From the theory of vulnerability to verified policy advice

Nicola Botta with P. Jansson and C. Ionescu

Part 2, Background: climate science, climate policy under uncertainty, 2024-04-29

Plan

Done:

- The computational structure of *possible*: Monadic dynamical systems
  - Recap vulnerability theory
  - *State*, *Evolution* and deterministic systems
  - Non-deterministic systems
  - Monadic systems

Now:

- Background: climate science, climate policy under uncertainty

Next week:

- Sequential decision problems
- Bellman's equation, backward induction
- Verified policy advice in a nutshell

Background: climate science, climate policy under uncertainty

- Basic notions
- Example 1: emission reduction policies
- Optimality, policies
- Example 2: a generation dilemma (Heitzig et al. 2018)
- Examples 1 and 2: common traits
- Towards sequential decision problems

Basic notions

- We expect climate science to improve our understanding of the climate system ...
- But also ... inform climate decisions that are transparent, accountable and yield possible evolutions of the climate-economic-social system that are safe and manageable
- It follows that climate decisions cannot be informed by climate science alone!
- Because we cannot make systematic climate-economic-social experiments, the problem of finding accountable climate decisions cannot be tackled empirically, see “Formal methods as a surrogate for empirical evidences” in the *Climate science and verified programming* note

Basic notions

- In the theory of vulnerability, the impact of decisions were encoded in *State* and *possible*
- Value predicates (what is safe, what is manageable) were encoded in *harm* and in *measure*
- To extend the theory to assist climate policy advice, we need to
- 1) model how climate decisions affect possible climate-economic-social evolutions
- 2) Given value predicates on evolutions, compute decisions that provably fulfill those predicates

Basic notions

- We have started working on such an extension in 2011

8-12.1

SDP, DP, optimal control, RL ...

X, Y state and control sets

$\Gamma : X \to \mathcal{P} Y$ feasible controls

$\sigma : (x : X) \to \Gamma\, x \to F X$ transition function

$\rho : (x : X) \to \Gamma\, x \to F \mathbb{R}$ payoff function

$F = Id, Prob, \ldots$

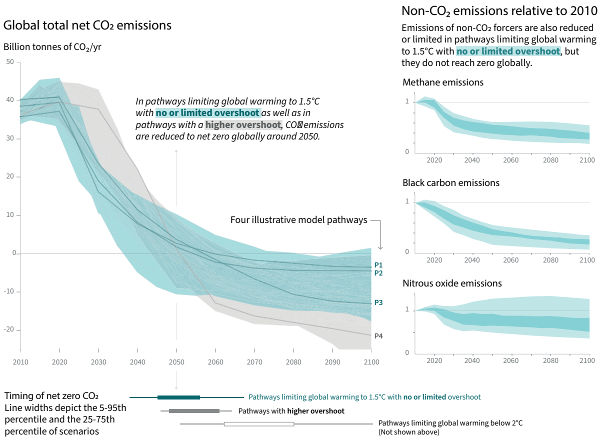
- 2014: *Sequential decision problems, dependent types and generic solutions*
- 2017: *Contributions to a computational theory of policy advice and avoidability*

Basic notions

- To motivate/explain the approach, we start by looking at a specific example
- The goal is to get an idea of the uncertainties that affect climate decision making and of ...
- ... how decision making can be accounted for in monadic systems
- The example is also an introduction to *The impact of uncertainty on optimal emission policies*

Example 1: emission reduction policies

- Global GHG emissions have to be reduced to negative by about 2050



IPCC Special Report - Global Warming of 1.5 °C, Oct. 2018

Example 1: emission reduction policies

- Too fast reductions may compromise the wealth of upcoming generations but ...
- ... they may promote a transition to societies that are more wealthy, safe and fair
- Technologies that allow emission reductions at low costs may become available soon
- Rules and regulations may not be implemented or they may be implemented with delays

Example 1: emission reduction policies

- Because of these uncertainties, emission corridors like the one of the IPCC Special Report are useful but . . . also raise a number of questions:

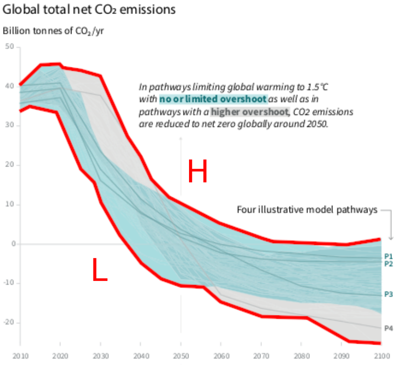
- How to make good plans for the next few decades?

