Bayesian OODA loops with MIDAS:

Augmented decision making in a complex future electromagnetic environment

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20th November 2023



Background: Bringing Bayesian Astrostatistics back to Earth





Astrophysicists interested in:

- Quantify uncertainty
- Fusion of diverse measurements
- Biggest data

Typically use Bayesian methods:

- Incorporation of prior info
- Quantifies updating knowledge
- Bayes theorem: unifying framework

 $P(H|D) = rac{P(D|H)P(H)}{P(D)}$ H: Hypothesis D: Data



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Complementary to machine learning

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Background: Challenges in the Electromagnetic Environment (CEME)

Since 2020 participated in 6 Maths of CEME workshops, with 5 DSTL-funded projects

- Optimising a search route to discover networks in a landscape of constraints (CEME1.2, [Jan20])
- 2. Optimisation of sensor location (CEME2.3 [Sep20])
- 3. Further optimisation of sensor location (CEME4 [Sep21])
- MIDAS: Maximum information data acquisition strategies (CEME6.4) [Jan23])
- Optimal dynamic manoeuvring & adaptation of communications networks driven by the MIDAS information-advantage mathematical framework (DASA GAN [Oct23])
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DSTL: Olly Gage, Emily Russell, Ben Jackson, Ben Gear, Emma Bowley PA: James Matthews, Richard Claridge, Emily Morrison, Rob Lambert PC Ltd: Catherine Watkinson, Thomas Mcaloone, Parul Janagal, Adam Ormondroyd UCAM/QML: Mike Hobson, Justin Ward, Oscar Bandtlow PolyChord UNIVERSITY OF CAMBRIDGE

Background: PolyChord Ltd & Nested Sampling

Nested sampling

- Framework of numerical algorithms for performing Bayesian analysis
- Performs three tasks:
 - 1. Optimisation $\max_{x} f(x)$
 - **2.** Exploration $x \sim f$
 - 3. Integration $\int f(x) dx$

on a-priori unknown-functions

- Key algorithm called polychord
- Developed in my Cambridge cosmology lab





PolyChord Ltd

- Data Science SME spun out of Astro group
- Applies nested sampling & Bayesian machine learning to industry problems
- Working with PA/DSTL for three years
- Protein folding, Nuclear fusion, Battery optimisation, predictive maintenance.





Toy example (conducted in CEME1 workshop):

- $\blacktriangleright \quad \text{Number of nodes } N = 3$
- Fully connected (unknown) network in black
- Path traced out by detector indicated by line of circles
- white circles indicate ``non detection"
- black circles indicate ``detection" (with direction by blue arcs)





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- Marginal posterior on P(N|D) (bottom right).
- Instead of plotting posterior contours, we plot samples from the full posterior distribution.
- Least compressed representation of the posterior.



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- TDOA sensors: blue, orange & green dots
- Transmitter: red cross
- Contours: posterior distributions
 - pairwise posteriors excluding one sensor in blue, orange & green (faint parabolic arcs)
 - combined posterior in red (solid peak)
- Where to put sensors?
- Compute the localisation (information gain D_{KL}), distributed over all uncertainties:
 - transmitter location,
 - buildings
 - reflections
- Find collection of good good solutions
- ▶ \Rightarrow nonlinear, nonconvex, ensemble optimisation.





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Example 3: MIDAS (CEME6.4)

- MIDAS: Maximum information data acquisition strategies
- Generalise ``best sensor location" to ``best data acquisition strategy"
- Use this to decide what data to take next.
- Add in adversarialism (two competing teams)
- Networks of communicating allied sensors
- Adversarial capacity (jamming)
- Ability re-roll (e.g. UAV) capability
- Use same approach to decide when & how to re-roll.



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MIDAS & the Mathematical OODA loop (DASA GAN)



- Mathematical instantiation of John Boyd's OODA loop.
- Tight coupling between Bayesian statistics (updating knowledge) and Information theory (how/when to gather more)
- Nested sampling (PolyChord) is used at both Orient and Decide steps, in Bayesian & Optimisation mode.
- However, given that all of these will only ever be *Models* of the real world, the Act step will need to be human-in-the-loop.

PolyChord **PolyChord** PolyChord

- **DSTL+PC/UCAM+PA** have shown that Bayesian methods capture natural data fusion at scale.
- We know the complex future EME is going to be too complex for unaugmented humans.
- The missing piece is the **Act** step.
- For human-in-the-loop decision-making the rest of the loop needs to present and compress the information in a way that is actionable and explainable.
- This is the frontier of our current research
 - Designing optimal theoretical system that assists in the decision cycle
 - Giving human agents what they need, when you need it
 - Should get out of the way given human insight



- Astrostatisticians continue to innovate at the frontier of inference.
- These techniques currently require laptop- to high-performance computing power.
- For generation-after-next techniques, we can assume they will be in our pocket/clothing.
- The Bayesian OODA loop quantifies optimal human-in-the-loop decision-making.
- Science & Technology explored here is not challenge-specific.
- These techniques are complementary to machine learning/AI

