

Jupiter

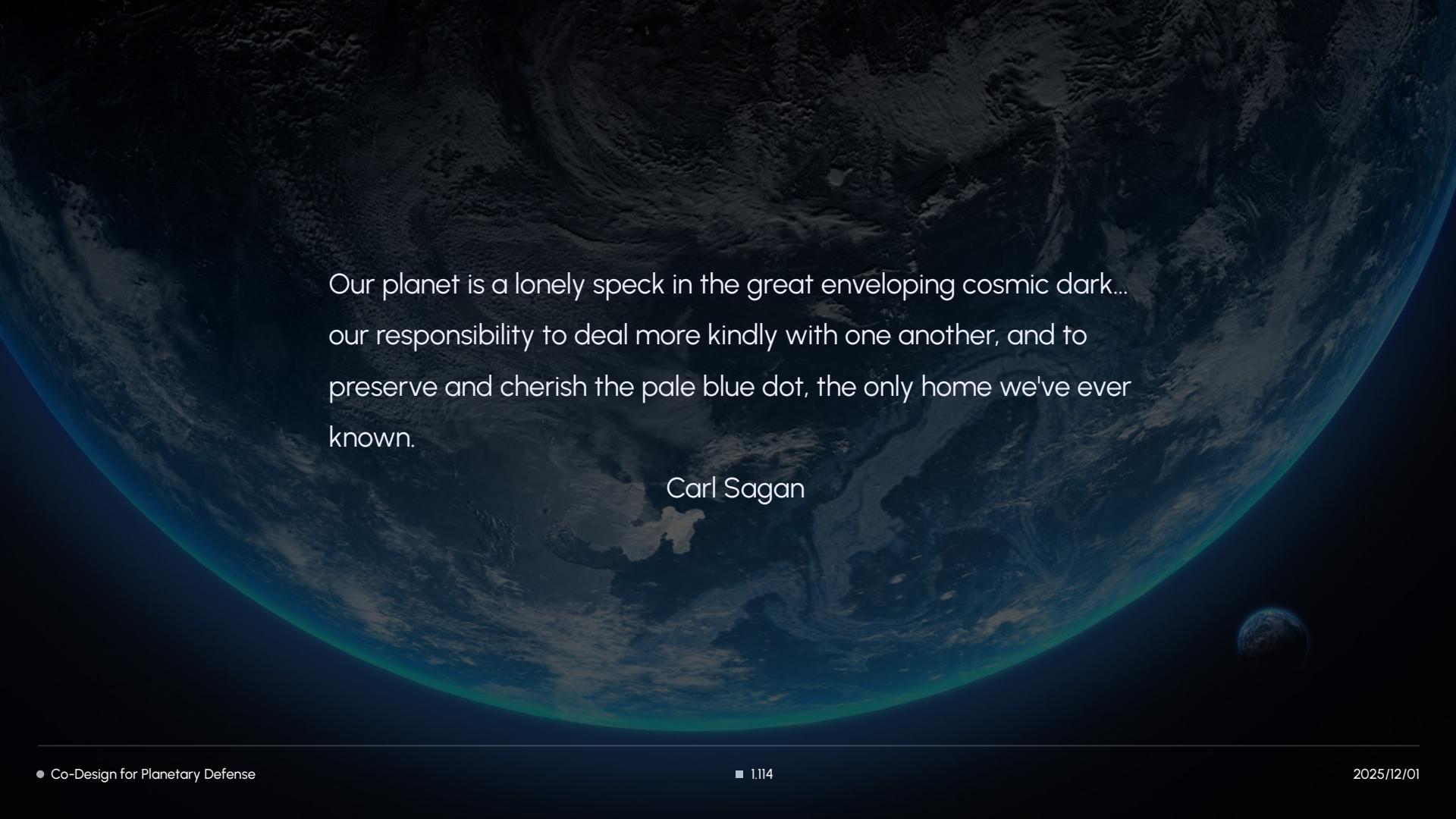
Earth Venus Mercury Sun

Mars

Co-Design for Planetary Defense

1.144 Final Presentation

Niclas Scheuer
Ananth Venkatesh



Our planet is a lonely speck in the great enveloping cosmic dark...
our responsibility to deal more kindly with one another, and to
preserve and cherish the pale blue dot, the only home we've ever
known.

Carl Sagan

How to defend our planet from Near-Earth Objects



Categorical Approach for **transparency**, **tractability**, and **interoperability**



Multiple Stakeholders



Complex Dynamics

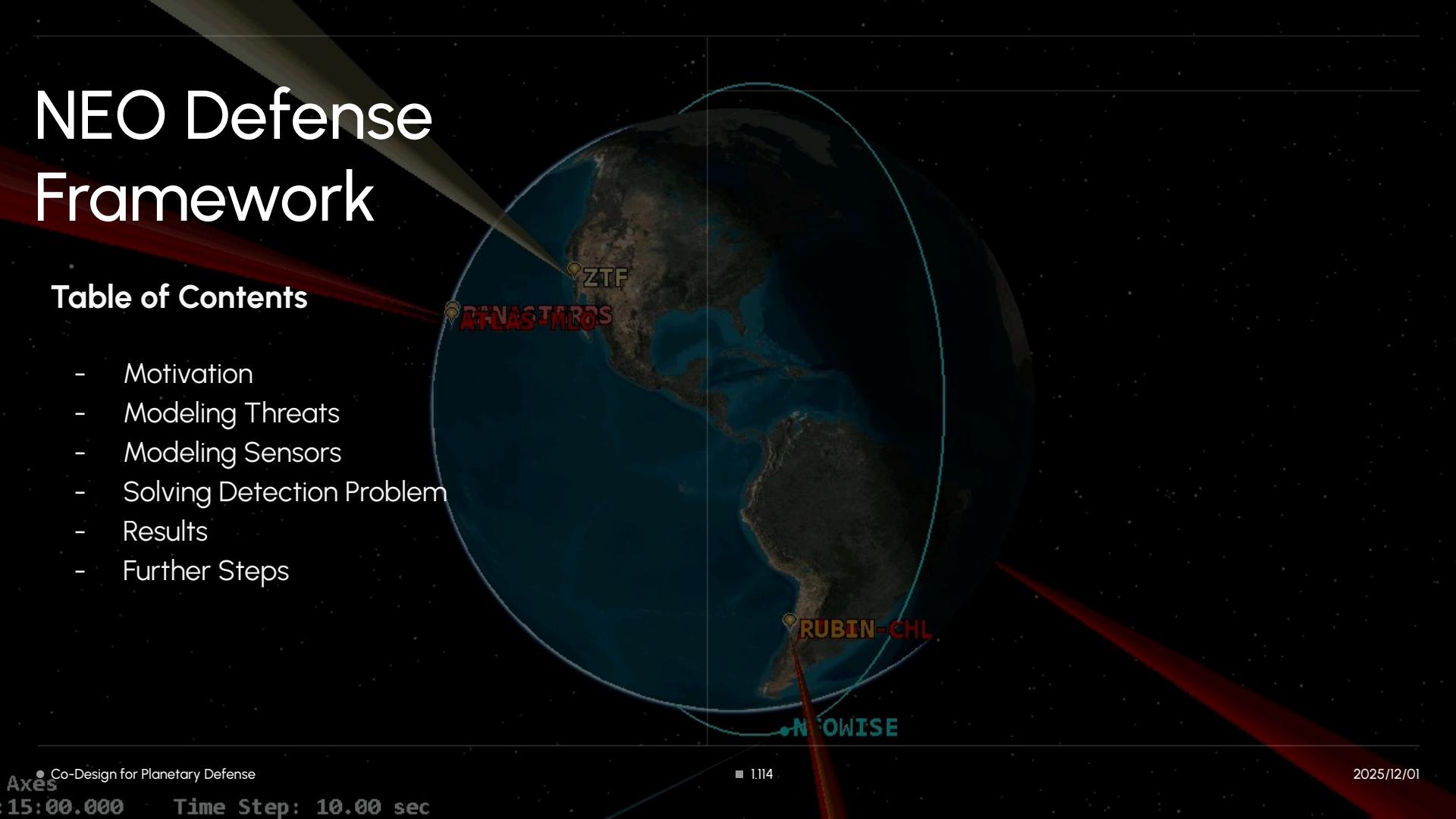


Multiple Approaches

NEO Defense Framework

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- Motivation
- Modeling Threats
- Modeling Sensors
- Solving Detection Problem
- Results
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Motivation



Near-Earth Objects (NEO) of size (>50m) pose a significant risk to human life on Earth.



