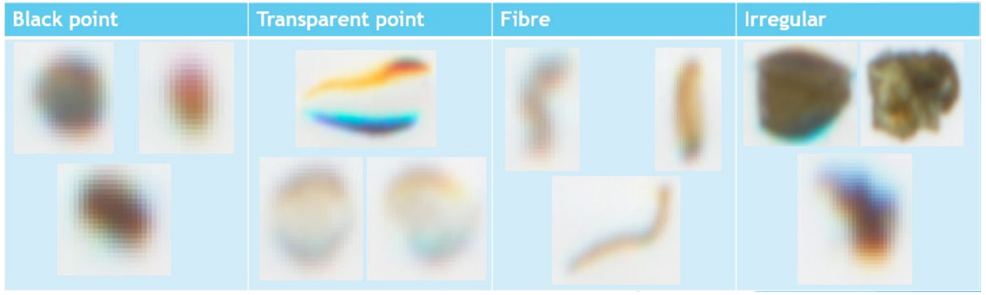
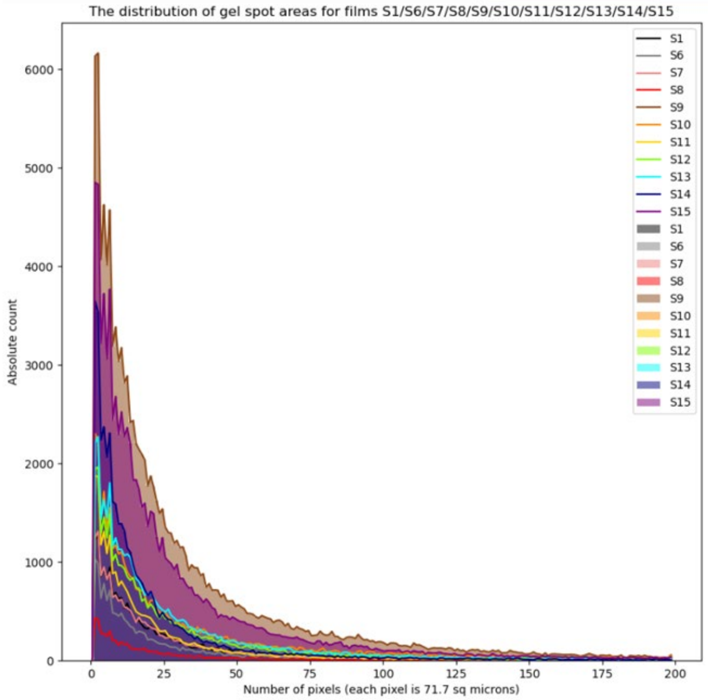
ZHANG Ruojun

NHS
The Clatterbridge Cancer Centre
NHS Foundation Trust

Data Science and AI for Smart Sustainable Plastic Packaging





Manufacturing companies make flexible films from polyethylene. The goal is to make these more sustainable by including more recycled materials.

Gels form in the films which represent areas of contamination and structural weakness. We use state-of-art computer vision techniques to classify film images.

We then attempt to understand the gel distribution for different industrial recipes to optimise packaging performance.

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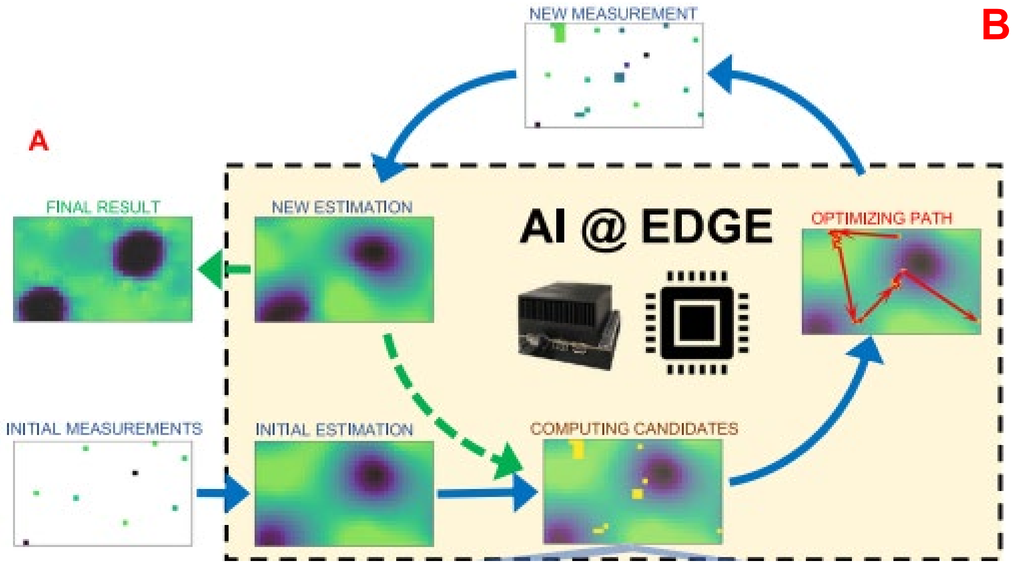
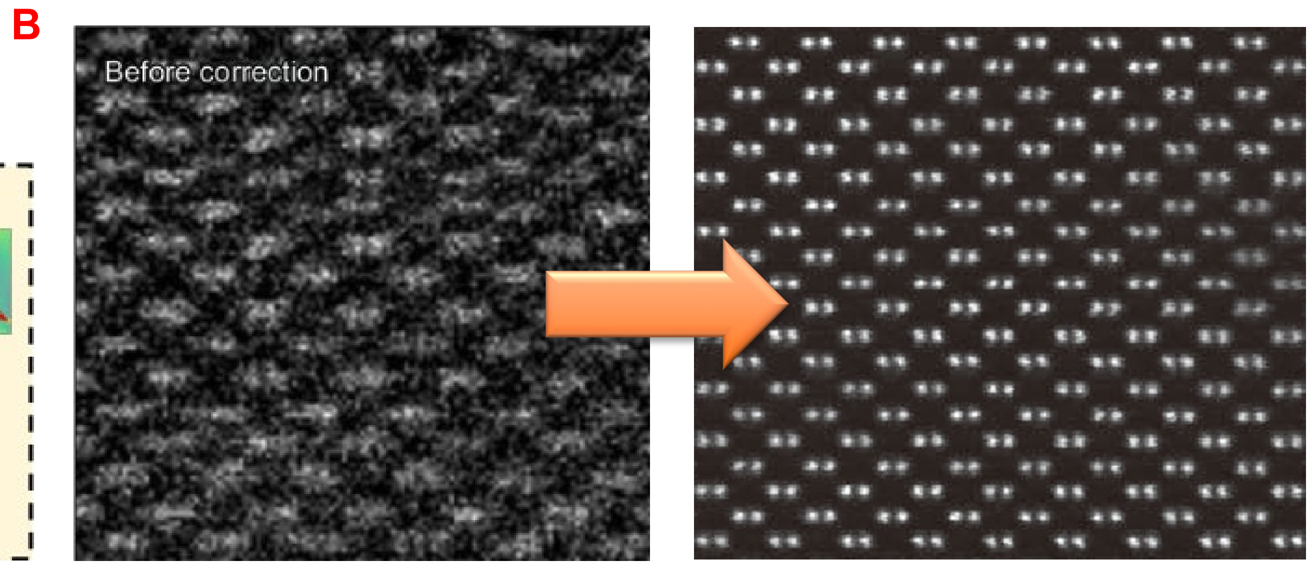
William Jeffcott

