AI and Earth Observation: A Match Made in Heaven

Holger H. Hoos

LIACS
Universiteit Leiden
The Netherlands

CS Department
University of British Columbia
Canada

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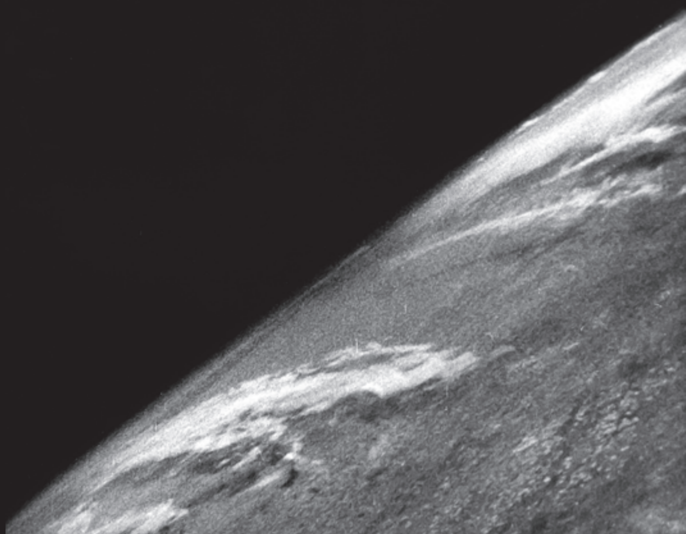
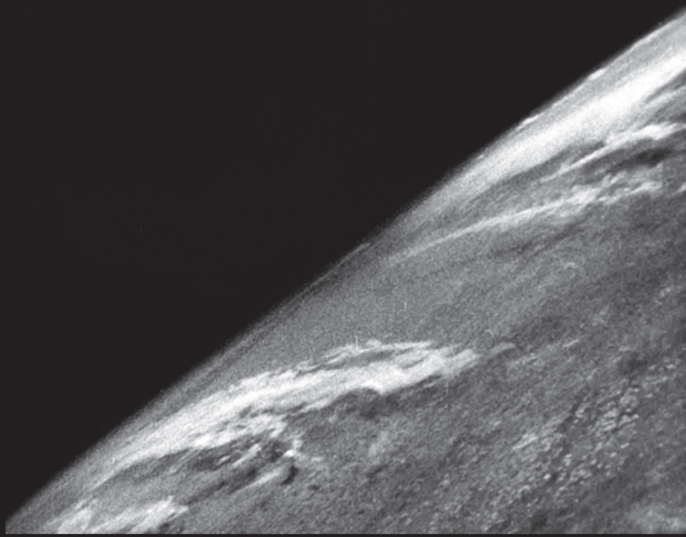
The Hague (Netherlands)
2019/10/10

