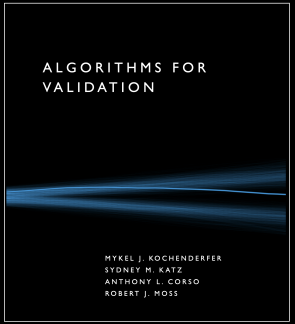
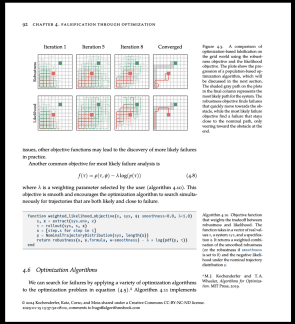
Julia in Academia

Textbooks, Stanford Courses, and the Future





Robert Moss, PhD

Stanford University | JuliaCon 2025

mossr@cs.stanford.edu

WHOAMI

WHOAMI

Recent Stanford PhD Graduate

Used Julia throughout my research

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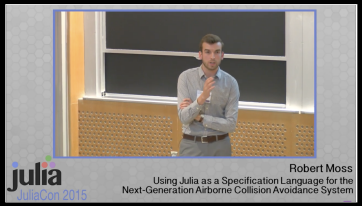

Prev. at MIT Lincoln Laboratory

Julia as a specification language

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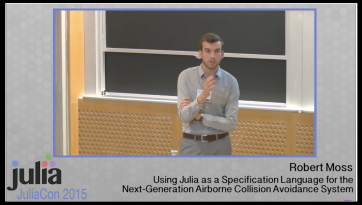

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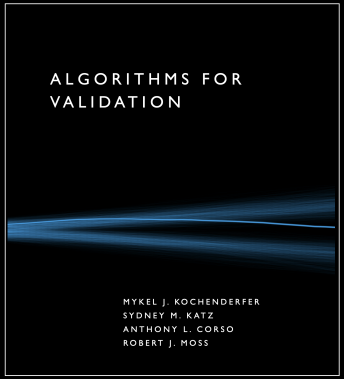
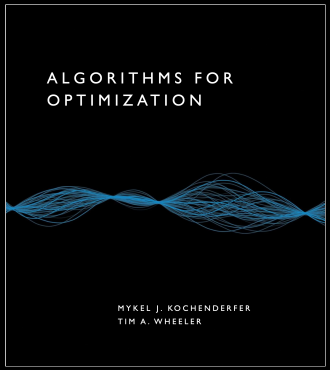


Textbook Co-Author/Head TA

Algorithms written in Julia

Textbooks using Julia

Textbooks using Julia



Algorithms for Optimization
MIT Press, 2019

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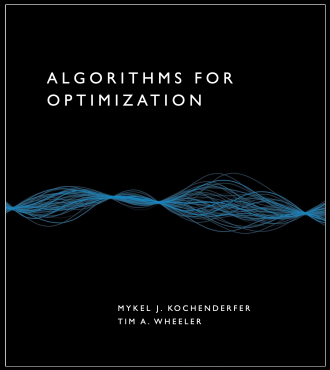

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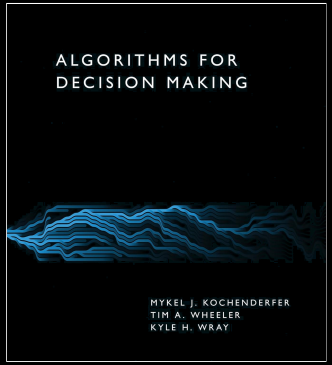

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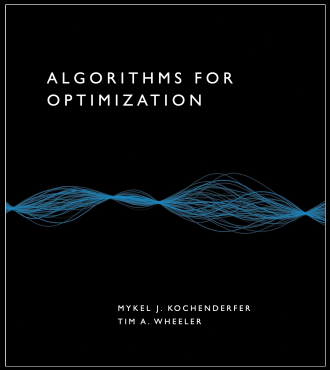