Unilever

Applications of Infinite Dimensional Compressive Sensing in STEM using Machine Learning to Enhance Results



Demonstration of an AI-driven workflow for autonomous high-resolution scanning microscopy - Saugat Kandel. et, al



High Speed and Sensitive X-ray Analysis System with Automated Aberration Correction Scanning Transmission Electron Microscope - Hiromi Inada, Et . al

Data acquisition optimisation with large dwell time-based reconstruction through FAST (A). Example of a resulting noisy image from a traditional STEM sampling methods into a cleaned image with well-defined atoms (B).

UNIVERSITY OF LIVERPOOL

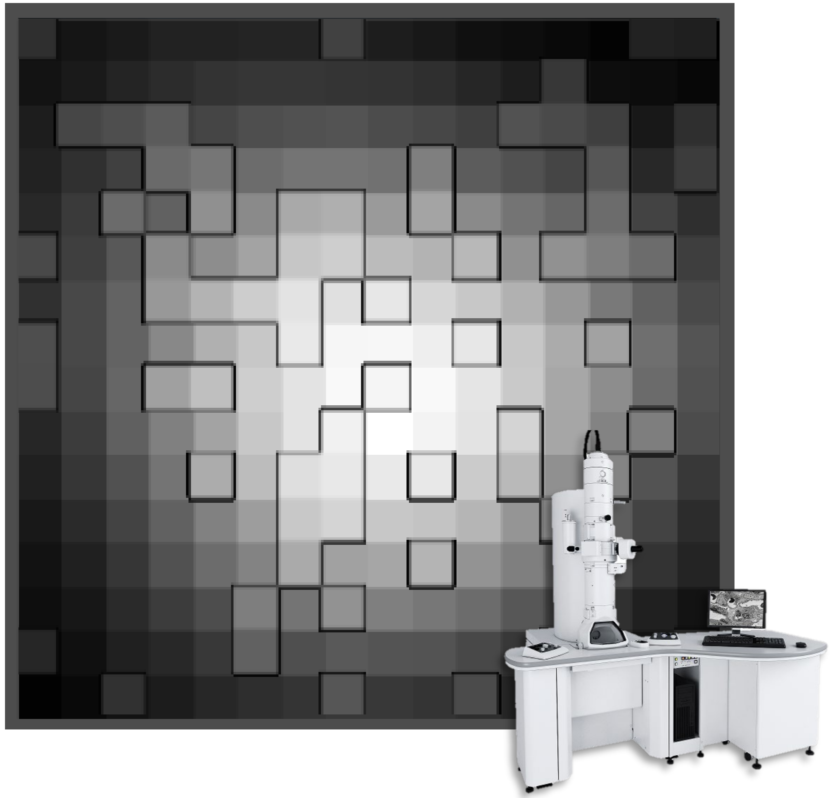
Alex Williams

senseai

Dr. Konstantinos Tsakalidis, Prof. Yaochun Shen, Prof. Nigel Browning

Computational Methods for Real-Time Subsampled Scanning (Transmission) Electron Microscopy

- **Perform a subsampled scan**
  measuring only a subset of the available pixels in a fraction of the time
- **Reconstruct the image**
  determining values for the missing pixels via dictionary learning and sparse-coding algorithms
- **Recover a fully-sampled image**
  with minimal *damage* to the sample