February 13, 2013

- 13-meter diameter meteor strikes Chelyabinsk, Russia
- > 1600 injured
- No prior warning

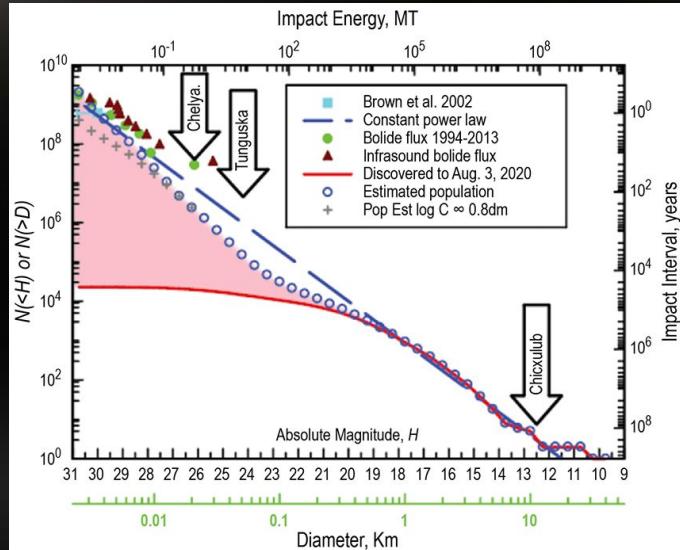
Motivation



Near-Earth Objects (NEO) of size ($>50\text{m}$) pose a significant risk to human life on Earth.



Majority of NEOs of size 50–140m remain **undiscovered**.



"The number of undiscovered NEOs larger than 140m is on the order of 10,000"

- NASA Decadal Planetary Defense Study [3]

Motivation



Near-Earth Objects (NEO) of size (>50m) pose a significant risk to human life on Earth.



Majority of NEOs of size 50-140m remain **undiscovered**.



Current NEO warning systems give us limited warning times.

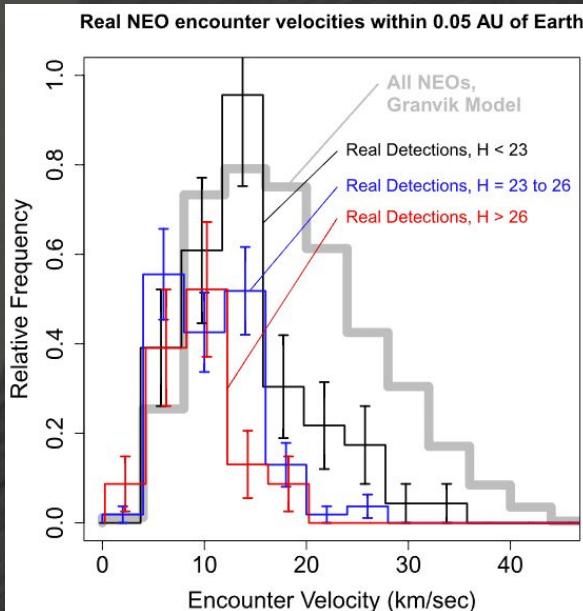


Warning Times [3]:

- 20m NEO: 1 day
- 100m NEO: 21 days

Current Interception Times [4]:

- 54 months



Size, Velocity, Albedo, Inclination,
Semi-Major Axis, Eccentricity Data and
Estimates Exist.

Modeling Threats

Models for NEO distributions exist and are piecewise validated by surveyors.

The population of near-earth asteroids revisited and updated

Alan W. Harris ^a, Paul W. Chodas

^a MoreData! Inc., La Cañada, CA 91011, USA

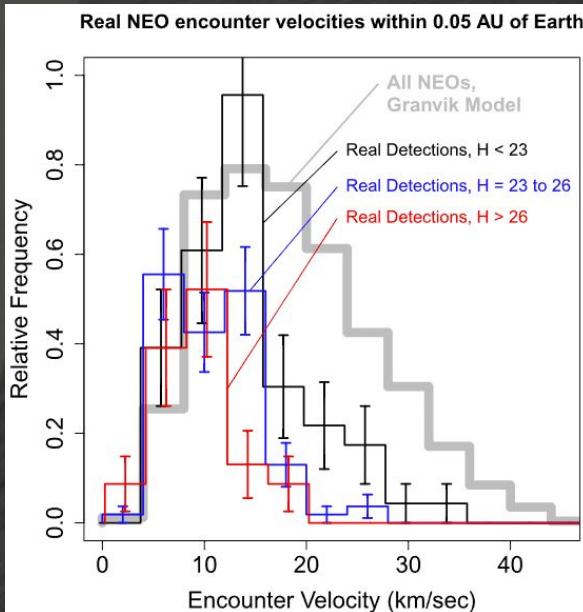
^b Jet Propulsion Laboratory, Pasadena, CA 91109, USA

National Aeronautics and Space Administration



Planetary Defense Missions

Rapid Mission Architecture Study



Size, Velocity, Albedo, Inclination,
Semi-Major Axis, Eccentricity Data and
Estimates Exist.

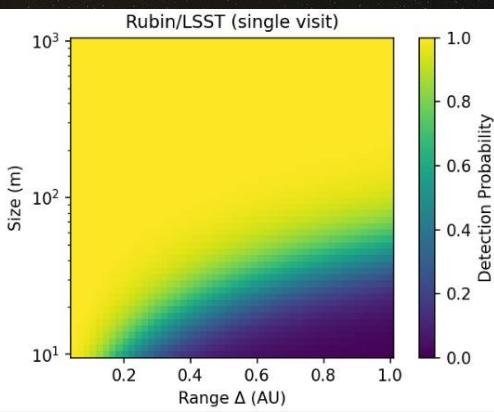
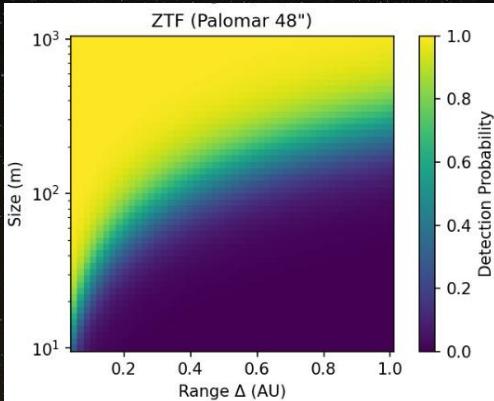
Modeling Threats

Models for NEO distributions exist and are piecewise validated by surveyors.

SizeDistribution : Size $\rightarrow [0, 1]$

VelocityDistribution : Velocity $\rightarrow [0, 1]$

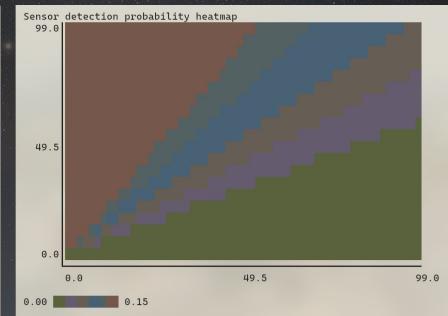
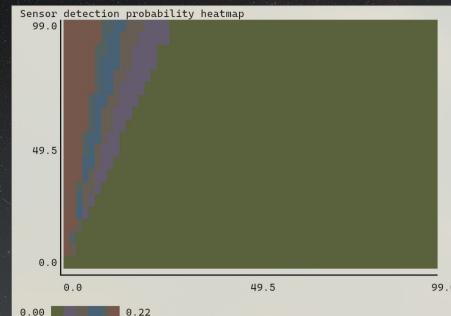
AlbedoDistribution : Albedo $\rightarrow [0, 1]$