~ 1600 BC, Nebra Sky Disk

$\sim$ 100 BC, Antikythera mechanism

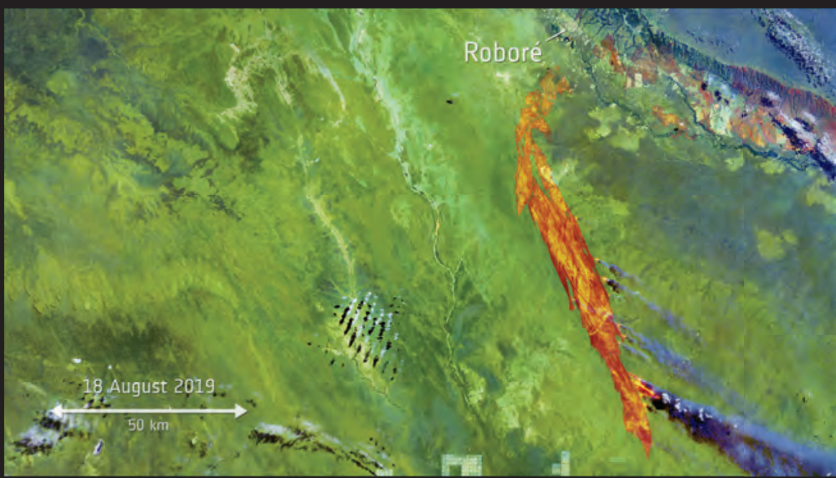


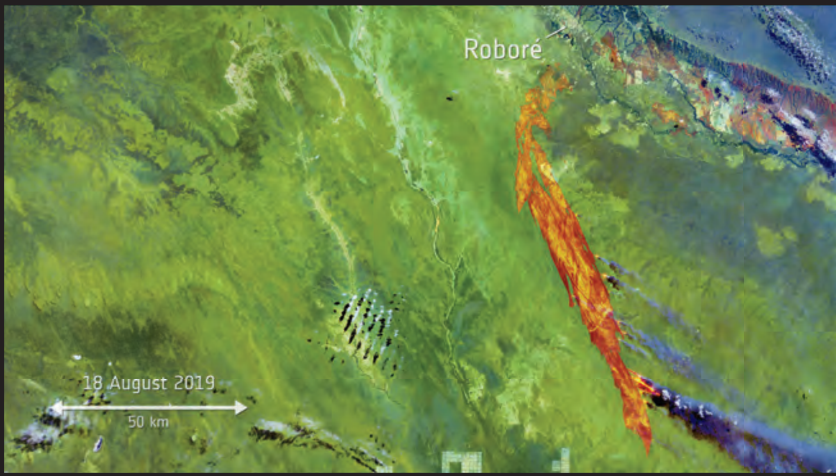


24 October 1946, US-launched V2, 105km above ground

21 December 1968, Apollo 8 leaving Earth orbit

4 October 2019, Copernicus Sentinel-2





23 August 2019, Copernicus Sentinel-2

1

"AI is a critical new enabling technology
for Europes earth observation sector,
whose growth will be accelerated
by Europe strengthening its own AI capabilities."

– Josef Aschbacher, Director of Earth Observation, ESA

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Interview with Turing Award Winner Yoshua Bengio

(Nature, 4 April 2019)

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We have this ability to reason about things that dont actually happen in the data. [...]

Combining machine learning and physical models

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(Baratchi, HH, Lamarre, Silvestro, Vollrath – project in progress)

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- iterative approach:
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- can handle missing data, noise

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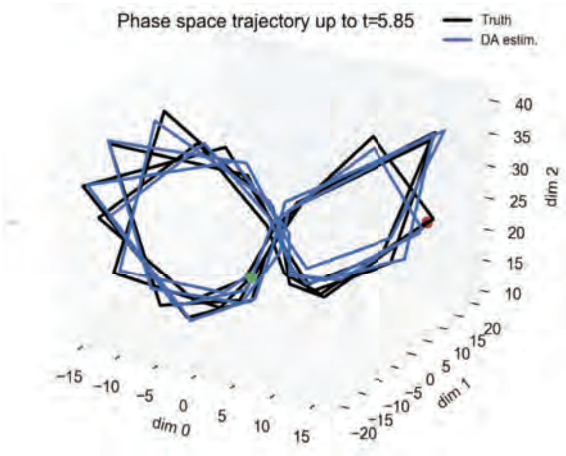
Key idea: Automate filter selection and tuning

EnKF filter optimisation for Lorenz65 (3-dim, synthetic data)



Default configuration: prediction accuracy (RMSE) = 7.43

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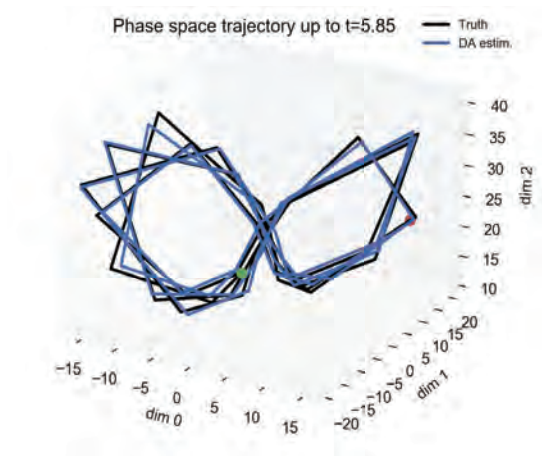

Automatically optimised configuration: prediction accuracy (RMSE) = 1.49

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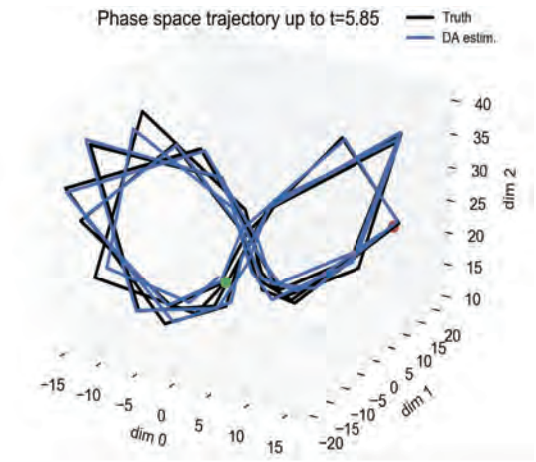

Expert-optimised configuration: prediction accuracy (RMSE) = 1.47

2

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Example: WEKA contains 39 classification algorithms,
3×8 feature selection methods

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$\rightsquigarrow$ Automated machine learning (AutoML)