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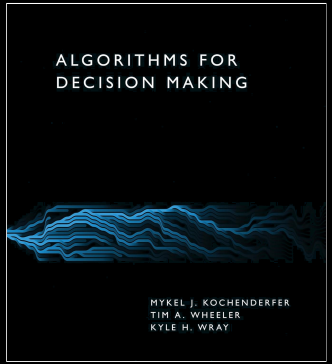

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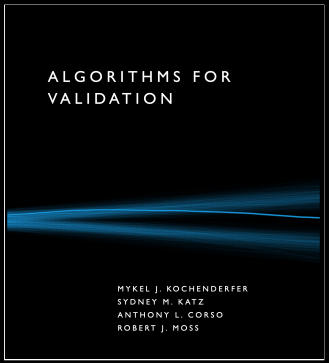

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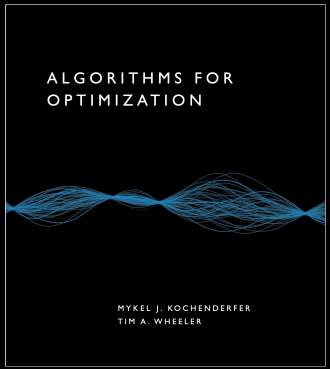

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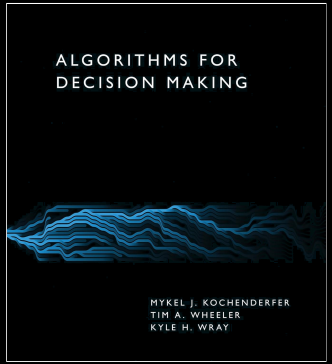

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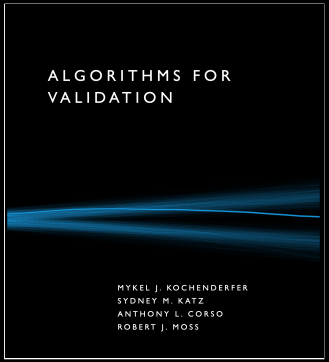

Algorithms for Validation
MIT Press, 2025

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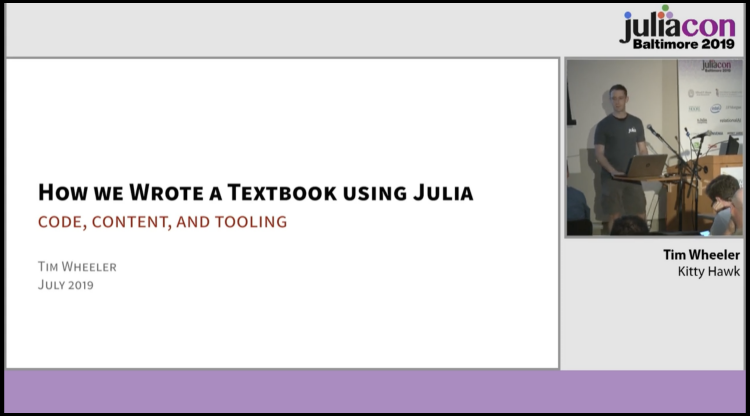
JuliaCon 2019



How We Wrote a Textbook using Julia

Tim Wheeler, JuliaCon 2019

Textbooks with integrated Julia

Textbooks with integrated Julia

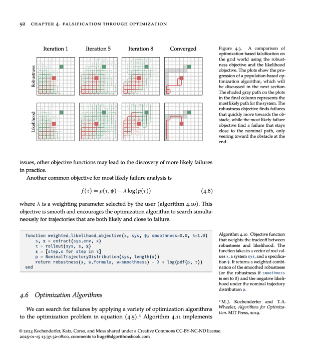


Figure 4.3. A comparison of optimization-based falsification on the grid world using the robustness objective and the likelihood objective. The plots show the progression of a population-based optimization algorithm, which will be discussed in the next section. The shaded gray path on the plots in the final column represents the most likely path for the system. The robustness objective finds failures that quickly move towards the obstacle, while the most likely failure objective find a failure that stays close to the nominal path, only veering toward the obstacle at the end.

issues, other objective functions may lead to the discovery of more likely failures in practice.