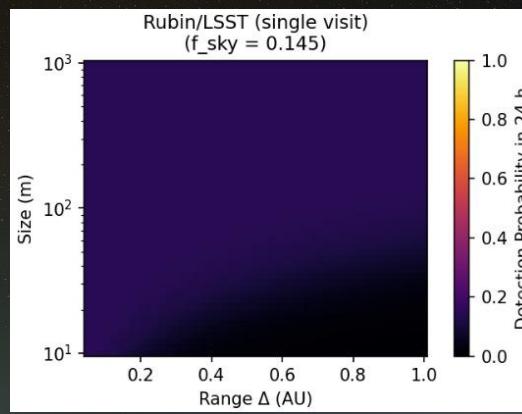
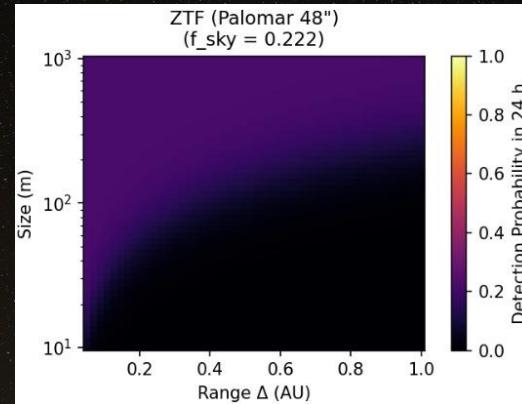
Modeling Sensors

Using publicly-available data on several ground stations, we characterize the single-exposure detection probability and 24-hour detection probability.

$$\mathbb{P}_{\text{single}} : \text{Range} \times \text{Size} \rightarrow [0, 1]$$



Discretized and linearized Haskellian plots using ASCII magic



Modeling Sensors

Using publicly-available data on several ground stations, we characterize the single-exposure detection probability and 24-hour detection probability.

$$\mathbb{P}_{\text{single}} : \text{Range} \times \text{Size} \rightarrow [0, 1]$$

Consider:

- Limited sensor cone of sensor
- 24h isotropic sky-coverage approximation

$$\mathbb{P}_{24 \text{ hr}} : \text{Range} \times \text{Size} \rightarrow [0, 1]$$

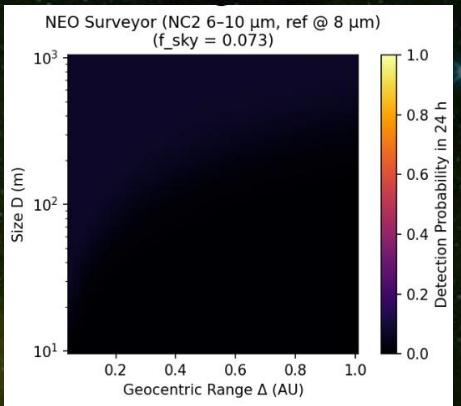
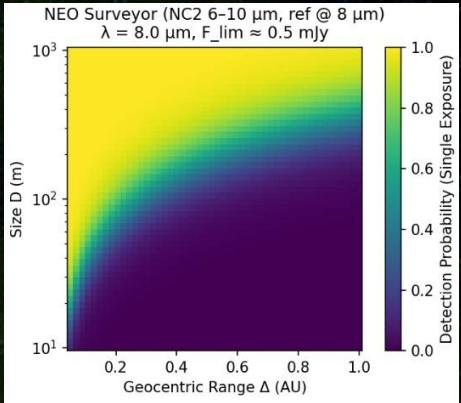
Modeling Sensors

Similar calculation for space-based sensors, using infrared emissivity.

- 24h isotropic sky-coverage approximation
- Efficacy scaling based on cone angle

$$\mathbb{P}_{\text{single}} : \text{Range} \times \text{Size} \rightarrow [0, 1]$$

$$\mathbb{P}_{24 \text{ hr}} : \text{Range} \times \text{Size} \rightarrow [0, 1]$$



Sensor topology

Sensor detection functions are distributions over **range x size** invariant to constant multiples of the same **range-size** pair; parametrized by **range:size** ratio



Sensor topology

Dimensionless poset of **range:size** ratios forms domain for sensor detection functions, which are **monotone maps** from the opposite of this poset to the **unit interval $[0, 1]$** .

Specifically, low range:size gives high probability of detection and high range:size gives low probability of detection. We then have an ordering of sensors based on the standard ordering of monotone maps.



Monoidal probability fusion

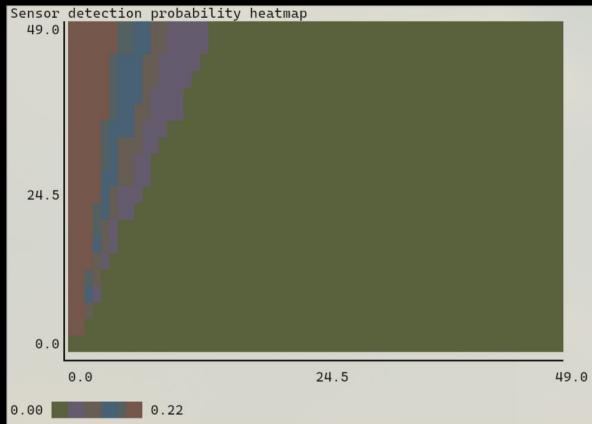
$$p_1 \otimes p_2 = 1 - (1 - p_1)(1 - p_2)$$

Commutative monoid on probabilities; gives a new detection function better than or the same as its composite detection functions

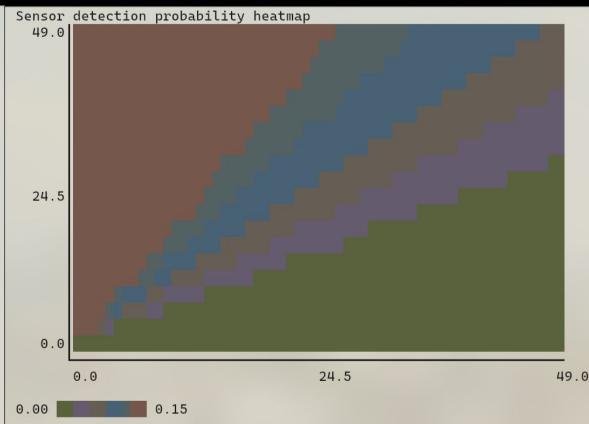
(This is **not** the probability monad)



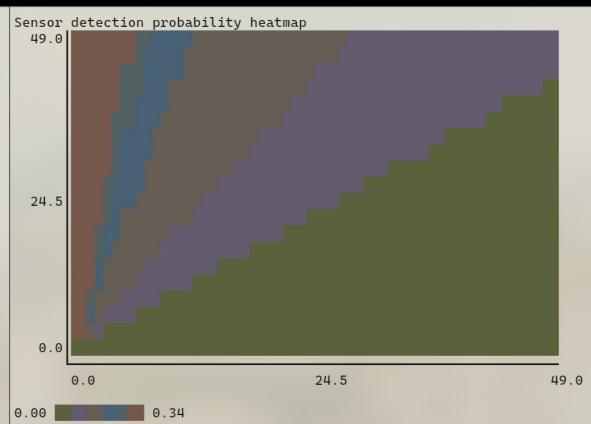
Monoidal probability fusion



ZTF (Palomar)
max detection probability:
22%



Rubin/LSST
max detection probability:
15%



Combined
max detection probability:
34%

Detection Problem



Given a distribution of **NEO sizes** and **velocities**, what combination of investments in **detection** and **redirection** yields the greatest **lead time** for planetary defense?



