

# Optimal Stopping for Drought Detection

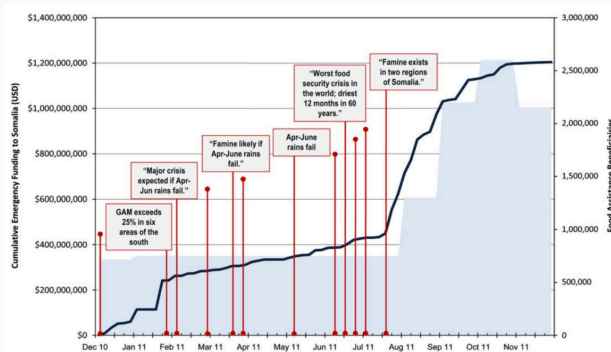
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SAMBa ITT9

# The Problem

- **Willis Towers Watson** arranges insurance against drought
- **Parametric insurance:** pay out based on proxy for damage
- **Goal:** find a trigger for when to send aid for drought



# Optimal Stopping Problem

Problem is to find

$$\max_{\tau} \mathbb{E} [g(\tau, L_{\tau})]$$

- $\tau$  - stopping rule - when to send aid
- $g$  - reward function:
  - benefit from action
  - constrain probability of false alarm
- $L_t$  - likelihood of drought at time  $t$

# Optimal Stopping Problem

Problem is to find

$$\max_{\tau} \mathbb{E} [g(\tau, L_{\tau})]$$

Reward function  $g$ :

- Should incorporate:

	Yes extreme event	No extreme event
Yes forecast-based action	Correct prediction - worthy action	False alarm – act in vain
No forecast-based action	Miss – response cost	Correct rejection – no cost

Contingency table of possible outcomes

Source: Coughlan de Perez et al. 2015

- e.g.  $g(t, l) = (f(t) - \gamma \mathbb{I}_{\{t < T\}})l$
- e.g.  $g(t, l) = f(t)l^2 - \gamma \mathbb{I}_{\{t < T\}}l$

$f$  decreasing in time,  $\gamma > 0$  chosen to get correct probability of false alarm

$T$  latest time drought can be declared

# Optimal Stopping Problem

Problem is to find

$$\max_{\tau} \mathbb{E} [g(\tau, L_{\tau})]$$

Likelihood process  $L$ :

- Describes our belief at time  $t$  of how likely it is that a drought will happen, based on combining data sources
- $L_t \in [0, 1]$
- Stochastic process fitted to data
- For example:

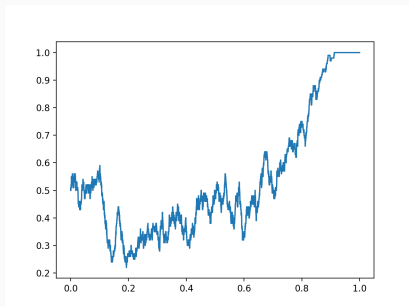
$$dL_t = \sqrt{L_t(1 - L_t)} dB_t$$

**Wright-Fisher** process

# Simulation

Simulate the likelihood process  $dL_t = \sqrt{L_t(1 - L_t)} dB_t$ :

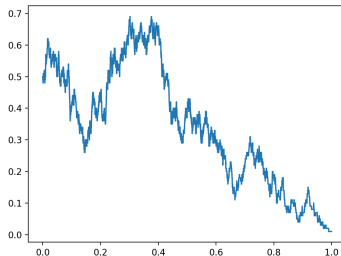
$$L_{i+1} = \begin{cases} L_i + \Delta x & \text{with prob. } \frac{p}{2}, \\ L_i - \Delta x & \text{with prob. } \frac{p}{2}, \\ L_i & \text{with prob. } 1 - p. \end{cases}$$



# Simulation

Simulate the likelihood process  $dL_t = \sqrt{L_t(1 - L_t)} dB_t$ :

$$L_{i+1} = \begin{cases} L_i + \Delta x & \text{with prob. } \frac{\rho}{2}, \\ L_i - \Delta x & \text{with prob. } \frac{\rho}{2}, \\ L_i & \text{with prob. } 1 - \rho. \end{cases}$$

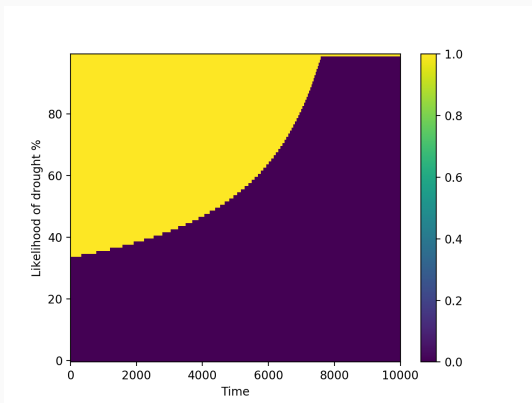


# Stopping Boundary

Problem is to find

$$\max_{\tau} \mathbb{E} [g(\tau, L_{\tau})]$$

Optimal stopping rule  $\tau^*$  is first time to hit a boundary.



**Figure 1:**  $g(t, l) = f(t)l^2 - \gamma \mathbb{I}_{\{t < T\}} l$

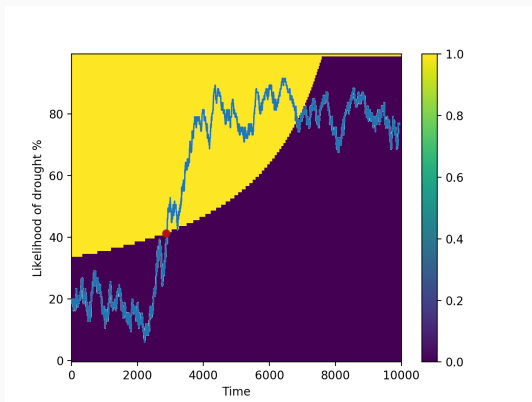


# Stopping Boundary

Problem is to find

$$\max_{\tau} \mathbb{E} [g(\tau, L_{\tau})]$$

Optimal stopping rule  $\tau^*$  is first time to hit a boundary.



**Figure 2:**  $g(t, l) = f(t)l^2 - \gamma \mathbb{I}_{\{t < T\}}$

# Free Boundary Problem

Problem is to find

$$v(t, l) := \max_{\tau} \mathbb{E}^{(t, l)} [g(\tau, L_{\tau})]$$

Value function  $v$  and boundary function  $b$  expected to solve free boundary problem:

$$\begin{cases} \frac{\partial v}{\partial t}(t, l) = -\frac{1}{2}l(1-l)\frac{\partial^2 v}{\partial l^2}(t, l), & l < b(t), \\ v(t, l) = g(t, l), & l = b(t), \\ \frac{\partial v}{\partial t}(t, b(t)-) = \frac{\partial g}{\partial t}(t, b(t)). \end{cases}$$

## Future Work

- Investigate more suitable reward functions
- Prove that the stopping boundary is increasing in time
- Analysis of free boundary problem
- Find a simple stopping rule that is a good approximation
- Incorporate multiple actions - sequential optimal stopping
- Fit underlying process to data and validate model