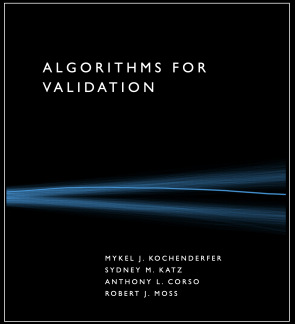
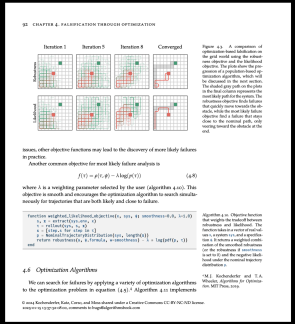
Julia in Academia

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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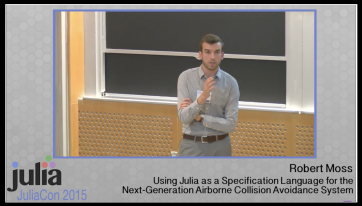
Recent Stanford PhD Graduate

Used Julia throughout my research



Prev. at MIT Lincoln Laboratory

Julia as a specification language

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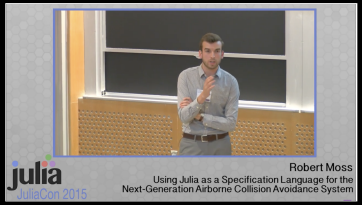

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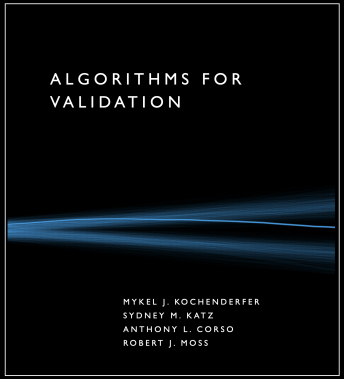

Textbook Co-Author/Head TA

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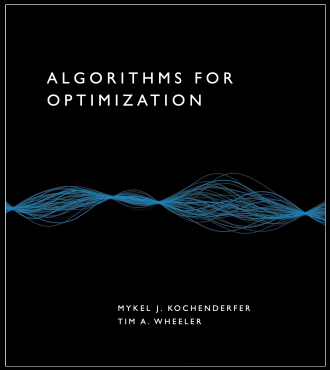
Textbooks using Julia



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MIT Press, 2019

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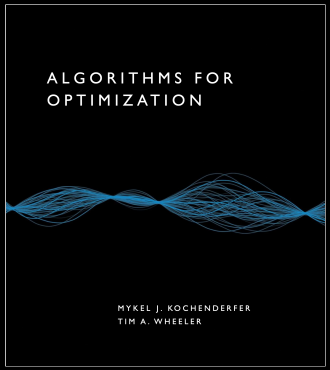

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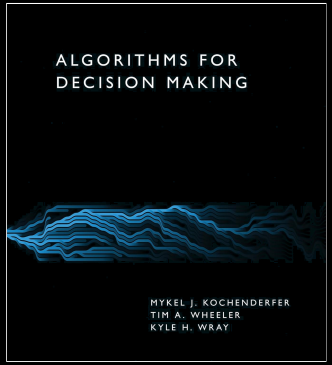

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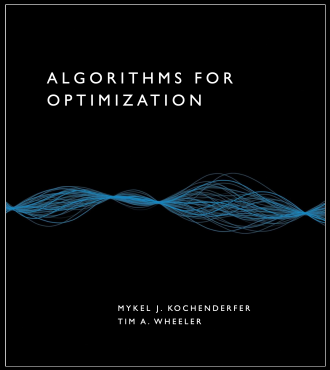

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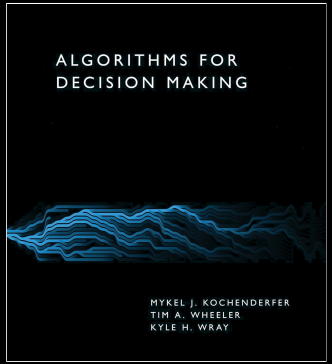

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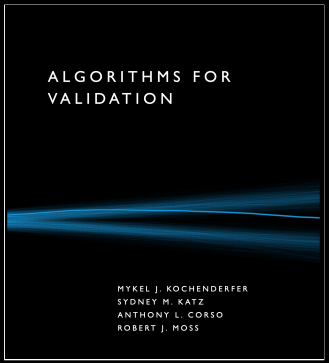

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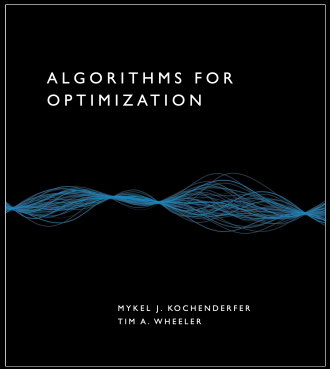

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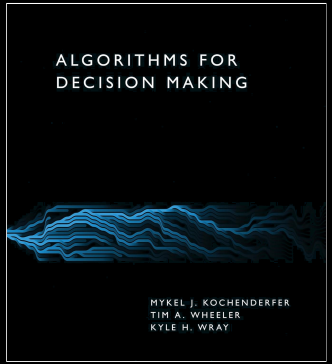