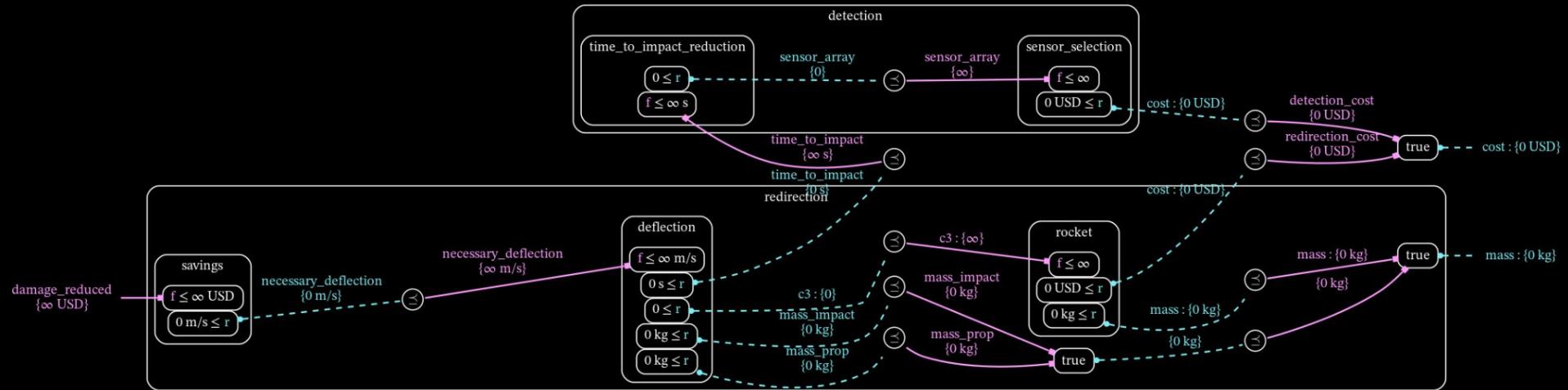
Ground-based Observatories



Space-based Observatories

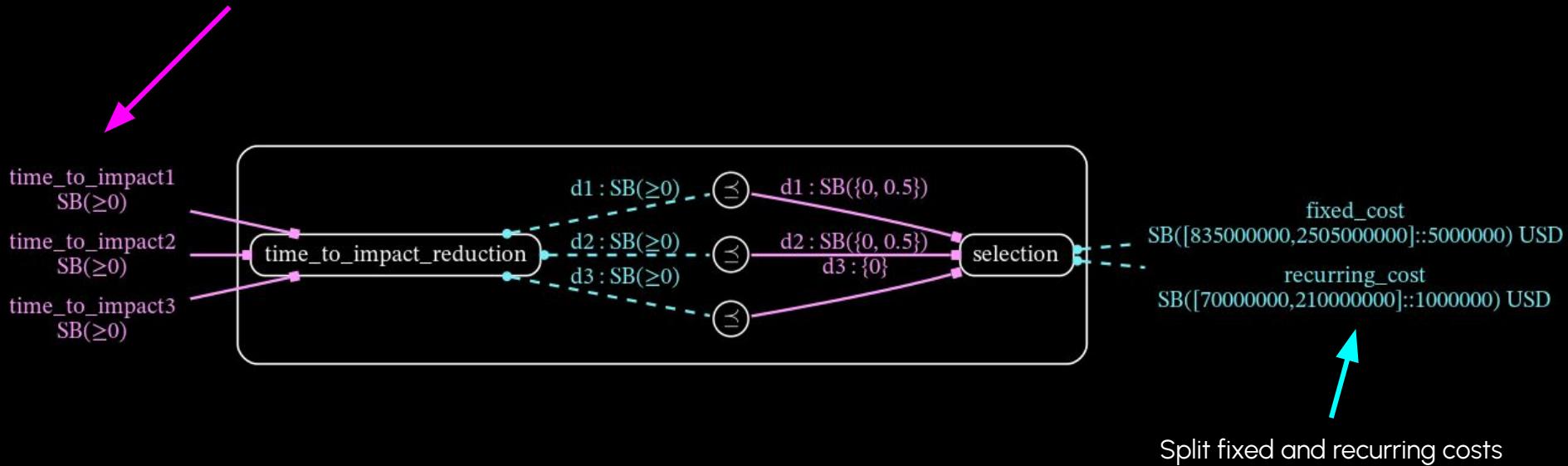
Detection Problem

Given a distribution of **NEO sizes** and **velocities**, what combination of investments in **detection** and **redirection** yields the greatest **lead time** for planetary defense?



System diagram

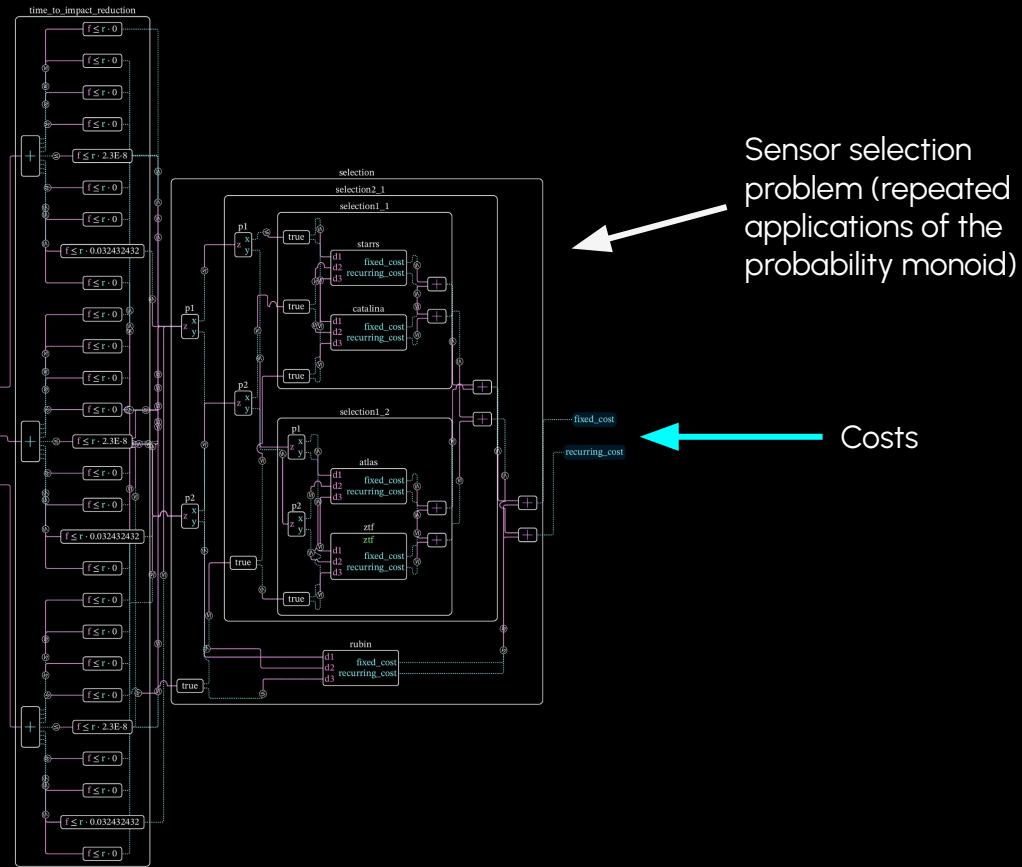
Instead of expected time to impact, compute the hazard function at representative times to get probabilities of detection