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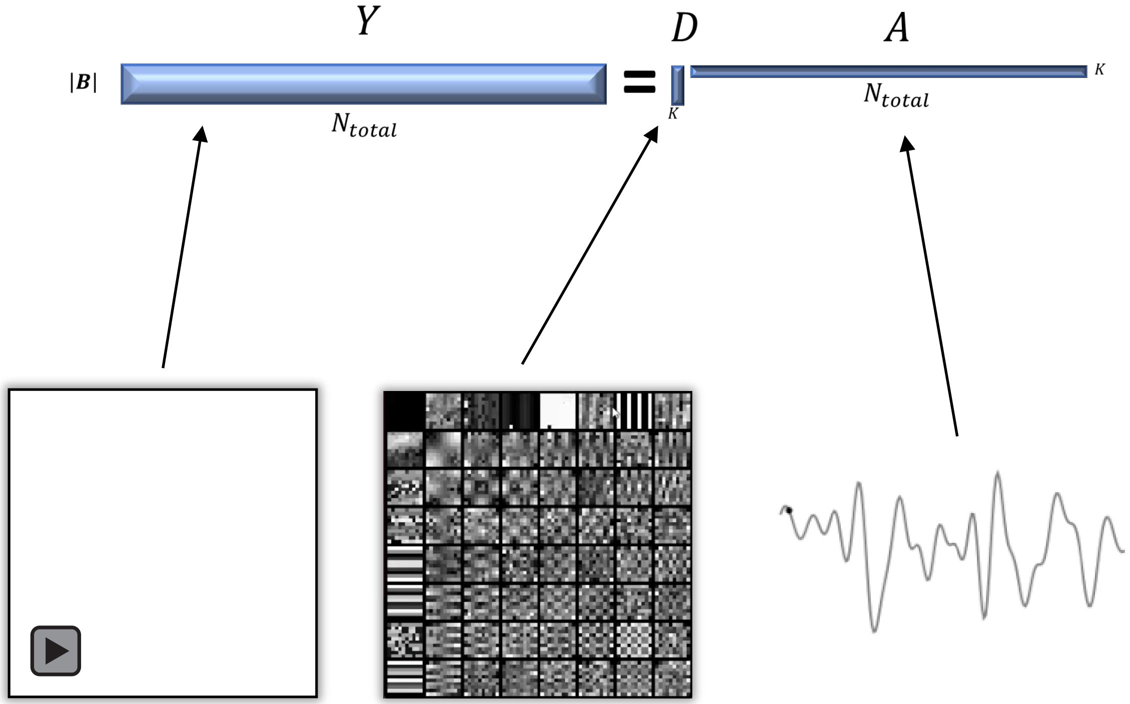
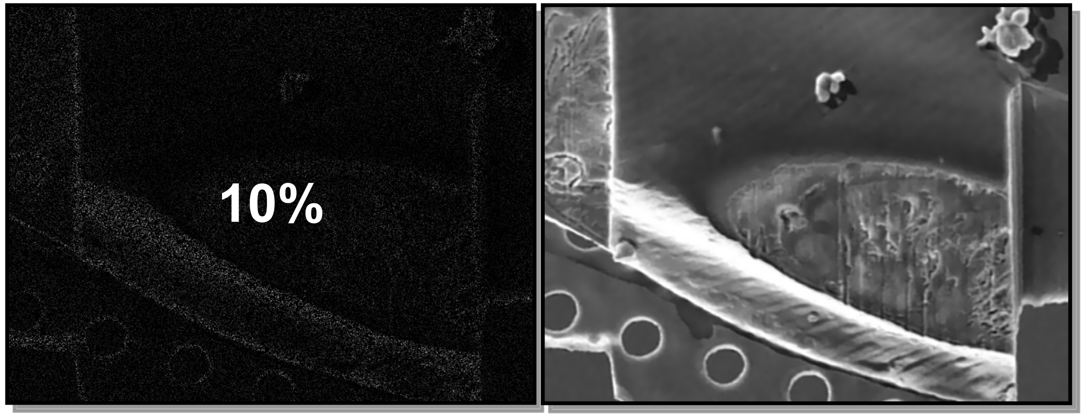
Jack Wells

Sivananthan Laboratories

senseai

Computational Methods for Real-Time Subsampled Scanning (Transmission) Electron Microscopy





Cryo-FIB [D. Nicholls et al. ICASSP 2023]