Another common objective for most likely failure analysis is

$$f(\tau) = \rho(\tau, \psi) - \lambda \log(p(\tau)) \tag{4.8}$$

where λ is a weighting parameter selected by the user (algorithm 4.10). This objective is smooth and encourages the optimization algorithm to search simultaneously for trajectories that are both likely and close to failure.

```
function weighted_likelihood_objective(x, sys, ψ; smoothness=0.0, λ=1.0)
    s, x = extract(sys.env, x)
    τ = rollout(sys, s, x)
    s = [step.s for step in τ]
    p = NominalTrajectoryDistribution(sys, length(x))
    return robustness(s, ψ.formula, w=smoothness) - λ * log(pdf(p, τ))
end
```

Algorithm 4.10. Objective function that weights the tradeoff between robustness and likelihood. The function takes in a vector of real values `x`, a system `sys`, and a specification `ψ`. It returns a weighted combination of the smoothed robustness (or the robustness if `smoothness` is set to 0) and the negative likelihood under the nominal trajectory distribution `p`.

4.6 Optimization Algorithms

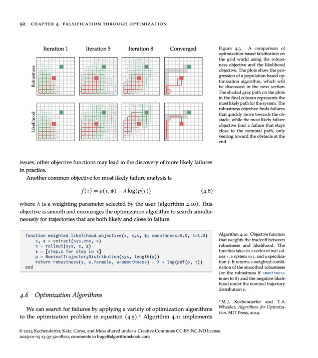
We can search for failures by applying a variety of optimization algorithms to the optimization problem in equation (4.5).[4] Algorithm 4.11 implements

[4] M. J. Kochenderfer and T. A. Wheeler, *Algorithms for Optimization*. MIT Press, 2019.

Algorithms for Validation

Figures and Julia code

Textbooks with integrated Julia



92 CHAPTER 4. FALSIFICATION THROUGH OPTIMIZATION

Iteration 1 Iteration 5 Iteration 8 Converged

Robustness

Likelihood

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Algorithms for Validation

Figures and Julia code

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    q # proposal distribution
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    p, q, m = alg.p, alg.q, alg.m
    τs = [rollout(sys, q) for i in 1:m]
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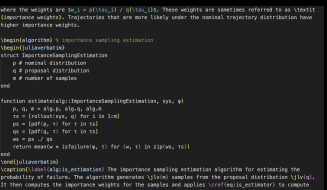
    ws = ps ./ qs
    return mean(w * isfailure(ψ, τ) for (w, τ) in zip(ws, τs))
end
```

Example algorithm

Importance sampling estimation of failure probability

Julia integrated into LaTeX code



```
where the weights are $w_i = p(\tau_i) / q(\tau_i)$. These weights are sometimes referred to as \textit
{importance weights}. Trajectories that are more likely under the nominal trajectory distribution have
higher importance weights.

\begin{algorithm} % importance sampling estimation
\begin{juliaverbatim}
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\end{juliaverbatim}
\caption{\label{alg:is_estimation} The importance sampling estimation algorithm for estimating the
probability of failure. The algorithm generates \(m\) samples from the proposal distribution \(q\).
It then computes the importance weights for the samples and applies \cref{eq:is_estimator} to compute
$\hat p_\text{fail}$.}
\end{algorithm}

\subsection{Optimal Proposal Distribution}
\label{sec:optimal_proposal}
The accuracy and efficiency of importance sampling approaches is highly dependent on the proposal
distribution. The variance of the estimator in \cref{eq:is_estimator} is
\begin{equation}
    \label{eq:is_var}
    \text{Var}\!\left[\hat p_\text{fail}\right] = \frac{1}{m} \mathbb E_{\tau \sim q}\!\left[\frac{p(\tau
    \mathbin{|}\tau \in \psi)}{q(\tau)}^2\right] - p(\tau)^2\right]
\end{equation}
In general, we want to select a proposal distribution that makes this variance low, and the optimal
proposal distribution is the one that minimizes this variance.