Zoom in on revised detection block

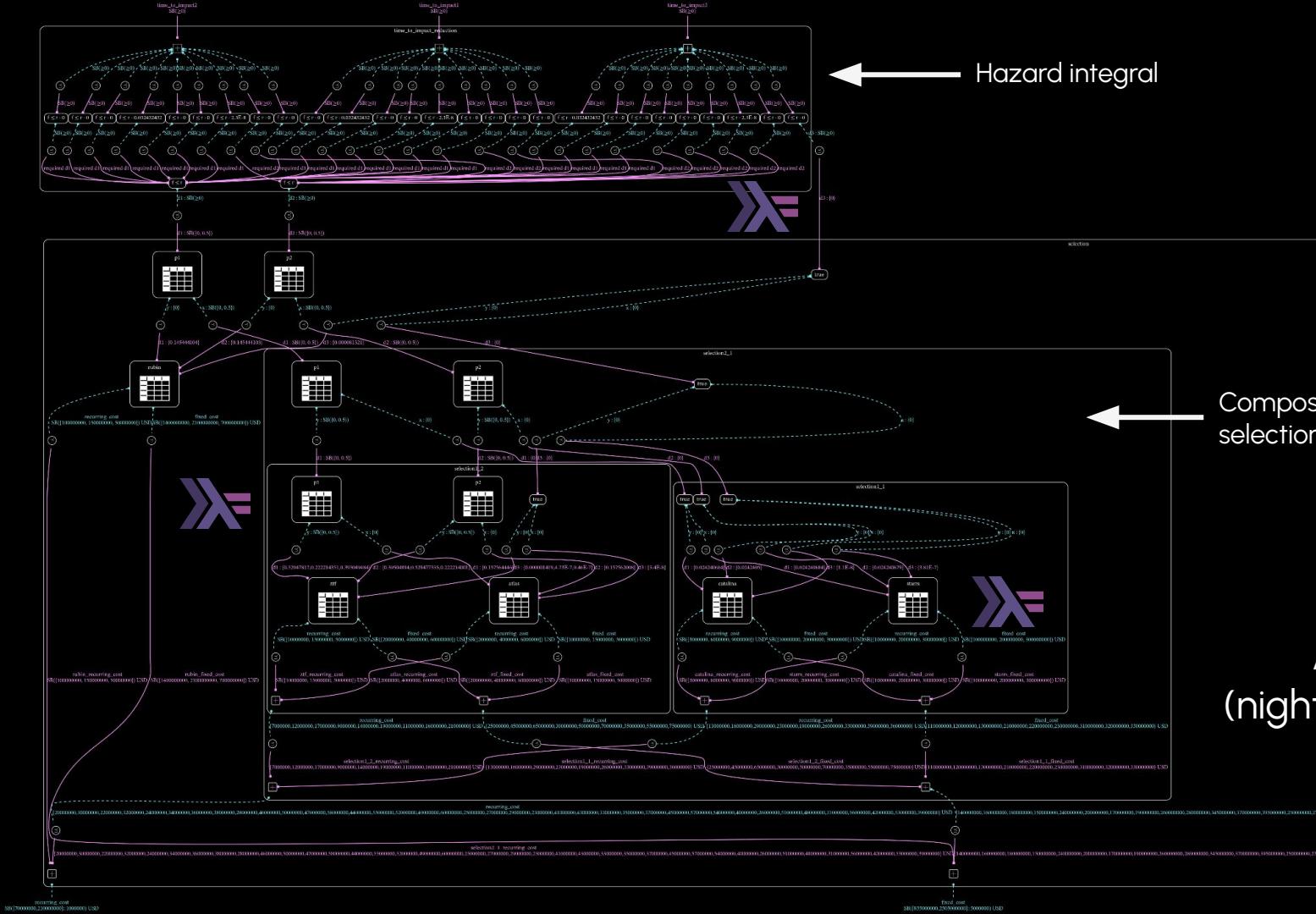
24 hour detection probabilities at representative times

Hazard function
(double integral approximated as Riemann sum)



Highly discretized (3 point approximation) DP representing sensor selection
(full DP is orders of magnitude more cursed)

Sensor selection problem (repeated applications of the probability monoid)



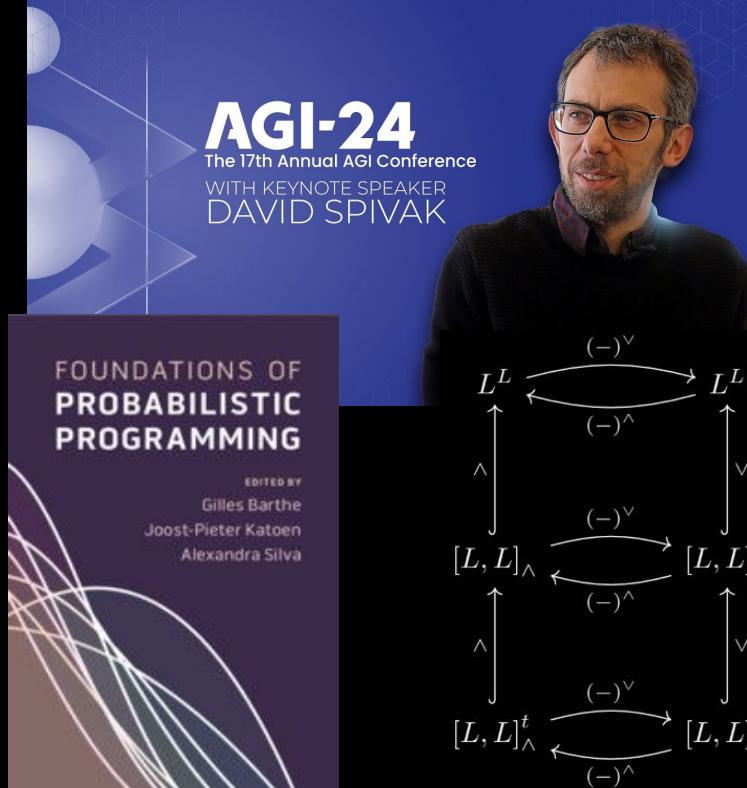
Hazard integral

Compositional sensor selection

Another view
(nightmare design problem)

The case for co-design

Categorical informatics,
probability monads, and the like

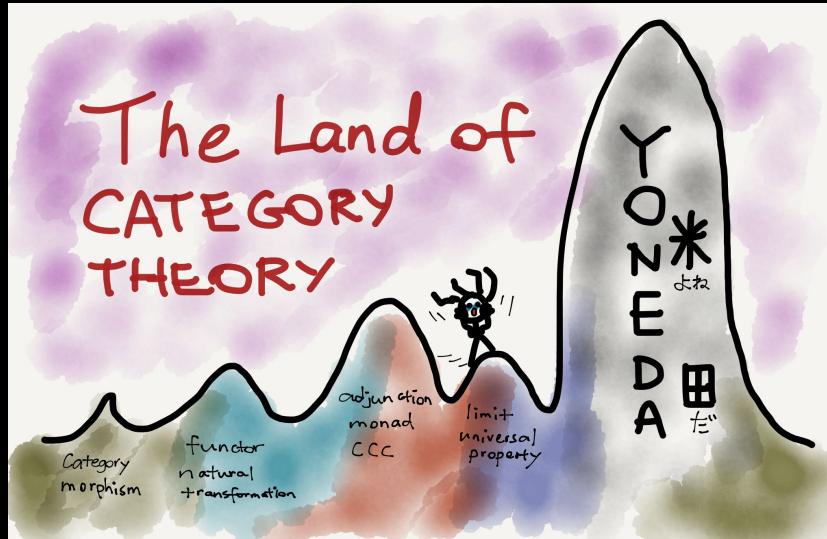


The Pareto Frontier



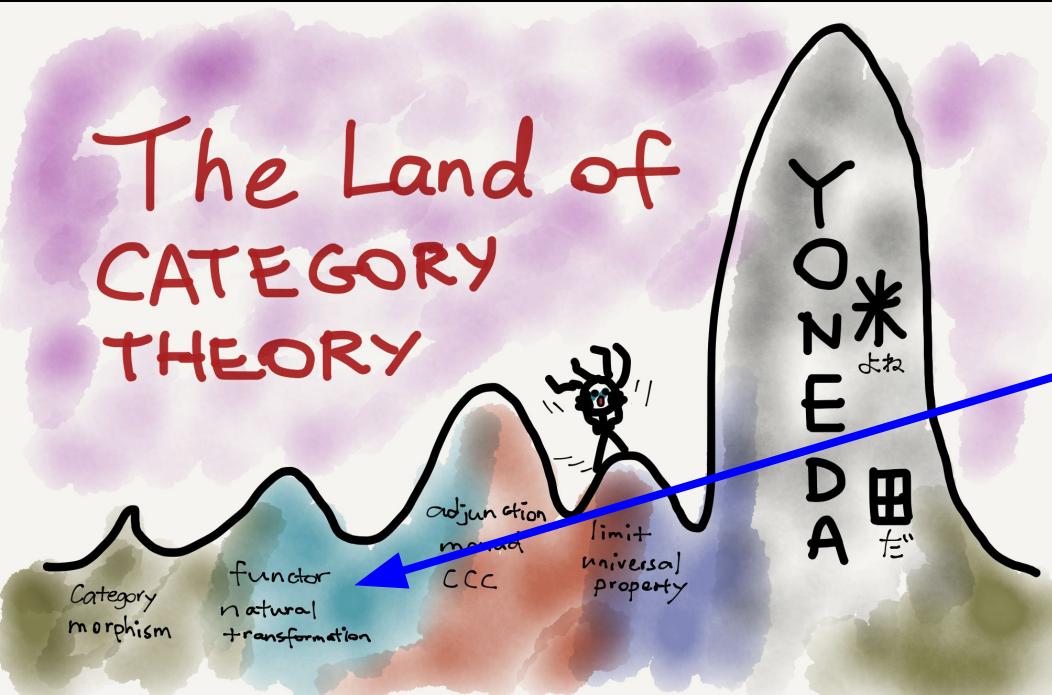
Given a fixed budget, what is the best we can do in terms of:

- Minimizing existential risk (i.e. detecting incoming asteroids early)
- Minimizing collateral damage (i.e. increasing our chances of preventing asteroid impact)
- What sensors do we invest in, and which interception mechanisms do we value?