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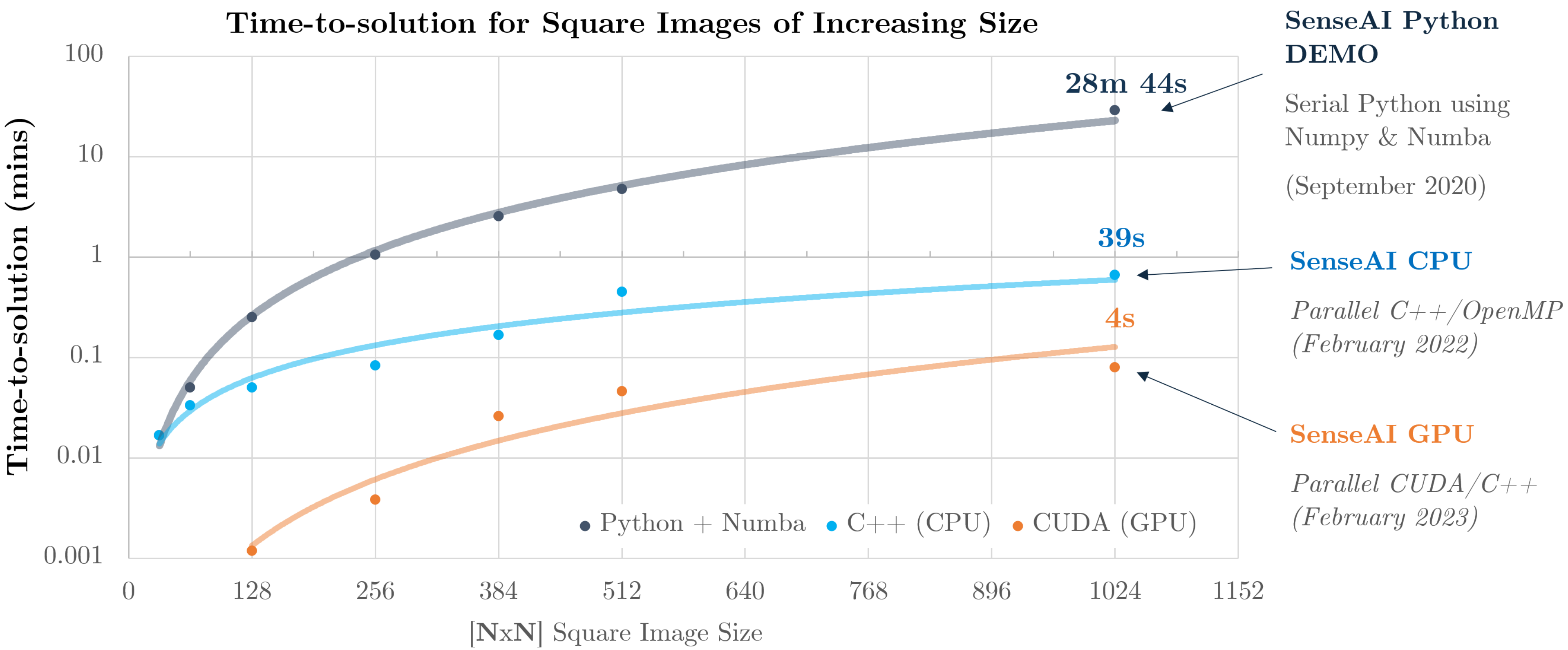
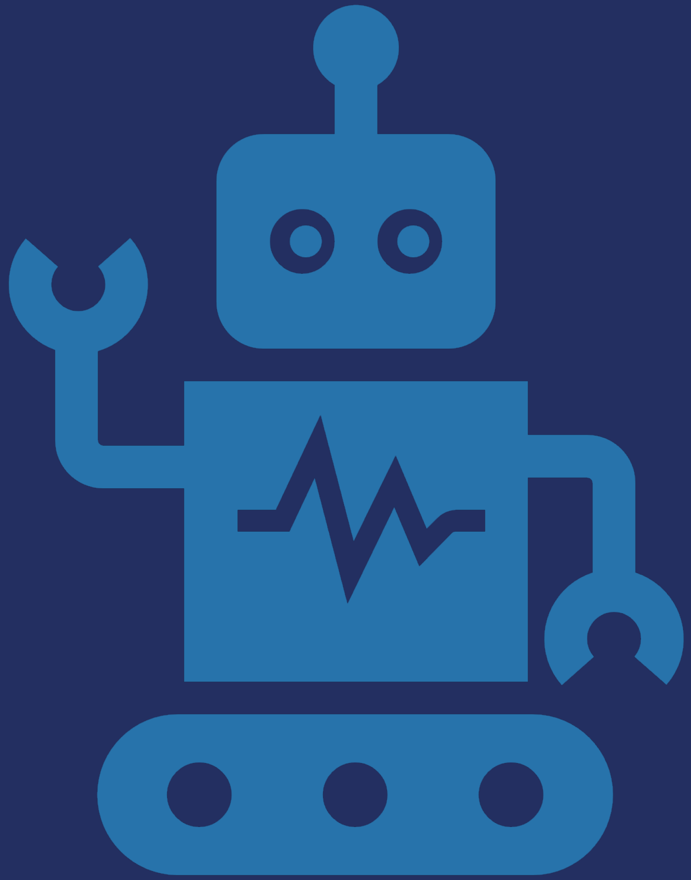
senseai

Computational Methods for Real-Time Subsampled Scanning (Transmission) Electron Microscopy



Jack Wells

Decision Making



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UKRI Engineering and Physical Sciences Research Council

Distributed Hypothesis Generation and Evaluation

- This project aims to develop **explainable decision-support tools for intelligence analysts**.
- This project combines **structured analytical techniques used within intelligence settings**, **computational argumentation**, **probability and information theory** to develop such tools.
- The **Diagnostic Argument Identifier (DAI)** can **identify the most critical** items of **evidence** which could change an analyst's conclusions dramatically, if removed.
- The DAI draws upon the notion of **sensitivity analysis**, used in the **Analysis of Competing Hypotheses**, along with the **mutual information (I)** between sets of semantically evaluated arguments.

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} P(x,y) \log \left[\frac{P(x,y)}{P(x)P(y)} \right]$$

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Jordan Robinson

dstl
The Science Inside

Developing AI Methods for Animal Health and Welfare Monitoring

Supervised by Dr PJ Noble, Dr Anh Nguyen and Dr Kirsten McMillan

Language Models

- Emerging Health and Welfare Challenges
- Standardise data from veterinary clinical notes
- Develop Early Warning Systems

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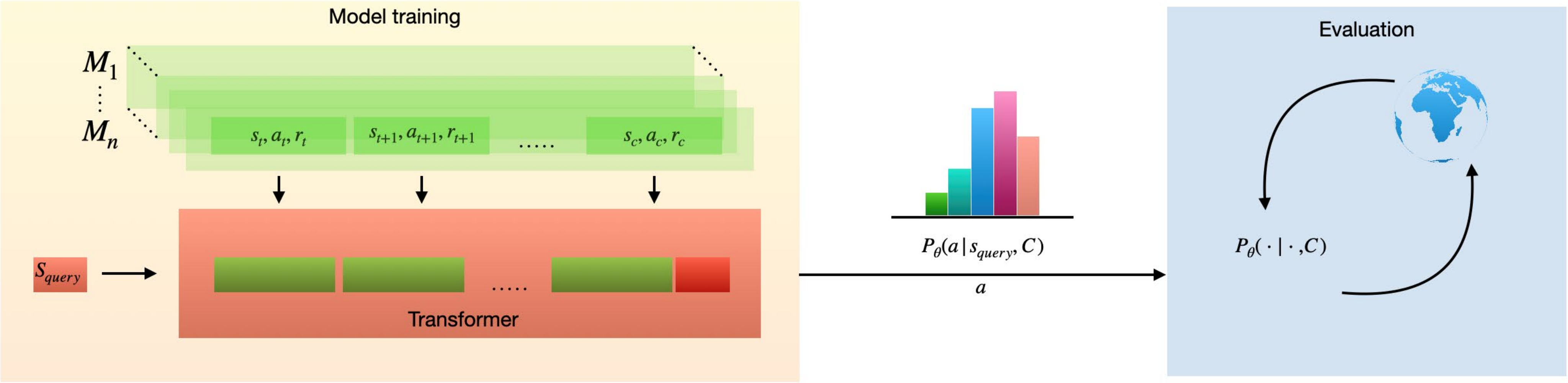
Adam Williams