It is evident from \cref{eq:is_var} that we can achieve a variance of zero when
\begin{equation}
    \label{eq:optimal_proposal}
    q^\ast(\tau) = \frac{p(\tau) \mathbin{|} \tau \in \psi}{p_\text{fail}}
\end{equation}
This distribution corresponds to the failure distribution $p(\tau \mid \tau \in \psi)$. As noted in
\cref{sec:failure_distribution}, computing this distribution is not possible in practice since we often
do not know the full set of failure trajectories and the normalizing constant $p_\text{fail}$ is the
quantity we are trying to estimate. Our goal is therefore to select a proposal distribution that is as
close as possible to the failure distribution.
```

LaTeX code example

Integrated Julia code using pythontex

Julia integrated into LaTeX code

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\caption{\label{alg:is_estimation} The importance sampling estimation algorithm for estimating the
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LaTeX code example

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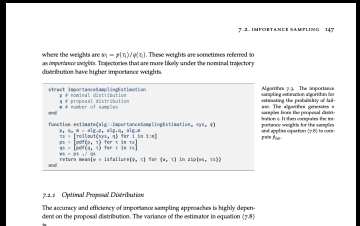

7.2. IMPORTANCE SAMPLING 147

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    return mean(w * isfailure(ψ, τ) for (w, τ) in zip(ws, τs))
end
```

Algorithm 7.3. The importance sampling estimation algorithm for estimating the probability of failure. The algorithm generates jm samples from the proposal distribution jq. It then computes the importance weights for the samples and applies equation (7.6) to compute $\hat{p}_{\text{fail}}$.

7.2.1 Optimal Proposal Distribution

The accuracy and efficiency of importance sampling approaches is highly dependent on the proposal distribution. The variance of the estimator in equation (7.8) is

$$\text{Var}(\hat{p}_{\text{fail}}) = \frac{1}{m} \mathbb{E}_{\tau \sim q(\cdot)}\left[\frac{\left(p(\tau)\mathbb{1}\{\tau \notin \psi\} - q(\tau)p_{\text{fail}}\right)^2}{q(\tau)}\right] \tag{7.10}$$

In general, we want to select a proposal distribution that makes this variance low, and the optimal proposal distribution is the one that minimizes this variance.

It is evident from equation (7.10) that we can achieve a variance of zero when

$$q^*(\tau) = \frac{p(\tau)\mathbb{1}\{\tau \notin \psi\}}{p_{\text{fail}}} \tag{7.11}$$

This distribution corresponds to the failure distribution $p(\tau \mid \tau \notin \psi)$. As noted in chapter 6, computing this distribution is not possible in practice since we often do not know the full set of failure trajectories and the normalizing constant p_{fail} is the quantity we are trying to estimate. Our goal is therefore to select a proposal distribution that is as close as possible to the failure distribution.

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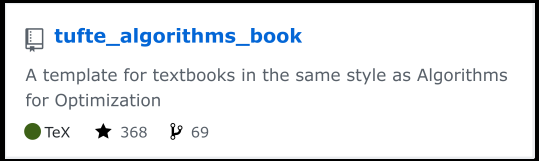

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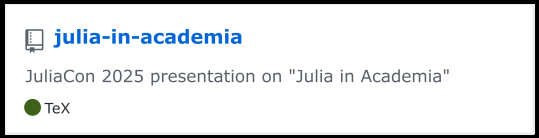

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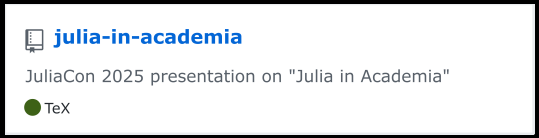

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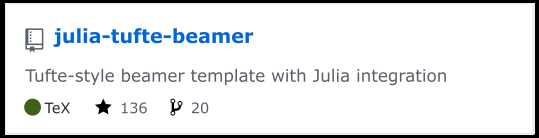

github.com/mossr/julia-tufte-beamer

Julia for Textbooks: The Good

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- Concise algorithm descriptions (fits within single page)

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Julia for Textbooks: The Good

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Shout-out to the following packages:
`Distributions.jl`, `LazySets.jl`, `IntervalArithmetic.jl`, `Flux.jl`, `Optim.jl`, and `JuMP.jl`