Categorically, we apply **FixResMaxFun** to obtain the Pareto frontier for detection probabilities given a fixed budget and **FixFunMinRes** to minimize costs required to achieve a given set of damage reduction targets

The Land of CATEGORY THEORY



Functionality of the solution map means we can get away with very inefficient specifications, provided they're compositional

(we will heavily abuse this property in order to represent our problem in MCDP)

MCDP

```
x required by p1 ≤ d1 provided by atlas
y required by p1 ≤ d1 provided by ztf
provided d1 ≤ z pro
  ...
  -- sampling
x required by p2 ≤
y required by p2 ≤
provided d2 ≤ z pro
x required by p3 ≤
y required by p3 ≤
provided d3 ≤ z pro
funProvSample :: Int -> [Tex
funProvSample i =
let
  prob :: Text
  prob = probabilityName <
  sample :: Text
  sample = sensorDetectionFunctionName >> show i
in
  [ (p1Name `reqBy` prob) `lessThan` (sample `provBy` s1)
, (p2Name `reqBy` prob) `lessThan` (sample `provBy` s2)
, provided sample `lessThan` (pName `provBy` prob)
]
```

```
linspace :: Int -> Bounds Double -> [Double]
linspace n (start, end) = [start, start + step .. end]
  where
    step = (end - start) / (fromIntegral n - 1)

stitch :: [Double] -> [Double] -> [[(Double, Double)]]
stitch xs ys = [[(x, y) | y <- ys] | x <- xs]

diag :: [Double] -> [[(Double, Double)]]
diag xs = stitch xs xs
```

```
043243243 * 0.0
00269 + d1 * 0.043243243 * 0.00000269 + d1
00000 * 0.00000000 + d4 * 0.043243243 * 0.0
00269 + d1 * 0.043243243 * 0.00000269 + d1
00000 * 0.00000000 + d4 * 0.043243243 * 0.0
00269 + d2 * 0.043243243 * 0.00000269 + d2
```

- Discretize everything
- Haskell-based templating metalanguage
- Dynamically set resolution and solve for antichains
- Describe sensor combination with compositions of the probability monoid



tomie ✅ @tomieinlove · 4d

I wonder how much money OpenAI has lost in electricity costs from people saying “please” and “thank you” to their models.

1.2K

5.8K

181K

5.7M



Sam Altman ✅

@sama

Replying to @tomieinlove

tens of millions of dollars well spent--you never know

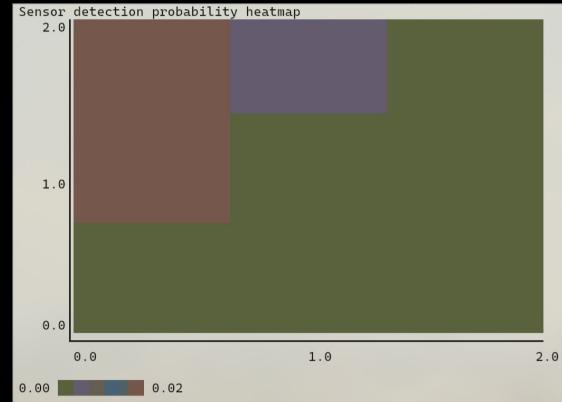
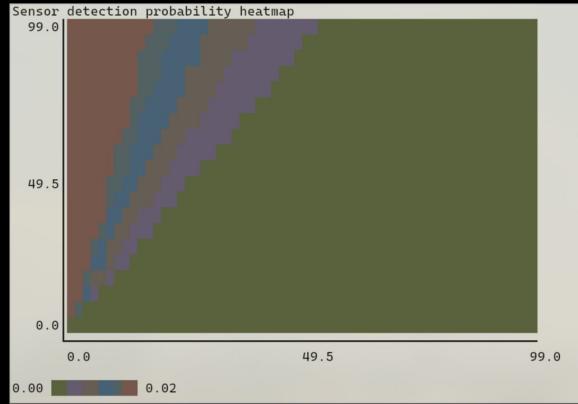
4:45 · 17 Apr 25 · 441K Views

Results

(with MCDP)



- Crashed web editor multiple times
- Wasted tremendous amounts of compute
- Haskell code worked flawlessly
- MCDP killed itself several times likely due to (d)OOM issues



Discretization :(

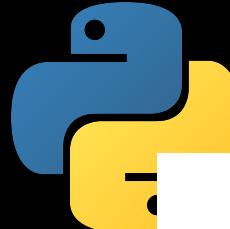
2.58%

Maximum 24-hour detection probability with a \$2.5 billion budget
(recurring cost bounded at 10% of total budget)

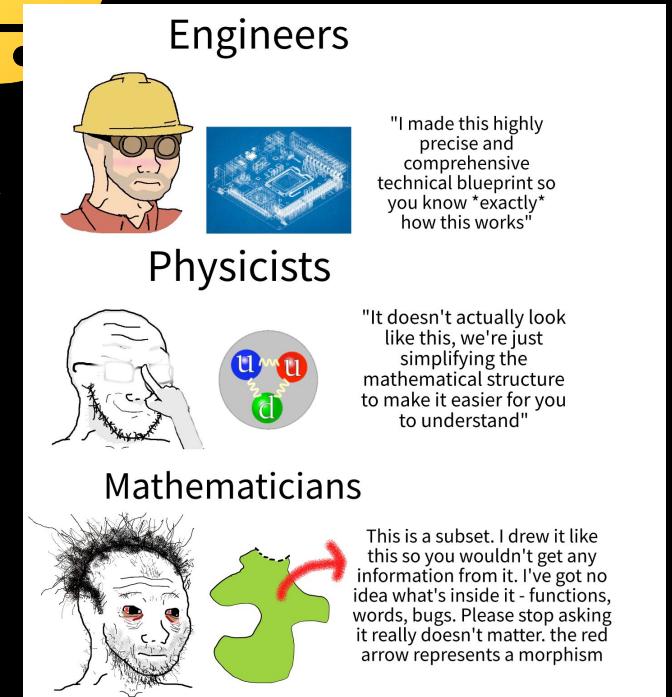
27 days

Average detection time with a \$2.5 billion budget
(recurring cost bounded at 10% of total budget)

