The Cloud Hunter's Problem

An Automated Decision Algorithm to Improve the Productivity of Scientific Data Collection in Stochastic Environments

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Hello. . .

IS THERE ANYBODY *in* THERE?

Theme: Data-driven decision making

Introduction: The problem

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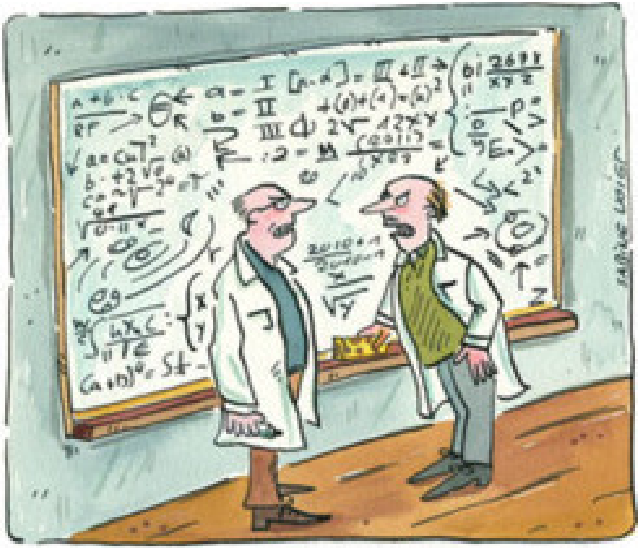
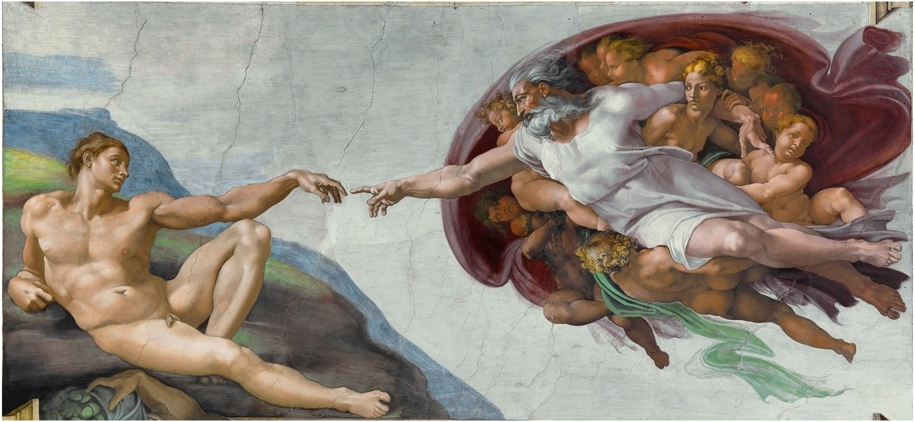
The Cloud Hunter's basic problem is to decide how to allocate a limited budget of flight time over the course of a field season.

Decisions must be made 1 day ahead, based on imperfect day-ahead forecasts of whether conditions are good or bad.

How they make their decisions now:



What we offer instead:



Formal model of the decision problem

Model setup

D : length of the field season in days

$F \leq D$: number of flights in the Cloud Hunter's budget.

$d = D, \ldots, 1$: index of dates

$f = F, \ldots, 1$: index of flights remaining in budget

X_d : binary random state variable indicating quality of conditions for data collection:

- $X_d = 1$ if conditions on date d are good, 0 otherwise
- x_d : realized value of X_d

a_d : binary control variable

- $a_d = 1$ iff they opt to fly on date d, 0 otherwise

$\mathbf{X} =< \mathbf{X_D}, ..., \mathbf{X_1} >$: conditions on dates $d = D, \ldots, 1$

$\mathbf{a} =< \mathbf{a_D}, ..., \mathbf{a_1} >$: actions chosen on dates $d = D, \ldots, 1$

Objectives

Choose **a** to

$$max_{\mathbf{a}} E[\mathbf{a} \cdot \mathbf{X}]$$

Decision taken on basis of day-ahead forecast

Before taking each decision, decision-maker receives a forecast signal $s_d \in \mathbb{S}$.

Based on a calibrated prediction model, can map this signal to a probability of good conditions:

$$p(s) = \Pr\{X_d = 1 | s_d = s\}$$

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Distribution of forecast signals

Distribution of forecast signals

$\pi(s)$: unconditional probability that forecast will take value s.