Julia for Textbooks: The Not-So-Good

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- Somewhat new to readers: Requires learning Julia in the process
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- Textbook tooling: Needed to be built out from scratch

Julia in the Classroom

Julia in the Classroom

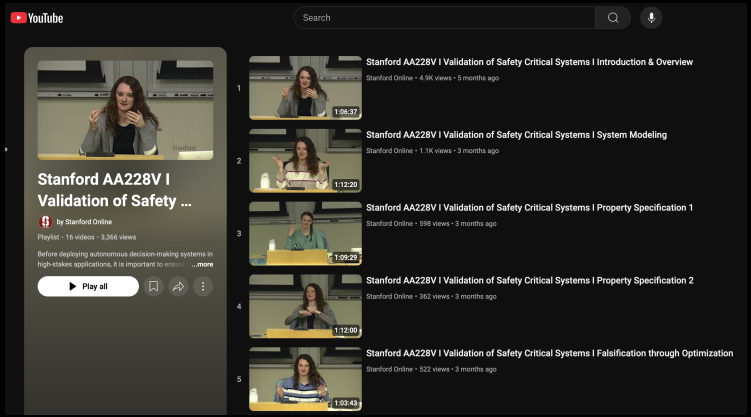
Grad-level course at Stanford

Follows *Algorithms for Validation* textbook

First offered in Winter 2025

Lectures

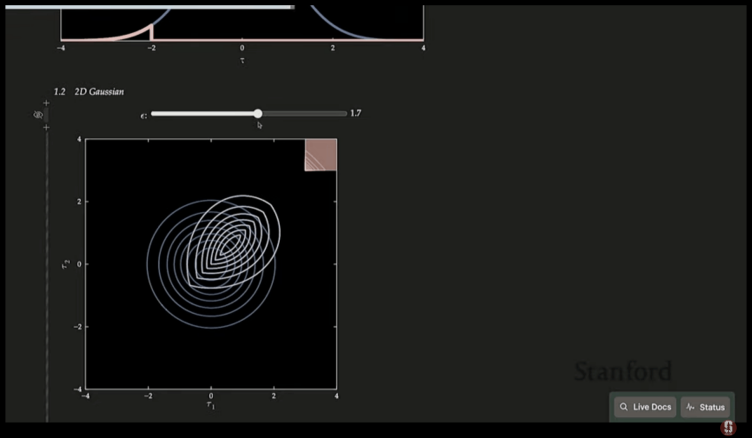
Lectures



All lectures available on YouTube

Led by Sydney Katz, textbook co-author and award-winning lecturer

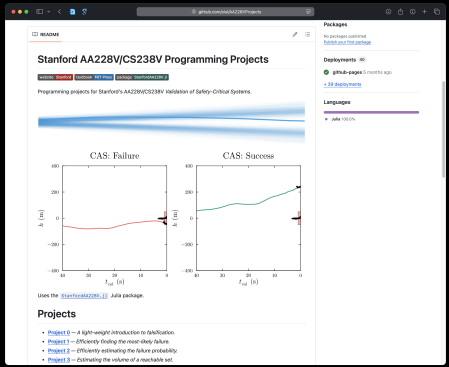
Interactive Lectures



Interactive lectures using `Pluto.jl`

Assignments in Julia

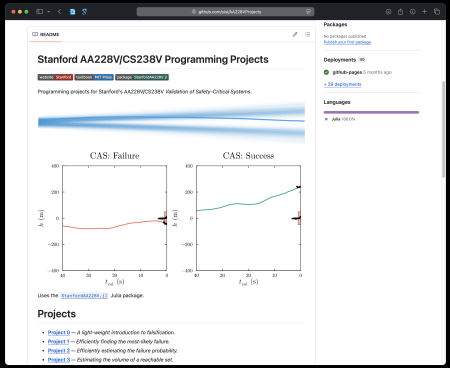
Assignments in Julia



Assignments repository

Student-facing code

Assignments in Julia



