Adaptive Resilience Through Real Options and Deep Reinforcement Learning

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Adaptive Resilience

We ask a lot of our infrastructure

Infrastructure needs:

- Developing world: start from scratch
- Developed world: manage aging structures (Ho et al., 2017)
- Mitigate greenhouse gas emissions (electrification, decarbonization)
- Protect from climate change

Yet planners must overcome:

1. Deeply uncertain future technology, climate, technology, regulation, demographics
   "It's tough to make predictions, especially about the future" – Yogi Berra
2. Limited appetite for public debt (Marohn, 2019; Papakonstantinou et al., 2016)
   Debt is fragility (Taleb, 2012)

How do we make systems more adaptive?

Integrate structural, financial, operational instruments:

- Build options *in* infrastructure (e.g., build foundations extra strong; de Neufville et al., 2006)
- Take options *on* infrastructure (e.g., parametric insurance to securitize disaster / maladaptation; Clarke and Grenham, 2013; Meyer et al., 2016)

But how do we prioritize / sequence?

- Cost-benefit analysis / NPV doesn't account for flexibility
- Classical real options: introduce arbitrary "exercising condition"
- Modern real options: binomial lattice / SDP

Despite deep uncertainty, we have some predictability...

...and some uncertainties will resolve over time. (*ask me about understanding & predicting structured climate variability!*)

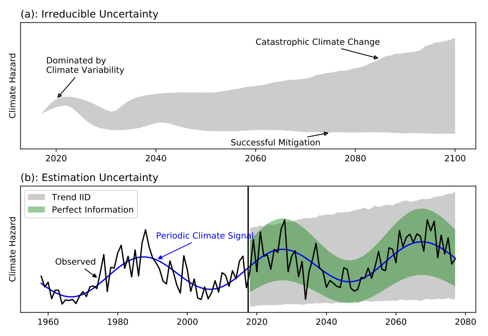

Figure 1: (a) Irreducible uncertainty cannot be resolved with better models or data; (b) informational uncertainty limits identifiability of different signals (Doss-Gollin et al., 2019, fig. 2).

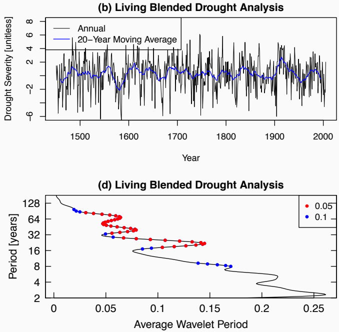

Figure 2: (a) 500 year reconstruction of summer rainfall over Arizona (Cook et al., 2010); (b) its wavelet power spectra (Doss-Gollin et al., 2019, fig. 1).

Hypothesis

Reducing near-term uncertainties should increase relative value of “adaptive” financial / operational instruments.

$\Rightarrow$ deep Reinforcement Learning

Case Study

Original premise

Following severe flooding in the Netherlands, van Dantzig (1956) wrote:

Taking account

of the cost of dike-building, of the material losses when a dike-break occurs, and of the frequency distribution of different sea levels, determine the optimal height of the dikes

Subsequent work emphasizes the need to consider uncertainty in parameter estimation (Oddo et al., 2017) and that investments are sequential (Eijgenraam et al., 2014; Garner and Keller, 2018)

RL in a slide

Reinforcement learning: reward hypothesis (equivalently: maximize expected discounted future utility) $\Rightarrow$ maximize

$$G_t \equiv R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots \tag{1}$$

where R is (negative) cost of construction and recovery.

Deep Q-learning: use *lots* of simulations to learn the state-action value

$$q_\pi(s, a) \equiv \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a] \tag{2}$$