$\pi(\cdot)$ defines a probability distribution over the set $\mathbb{S}$ of possible forecast signals.

Intertemporal optimization via dynamic programming

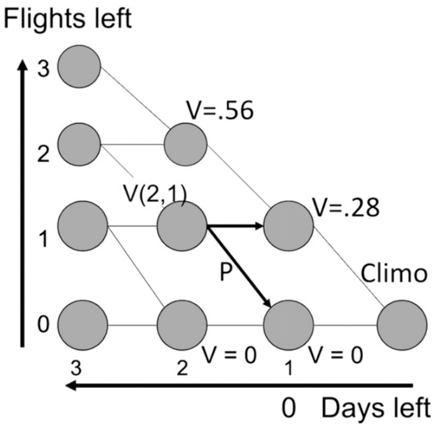

Figure 1: Graphical representation of the decision algorithm.

Probabilistic forecasting of favorable conditions using self-organizing maps

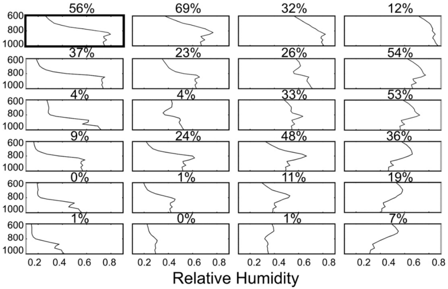

Figure 2: 6 X 4 SOM grid for relative humidity profiles

13.3%	20.6%	4.4%	3.7%
1.5%	8.1%	1.5%	4.4%
0%	3.7%	4.4%	11.8%
2.9%	3.7%	7.4%	6.6%
0%	0%	0.7%	1.5%
0%	0%	0%	0%

Figure 3: Conditional probability distribution of SOM state realizations following a forecast of SOM state 1

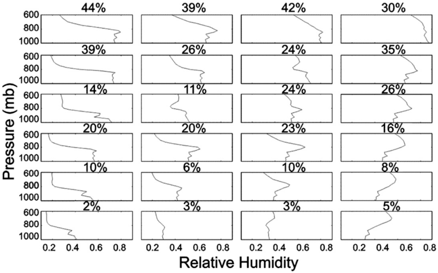

Figure 4: Estimated probabilities of good conditions for data collection, as a function of day-ahead SOM forecast

Results

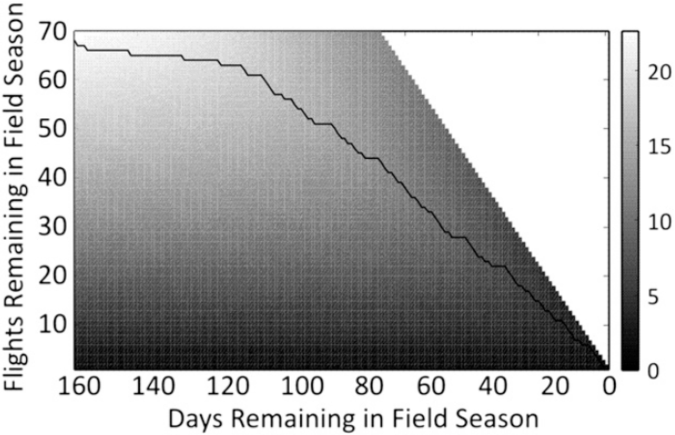

Figure 5: Computed values for the value function $V(d, f)$

Dark line : simulated sequence of flight decisions

- Diagonal movements = fly dates, horizontal movements = no-fly dates

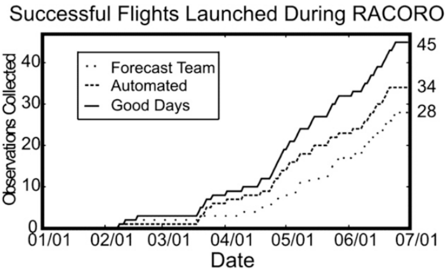

Figure 6: Results: the algorithm's simulated performance during 2009 field season, compared with realized performance of heuristic decision procedure.

The algorithm achieves a 21% increase in the number of successful flights.

	Heuristic procedure	Automated algorithm
Flights launched	56	66
Successes	28	34
Type I errors	28	32
Type II errors	17	11

Figure 7: Summary of outcomes

Successes are flights launched on days with good conditions.

Type I errors are decisions to fly only to find no clouds.

Type II errors are decisions to stand down only to find that the desired conditions existed.