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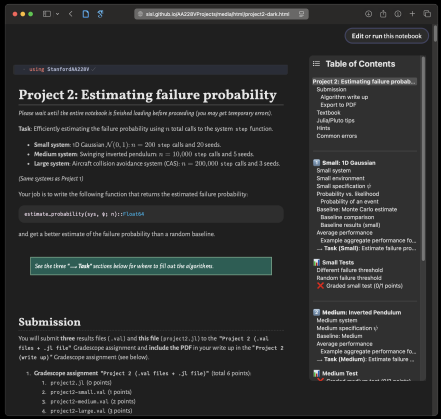
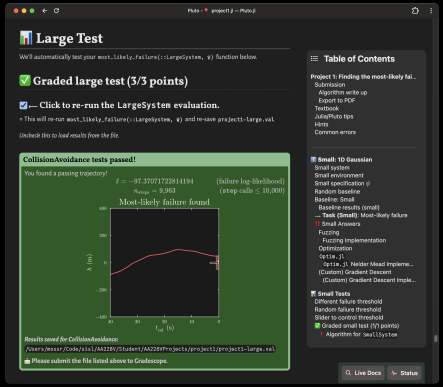


Pluto assignments

Includes local tests

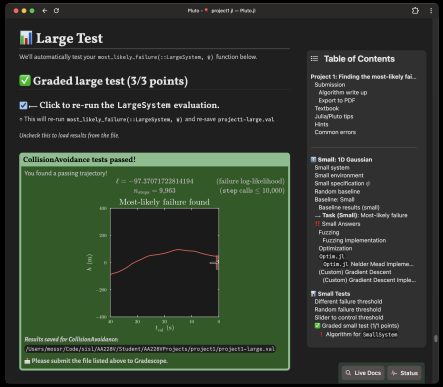
Assignments in Julia



Interactive Pluto tests

Get feedback instantly

Assignments in Julia



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Interactive Pluto tests
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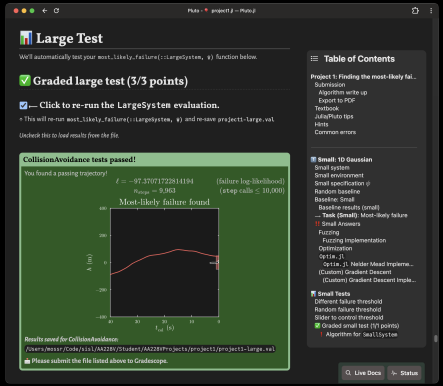

Interactive Pluto tests
Get feedback instantly

- Separated assignment code from core library (`StanfordAA228V.jl`)
- Local tests exactly match graded tests

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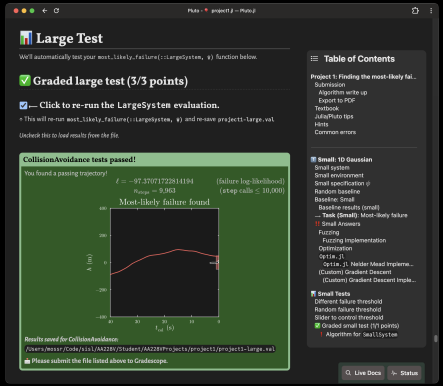

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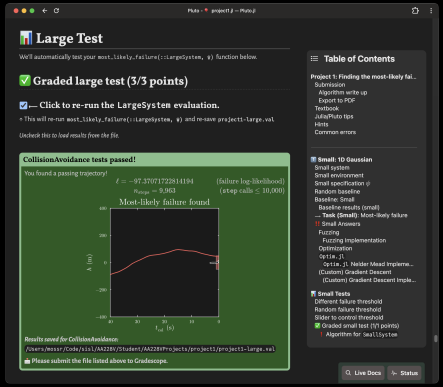

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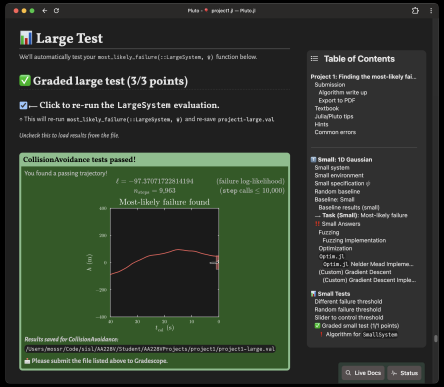