Dogs Trust

Reinforcement Learning for Continuous Processes

Goal: Learn a meta-policy from offline data under task uncertainty using contextual information

Predict Posterior distribution over actions given a query state and a context



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Oliver Dippel

Developing Reinforcement Learning and Artificial Intelligence Tools to Support Clinical Care Including Care for Women with Perimenopausal and Menopausal Symptoms

Supervised by Dr Bei Peng, Dr Anna Fowler, Dr Dan Reisel (Newson Health)

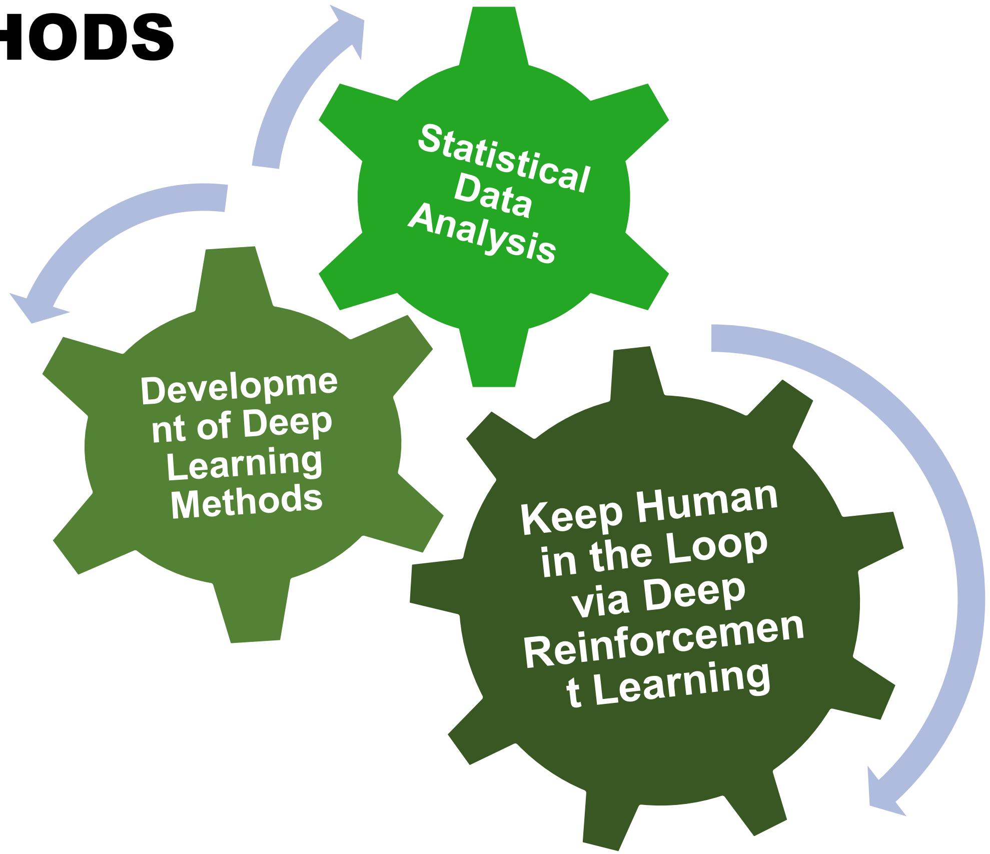
PROBLEMS

The relationship between menopause, treatments and complex diseases:

- Breast cancer
- Lung health (COPD)
- Endometrial cancer
- Brain health
- Bladder health (UTI)
- Heart health (SCAD)
- Mental health

Effective treatment requires the optimisation of multiple interacting drugs.

METHODS



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Wenping (Vicky) Jiang

Newson Health
Menopause & Wellbeing Centre

Reinforcement Learning for Attack Intention Inference

Supervised by Dr Dominik Wojtczak, Prof Sven Schewe and Paul Waller

Object:

- To figure out the intentions of an attacker based on its behaviors

Methodology:

- Utilizing cutting-edge reinforcement learning techniques
- Comprehensive training and performance evaluation

Possible outputs:

- Enhancing our cybersecurity defenses
- Invaluable insights into the real motivation of attackers

Thanks for Dr Chris Hicks and Dr Stephen Pasteris from Alan Turing Institute providing future cooperation on the project