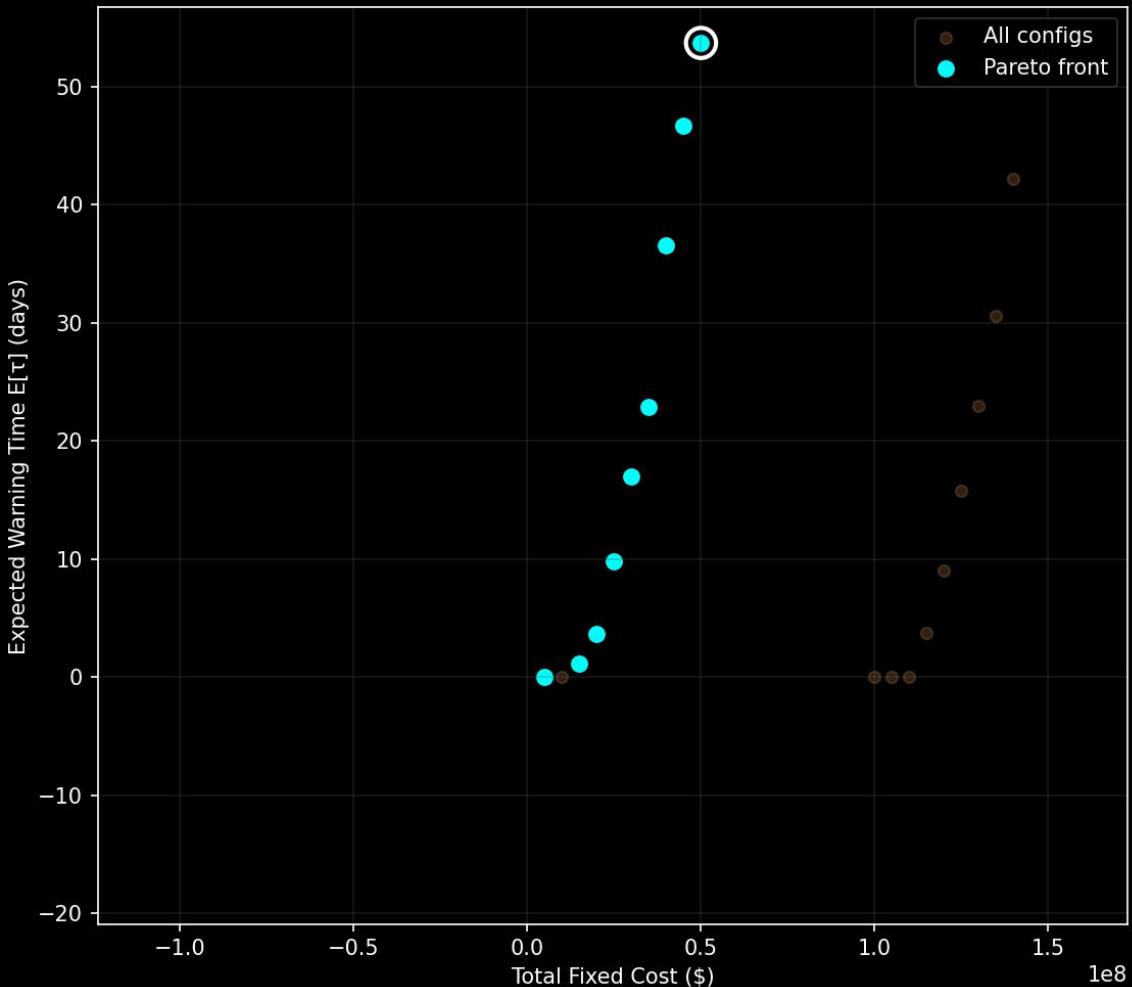
Reimplemented everything in
Python for approximate
high-fidelity solution



Haskell/MCDP pipeline gave
provably optimal design solutions
(for 3 data points)



Pareto Front: Early Detection vs Cost

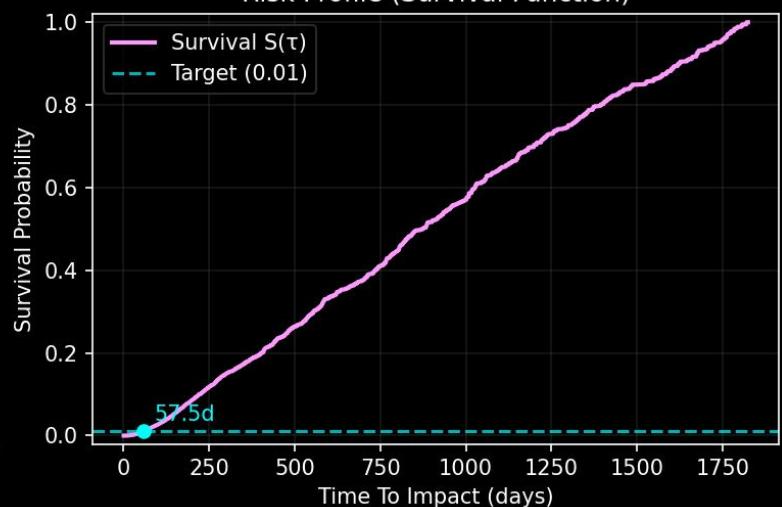


Configuration Details

Index: 350
 $E[\tau_{det}]$: 53.71 days
 Cost: \$50.0 M

Ground:
 ATLAS (per unit): 2
 ZTF (Palomar 48"): 2
 Space:

Risk Profile (Survival Function)



Modeling



Burritos for the Hungry Mathematician

Ed Morehouse

April 1, 2015

Abstract

The advent of fast-casual Mexican-style dining establishments, such as Chipotle and Qdoba, has greatly improved the productivity of research mathematicians and theoretical computer scientists in recent years. Still, many experience confusion upon encountering burritos for the first time.

Numerous burrito tutorials (of varying quality) are to be found on the Internet. Some describe a burrito as the image of a crêpe under the action of the new-world functor. But such characterizations merely serve to reindex the confusion contravariantly. Others insist that the only way to really understand burritos is to eat many different kinds of burrito, until the common underlying concept becomes apparent.

It has been recently remarked by Yorgey [9] that a burrito can be regarded as an instance of a universally-understood concept, namely, that of monad. It is this characterization that we intend to explicate here. To wit, *a burrito is just a strong monad in the symmetric monoidal category of food, what's the problem?*

1 The Category of Food

Modeling uncertainty has a natural monadic interpretation, and probability monads can be put in one-to-one correspondence with the different types of tortilla endofunctors. The proof is trivial given the generalization of the burrito presented by [Morehouse \(2015\)](#).

Modeling Sensors

A sensor is characterized by its **angular resolution**, which relates range and diameter of target.

Sensor : Range \times Diameter $\rightarrow [0, 1]$

$$P_i(r, d)$$

We combine this with the angular cadence, i.e. percent of sky covered in 24 hours

DailySensor : Range \times Size \times St $\rightarrow [0, 1]$

$$\bar{\alpha}_i \approx \frac{c_i}{4\pi} \quad \bar{P}_i(r, s) = \bar{\alpha}_i P_i(r, d)$$

Finally, we define combined detection probability:

$$F(r, d) = 1 - \Pi_i(1 - \bar{P}_{ground,i}(r, d)) \Pi_j(1 - \bar{P}_{space,j}(r, d))$$

Modeling Sensors



NEO absolute magnitude:

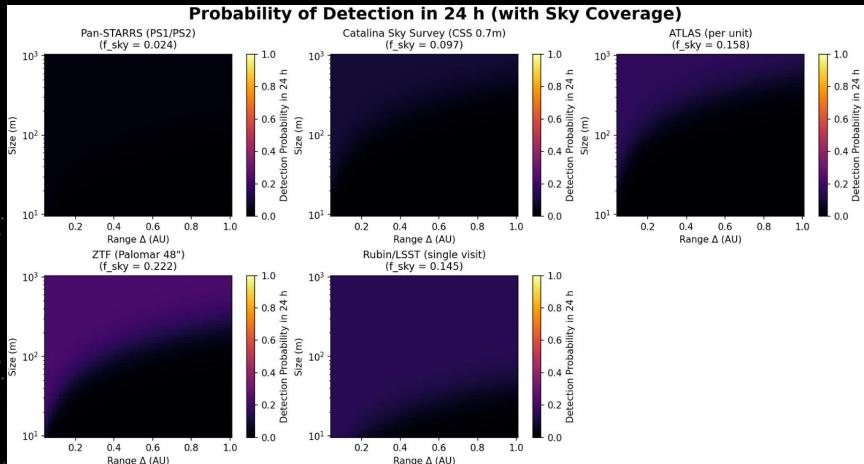
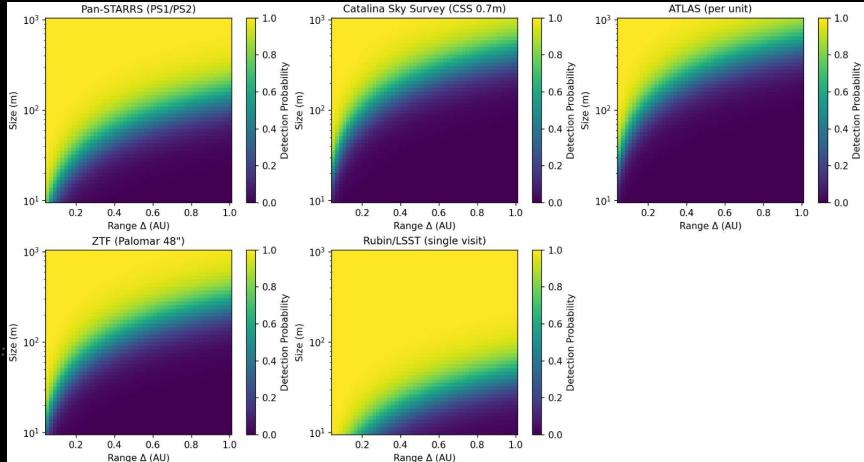
$$H = 5 \cdot \log_{10}\left(\frac{1329}{D_{\text{km}} \sqrt{p_v}}\right)$$