where $q_\pi(s, a)$ is estimated and updated with deep learning

Action a: how much to raise levee

$$C_t = a\left(H_t^- \Delta H\right)_t^2 + b(\Delta H)_t + c. \tag{3}$$

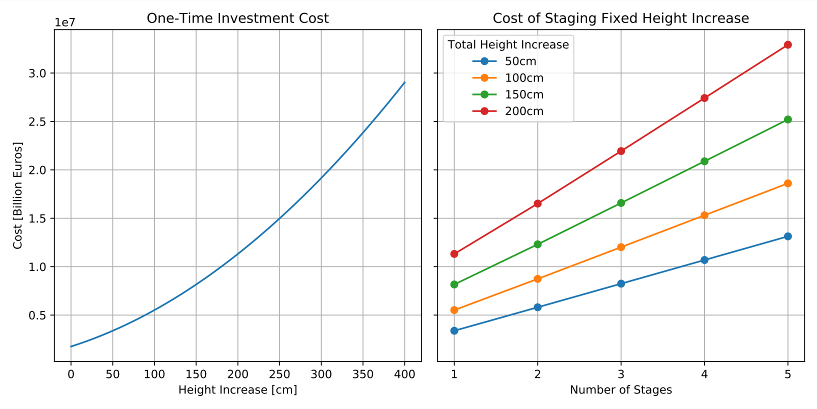

Figure 3: Nonlinear investment costs make over-building costly

The environment model

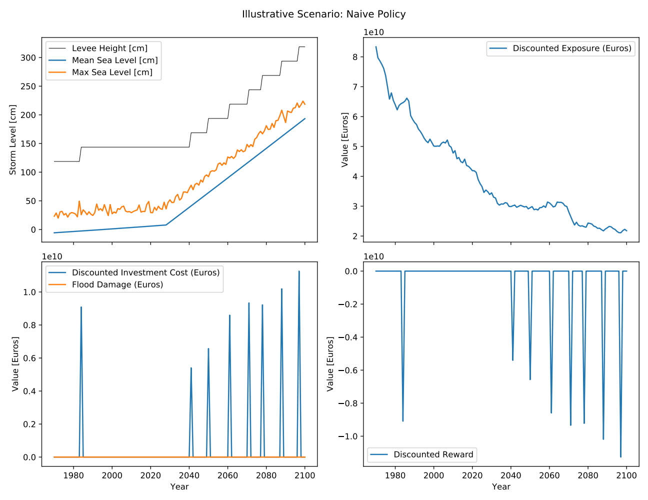

Figure 4: Over-simplified (but still interesting!) models of sea level rise, economic growth, flood loss, nonstationary storm surges

More sea level scenarios

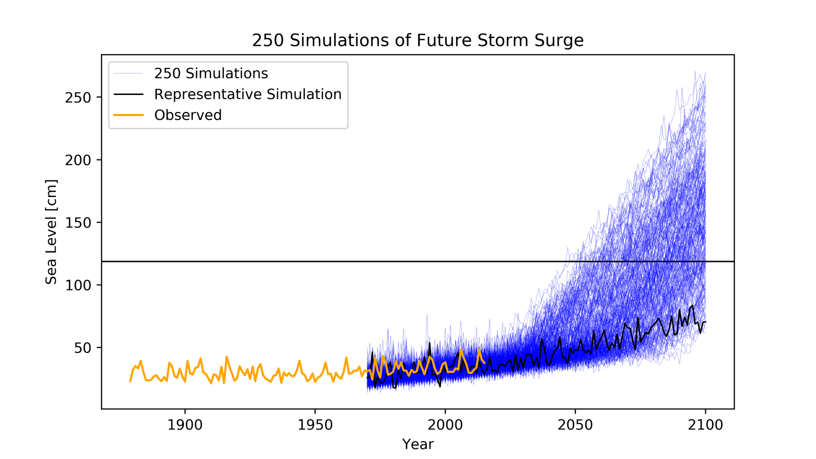

Figure 5: Two key parameters in the sea level rise module resolve over time, and the agent should identify and use them.

More formally

Using simulated experience (under an ϵ-greedy policy), estimate $q_\pi(s, a)$, where

- $a \in 0, 0.05, 0.10, \ldots 1.50$ is the levee height increase
- $s \in \mathbb{R}^d$ is the *filtered and lagged* levee height, mean sea level, maximum storm surge, exposed flood losses, and observed flood losses

Preliminary findings:

- As the uncertainties are "ratcheted up", the relative value of making big initial investments decreases
- If you have expertise in deep Q learning, let's talk!

Conclusions

Summary

1. To meet fast-changing needs, we need to make infrastructure systems more adaptive
2. Real and financial options can help systems be more adaptive
3. To value options effectively, we should leverage the fact that future decisions can be informed by the information available at future times
4. Deep RL might help

(Some) remaining challengs

- Iron out bugs / unit issues from literature
- Very large number of simulations may be required to accurately reflect the risk of low-probability, high-impact flood events
- Systems knowledge $\rightarrow$ computer scientists:
  it's tempting to try to optimize your entire system with Deep RL, but...
    - Complex systems are complex!
    - What is your objective? What are your costs?
    - This is a "wicked" (Rittel and Webber, 1973) problem, caution advised!

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