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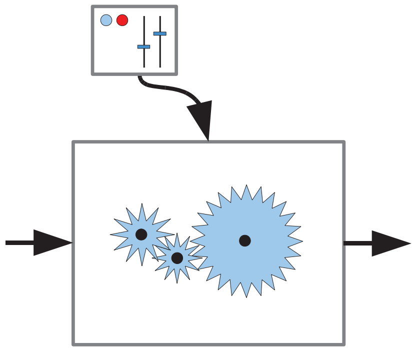
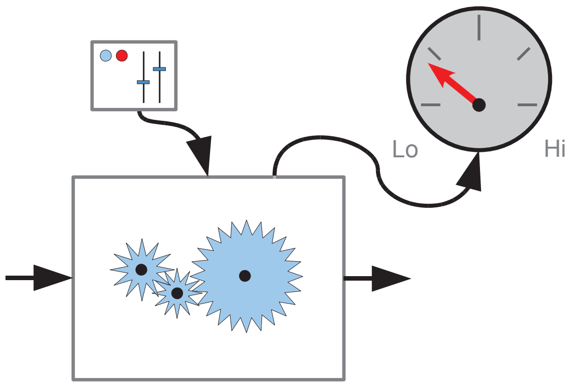
How does it work?

Key idea: Use general-purpose algorithm configurator
leveraging cutting-edge ML + optimisation methods

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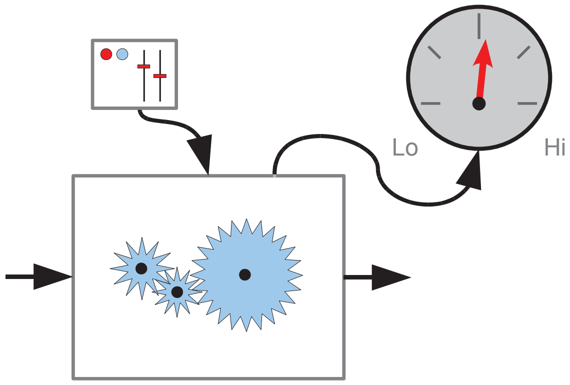

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3

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Excellence across all of AI. For all of Europe.
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"CLAIRE has planted the flag for Europe's ambitions on AI, and we congratulate you. [...]

I am sure our collaboration with CLAIRE will help us realise Europe's ambitions for space technologies and on Earth, and for the advancement of AI in all our Member States."

— Johann-Dietrich Wörner
Director General,
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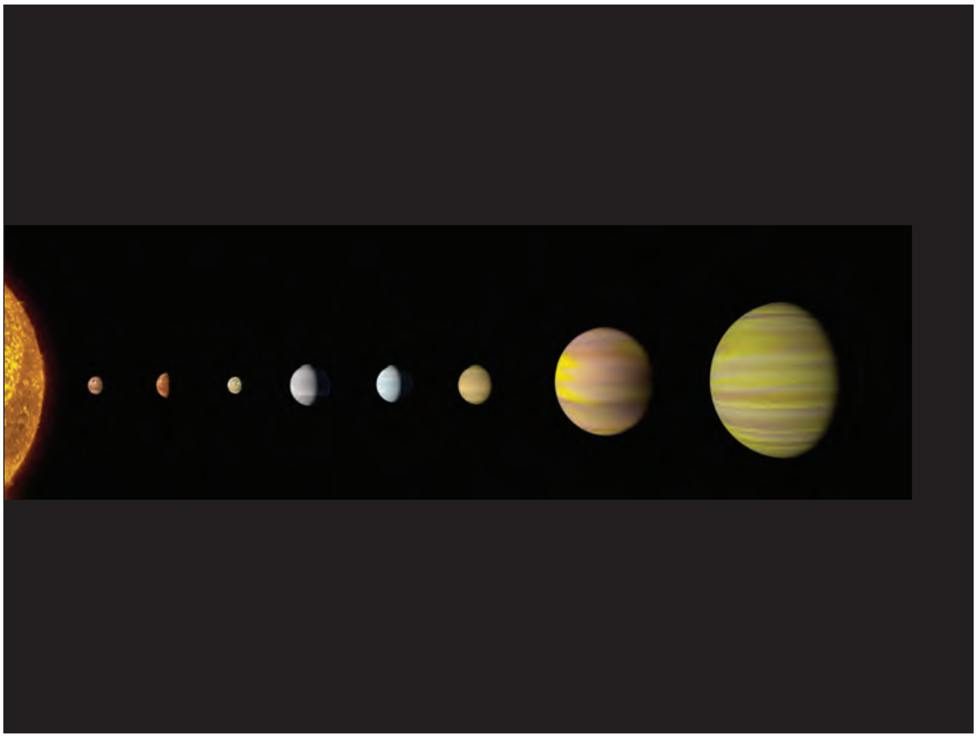

2017/12/14: “NASA and AI spot eighth planet in solar system rivaling ours”

Machine intelligence transforms science.

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- EO poses fascinating challenges to AI
- AutoML / AutoAI can help overcome talent bottleneck, facilitate use, boost results
- Close collaboration initiated through ESA/ESRIN, CLAIRE
- plenty of challenges, opportunities & momentum