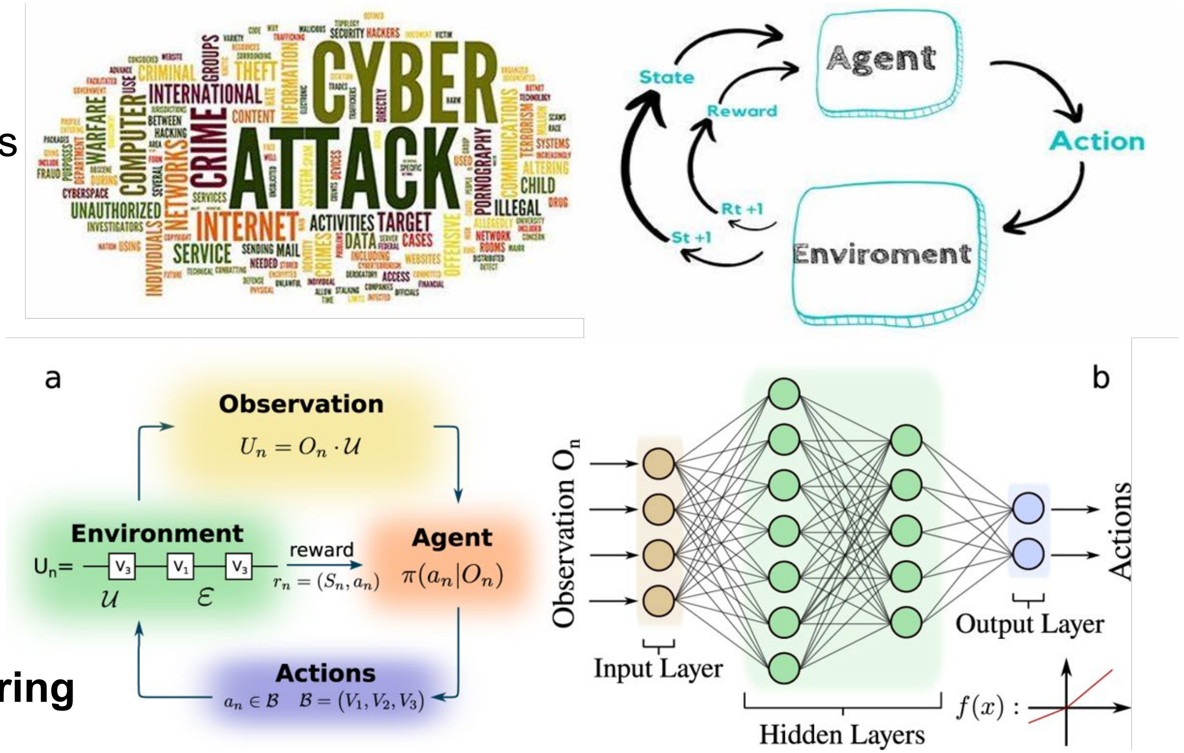

Figure 1. Overview of the project

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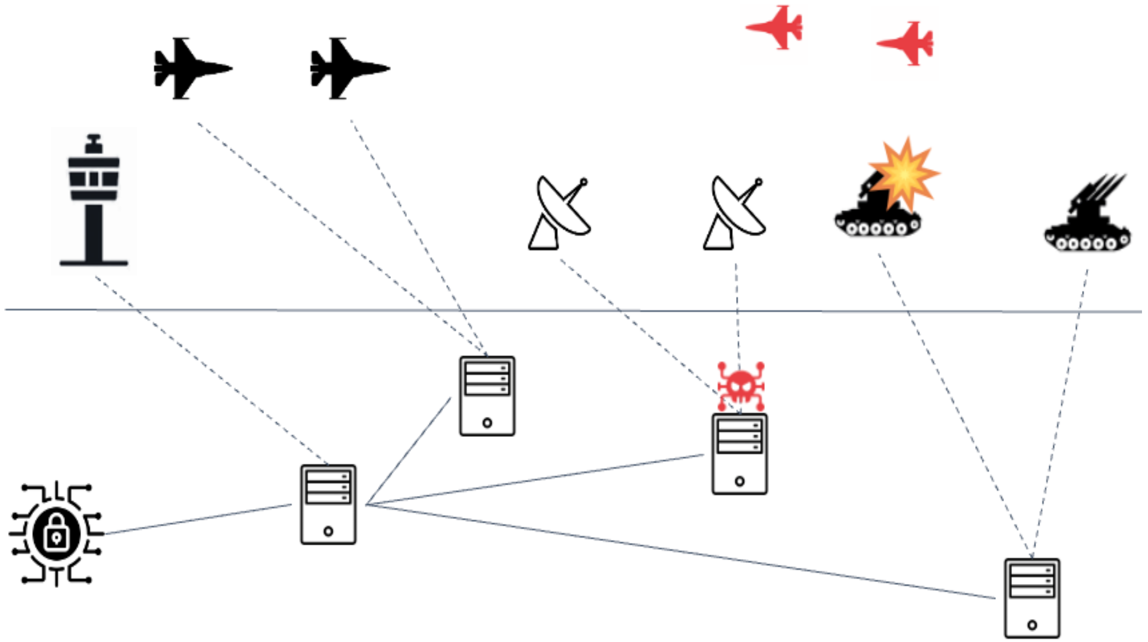
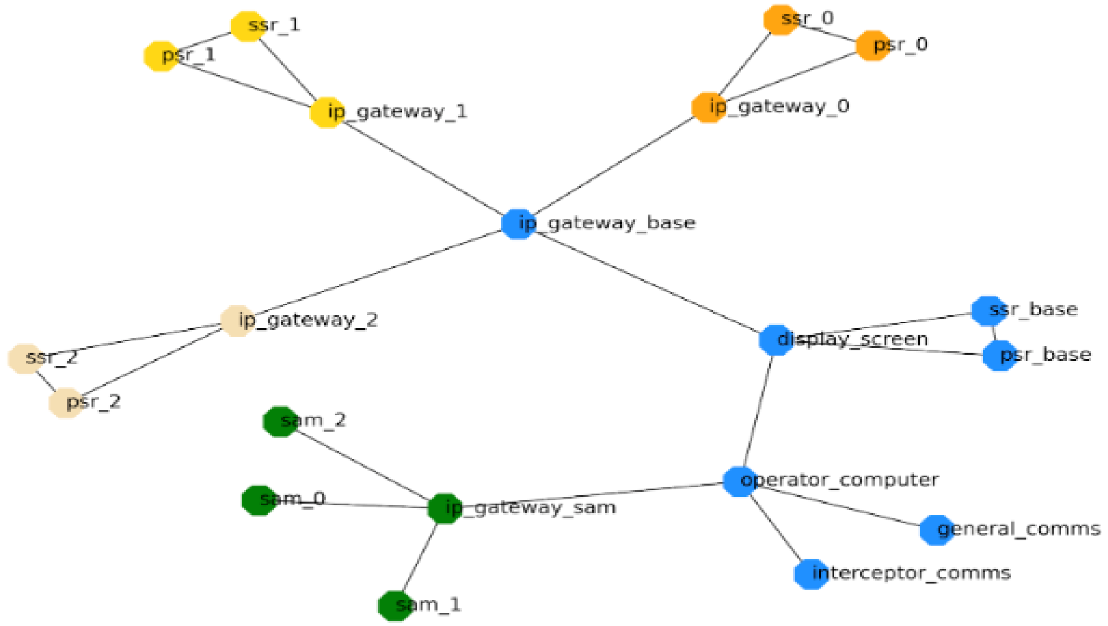
Wanrong Yang

National Cyber Security Centre

Cyber Defence with Real-World Impact Awareness





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Adam Neal

Aleph.