- Which plans are good under uncertainty?

- How safe is the corridor recommended by the IPCC Special Report?

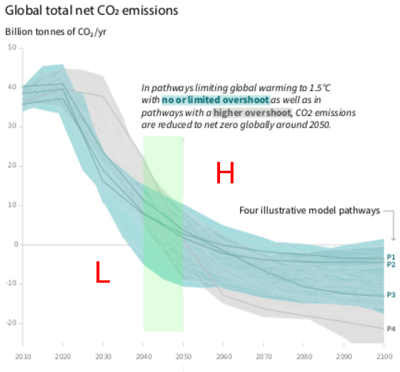
Example 1: emission reduction policies

- What are the odds of paths along the boundaries of the emissions corridor?



Example 1: emission reduction policies

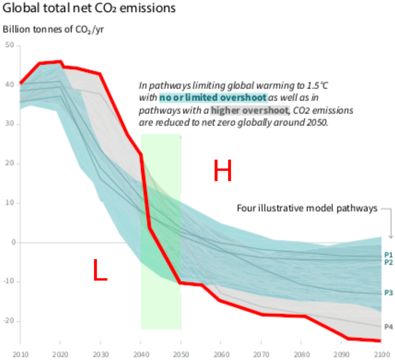
- If new technologies to reduce GHG emissions become available around 2050 . . .



- . . . how could optimal emission plans look like?

Example 1: emission reduction policies

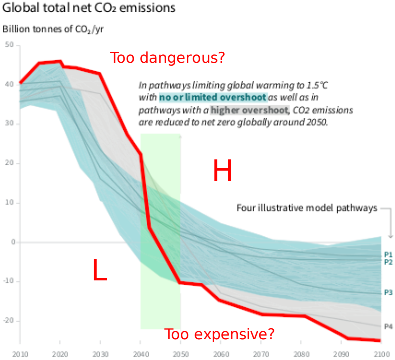
- Minimizing costs requires delaying reductions until the technologies are available



- But is this an optimal emission plan? In which sense?

Example 1: emission reduction policies

- Are H emissions until 2040 perhaps too dangerous?



- Are L emissions after 2050 possibly too expensive?

Optimality, policies

- Studying these questions requires understanding a simple but fundamental idea
- When the evolution of a system is uncertain, the notion of an optimal sequence (plan, path) of decisions becomes problematic, no matter whether F is $List$, $Maybe$, SP, or something else
- This is because, under uncertainty, more than one evolution is possible, for example

$$possible\ x \;=\; nonDetTrj\ next\ 1\ x$$

- How could a second decision possibly be optimal for all states in $nonDetFlow\ next\ 1\ x$? These could be very different from each other!

Optimality, policies

Exercise 5.1

Not every decision can be applied in every state. Decisions (controls) that can be applied in a given state are said to be feasible for that state. Give an example of a simple control problem in which certain controls are not feasible. What could be the type of a *feasible* predicate?

Exercise 5.2

Even a two-steps decision plan could be unfeasible. Explain why.

Exercise 5.3

Under stochastic uncertainty, it is generally not a good idea to take decisions which are optimal for expected states. Explain why. Give an example in which this is in fact the worst that one can do!

Optimality, policies

- Taking $1 + n$ optimal decisions from s requires finding one optimal decision for s and . . .
- . . . one for every possible state at decision step 2, 3, . . . $1 + n$
- In control theory, functions that map states to decisions are called policies (in economics *contingency* plans, decision *rules*, . . .)
- Thus, taking $1 + n$ optimal decisions under uncertainty requires computing n optimal policies
- For finite state space X and finite control (decision) space Y, this means computing at most $1 + n \cdot |Y|^{|X|}$ optimal decisions

Exercise 5.4

Explain the at most $1 + n \cdot |Y|^{|X|}$ estimate.