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- Open-source nature requires clever obfuscation of solution code

Grading Assignments

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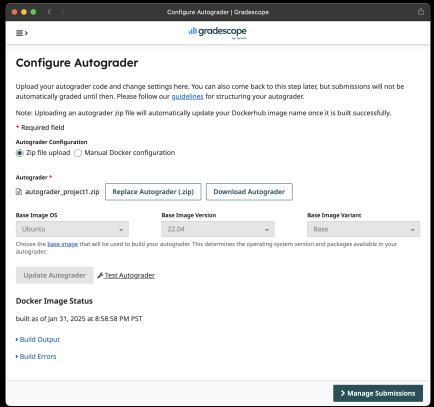
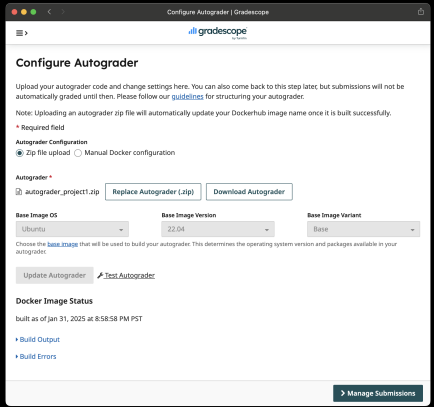
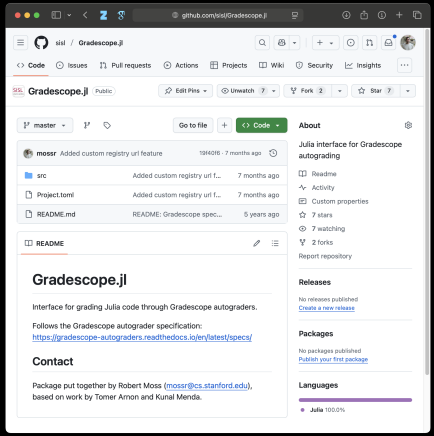


Autograde via Gradescope

Students upload Pluto notebook

Grading Assignments





Autograde via Gradescope

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Light-weight `Gradescope.jl` package

Manage deps and create autograders

Future use of Julia in Academia

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- Write interactive research papers in Julia/Pluto

PlutoPapers.jl

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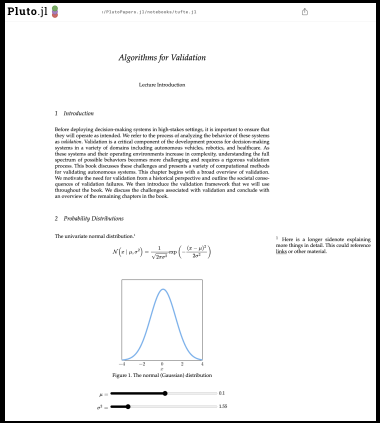
What if we could interact directly with the code in research papers?

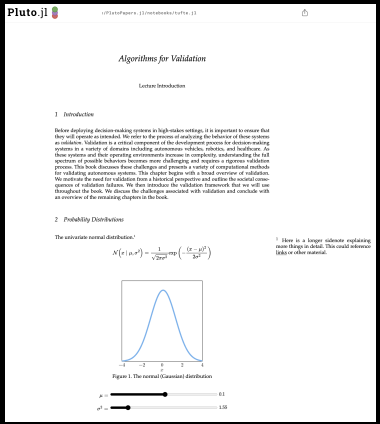
PlutoPapers.jl



Interactive research papers

Run code directly in the paper

PlutoPapers.jl



Interactive research papers

Run code directly in the paper

PlutoPapers.jl

Interactive and LaTeX-styled papers in Pluto.jl

Julia ★ 5

https://github.com/mossr/PlutoPapers.jl

Thank you!

Questions?

mossr@cs.stanford.edu