Algorithms and Decision-Making Processes in Distributed Attacker-Defender Games

Goal:

- Build an abstract representation of aerial combat involving two opposing sides.
- Develop Theoretical Computer Science techniques to overcome computational constraints coming from real life problems.

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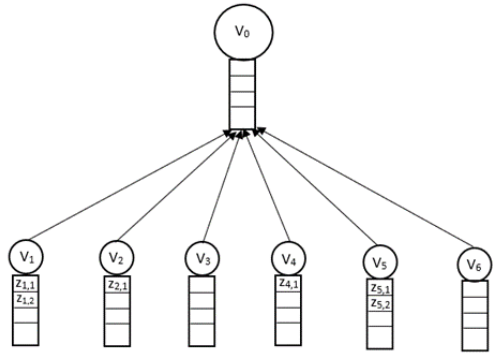
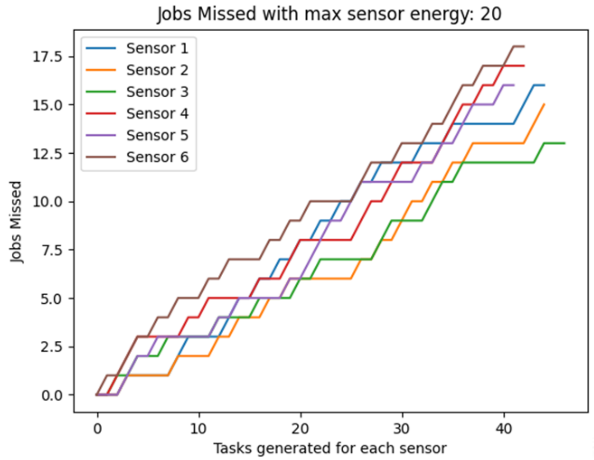
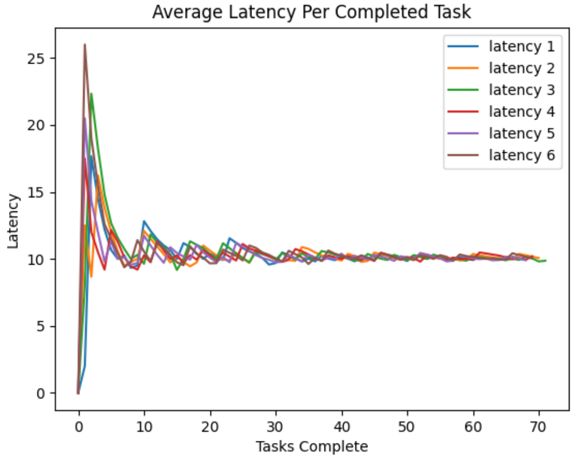
Tim Prokopenko