NEO apparent magnitude:

$$m \approx H + 5 \cdot \log_{10}(r_{\odot} \Delta)$$

Single-Exposure Detection Probability

$$P_{\text{det}} = \frac{1}{1 + \exp\left(\frac{m(r, d) - m_{\text{lim}}}{k}\right)}$$



Modeling Sensors



Equilibrium Temperature:

$$T(r) = 278\text{K} \left(\frac{1 - A}{\epsilon\mu} \right)^{\frac{1}{4}} r^{-\frac{1}{2}}$$

Planck Radiation

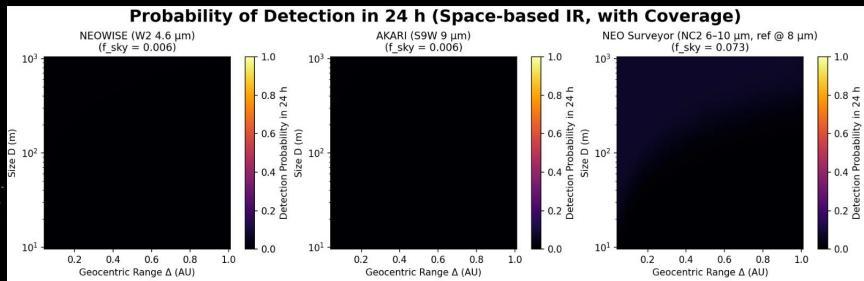
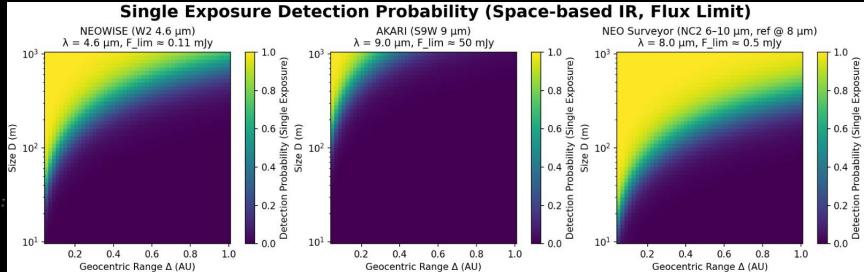
$$B_\lambda(T) = \frac{2hc^2}{\lambda^5} \frac{1}{e^{\frac{hc}{\lambda k_B T}} - 1}$$

Flux at Earth

$$F_v(r, d) = \frac{\epsilon\pi B_\lambda(T)d^2}{4\Delta^2} \frac{\lambda^2}{c}$$

Single Exposure

$$P_{\text{det}} = \frac{1}{1 + \exp \left(\frac{\log_{10}(F_{v,\text{lim}}) - \log_{10}(F_v(r,d))}{k} \right)}$$



Modeling Time to Impact

Provided the distributions:

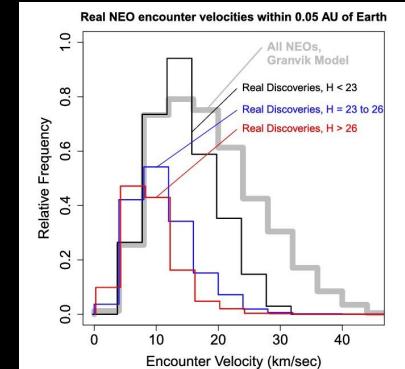
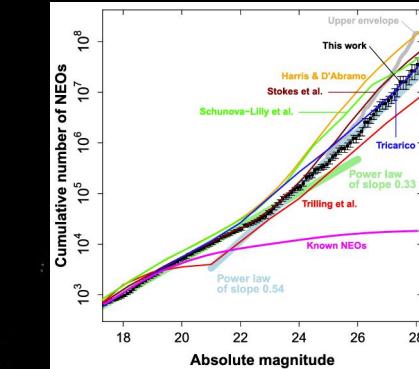
- Size: $p_D(d)$
- Velocity: $p_V(v)$
- Orbit Geometry: $p_\Phi(\phi)$

Hazard Function:

$$\lambda(\tau) = \int_d \int_v \int_0^{\frac{\pi}{2}} F(v\tau \cos(\phi), d) p_D(d) p_V(v) p_\Phi(\phi) d\phi dv ds$$

Survival:

$$S(\tau) = \exp \left(- \int_{\tau}^{\tau_{max}} \lambda(u) du \right)$$



Probability Distribution Function:

$$p_\tau(t) = \frac{\lambda(t) S(t)}{1 - S(0)}$$

Modeling Delta V

Provided the distributions:

- Size: $p_D(d)$
- Velocity: $p_V(v)$
- Time to Impact: $p_T(t)$

Tangential Delta-V that must be transferred for
a 2-Earth Radii Miss [4][8]

$$\Delta v = \frac{2R_{\oplus}}{t_{TTL}}$$

Interception angle plays an important role,
difficult to model without simulation.

Modeling Kinetic Interceptor

$$m_{\text{NEO}} = \rho \frac{2000}{6} D^3$$

Rocket : Mass × C₃ → Bool

$$m_{\text{sat}} = m_{\text{prop}} + m_{\text{impactor}}$$

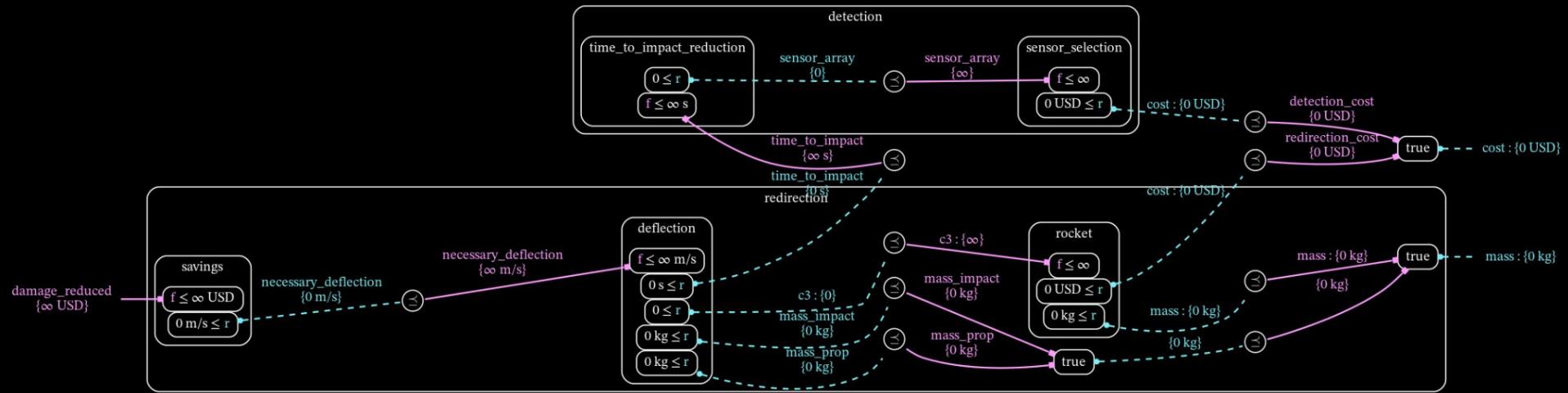
$$v_{\text{impact}} = v_e \ln \left(\frac{m_{\text{sat}}}{m_{\text{impactor}}} \right) + \sqrt{C_3}$$

$$t_{\text{flight}} = \frac{R}{\sqrt{v_{\text{ast}}^2 + v_{\text{impact}}^2}}$$

$$\Delta v_{\text{req}} = \frac{2R_{\text{Earth}}}{t_{\text{TTL}} - t_{\text{flight}}} \leq \frac{m_{\text{impactor}} v_{\text{impact}} \beta}{m_{\text{ast}}}$$



"The most important application of Toquos Theory is combating the devastating effects of Subgroup Psychosis stemming from several somnial attacks from the Number Devil, as he has the ability to invade dreams, especially those related to mathematics." —Emma O'Neil



Proprietary MCDPL-generated design schematics; for more information see:
<https://code.functor.systems/q9i/blue-dome>