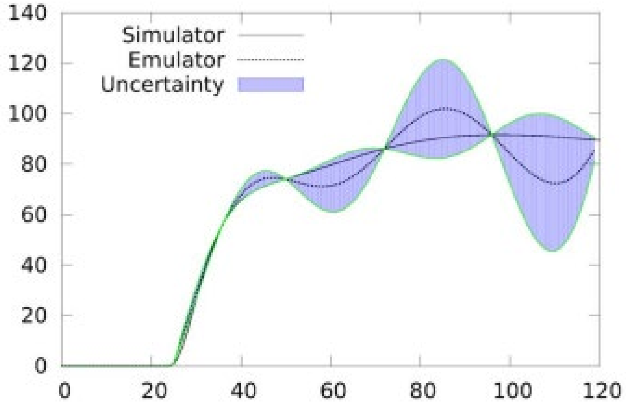
MBDA MISSILE SYSTEMS

Scheduling of Distributed information processing









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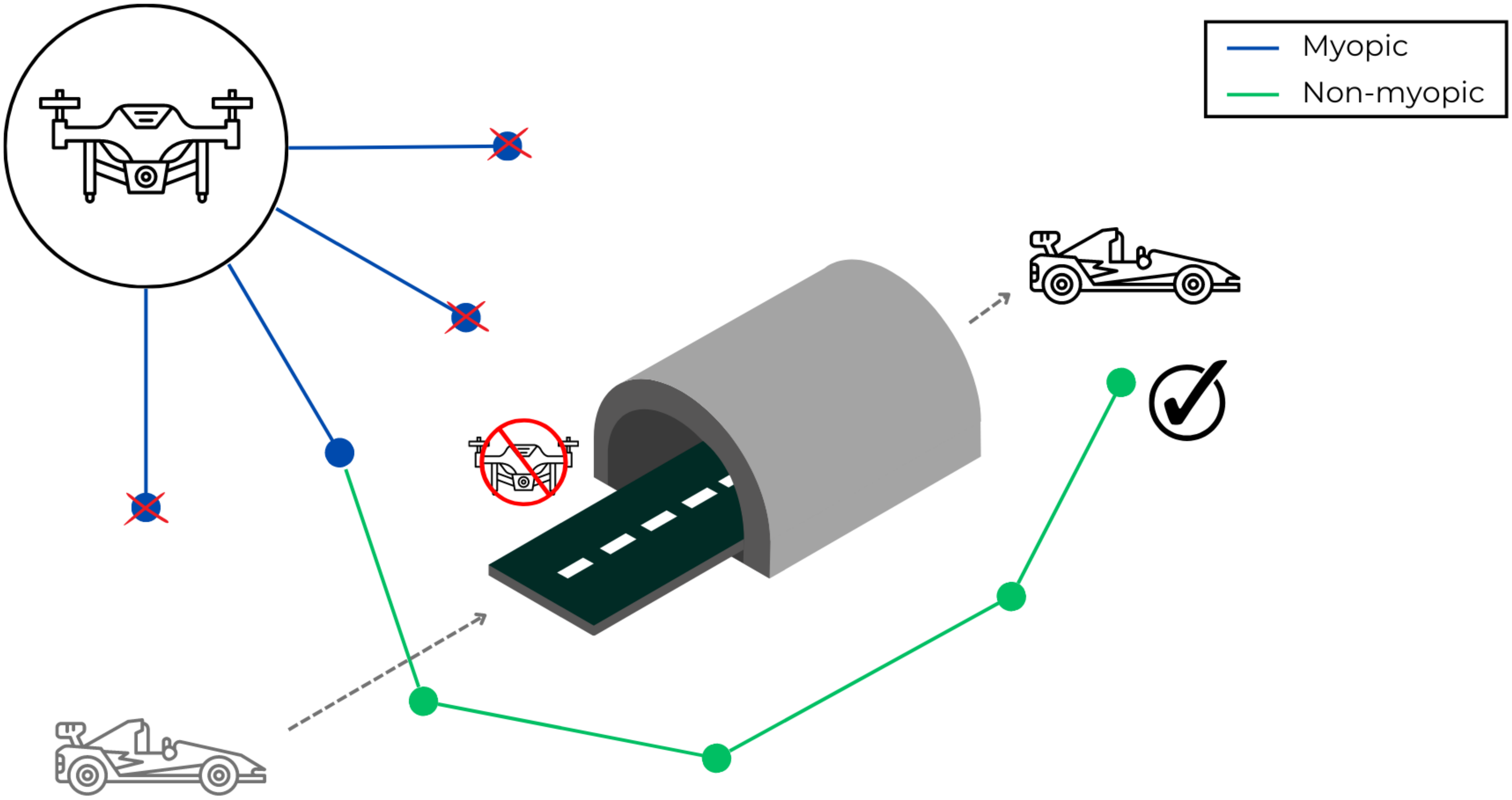
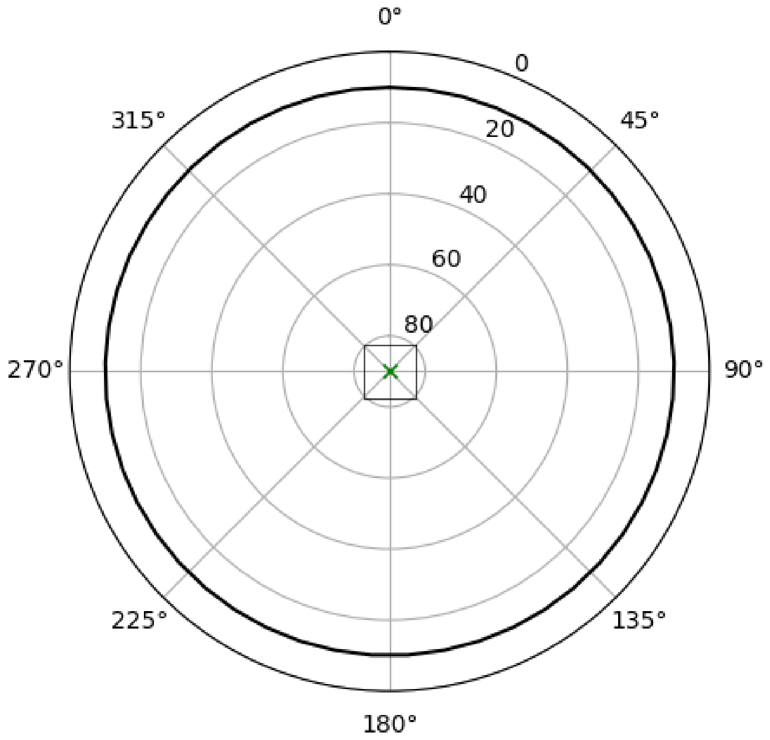
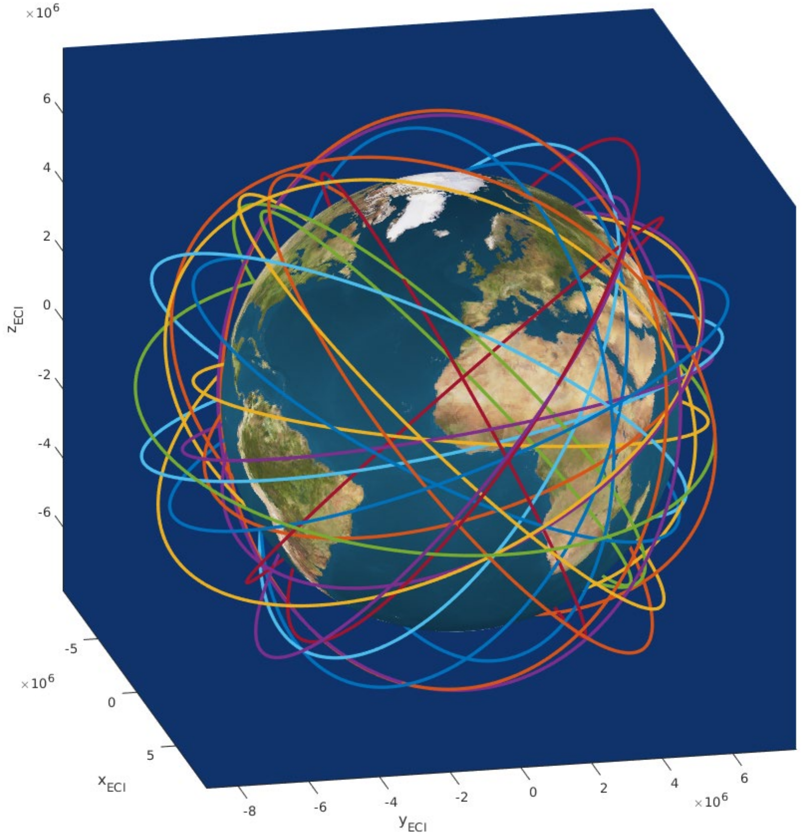
Alex Bird

[dstl]
The Science Inside


Myopic
Non-myopic

Scheduling Surveillance of Space Objects





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Benedict Oakes

[dstl]
The Science Inside