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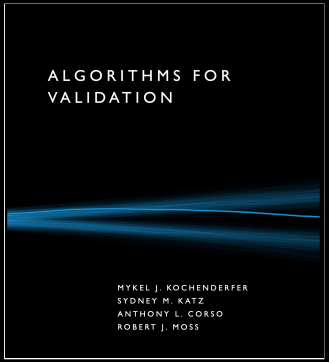
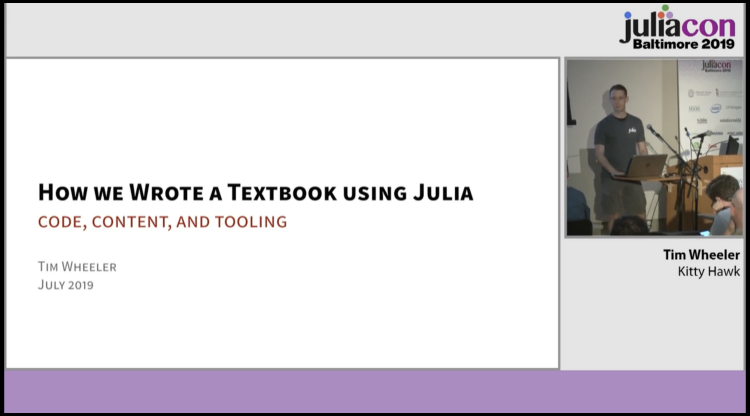


Algorithms for Validation
MIT Press, 2025

All PDFs available for free at `https://algorithmsbook.com`

JuliaCon 2019

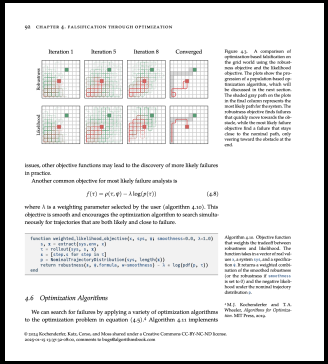


How We Wrote a Textbook using Julia

Tim Wheeler, JuliaCon 2019

Textbooks with integrated Julia

Textbooks with integrated Julia



60 CHAPTER 4. FALSIFICATION THROUGH OPTIMIZATION

Iteration 1 Iteration 5 Iteration 8 Converged

Robustness

Likelihood

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 the gradient-based optimization algorithm, which will be discussed in the next section. The shaded gray path on the plots in the final column represents the full path taken. Optimizing the robustness objective finds failures that quickly move towards the obstacle, while the most likely failure objective find a failure that stays near the center before abruptly 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

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

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, ϕ; smoothness=0.0, λ=1.0)
    τ, X = extract(sys, x)
    τ = rollout(sys, τ, X)
    p = logtrajectorypdf(τ)
    ρ = robustness(trajectory(τ)[1:length(X)])
    return robustness(ρ, ϕ.formula, smoothness) - λ * log(pdf(p, τ))
end
```

Algorithm 4.10. Objective function that weights the trained between robustness and likelihood. This function takes as a vector of real values x, a system sys, and a specification ϕ. It returns a weighted combination of the smoothed robustness (with a smoothness parameter set to 0.0) 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).[1] Algorithm 4.11 implements

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

Algorithms for Validation

Figures and Julia code

Textbooks with integrated Julia

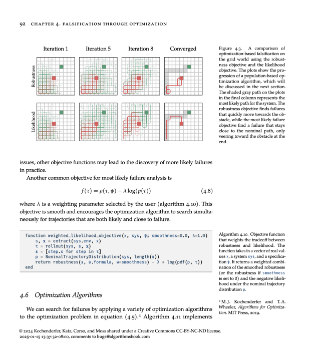

92 CHAPTER 4. FALSIFICATION THROUGH OPTIMIZATION

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.

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2025-01-15 13:37:32-08:00, comments to bugs@algorithmsbook.com

Algorithms for Validation

Figures and Julia code

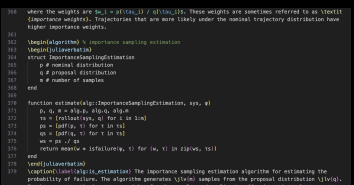
```
struct ImportanceSamplingEstimation
    p # nominal distribution
    q # proposal distribution
    m # number of samples
end

function estimate(alg::ImportanceSamplingEstimation, sys, ψ)
    p, q, m = alg.p, alg.q, alg.m
    τs = [rollout(sys, q) for i in 1:m]
    ps = [pdf(p, τ) for τ in τs]
    qs = [pdf(q, τ) for τ in τs]
    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{julieverbatim}
struct ImportanceSamplingEstimation
    p # nominal distribution
    q # proposal distribution
    m # number of samples
end

function estimate(alg::ImportanceSamplingEstimation, sys, ψ)
    (p, q, m = alg.p, alg.q, alg.m
    τs = [rollout(sys, q) for i in 1:m]
    ps = [pdf(p, τ) for τ in τs]
    qs = [pdf(q, τ) for τ in τs]
    ws = ps ./ qs
    return mean(w * isfailure(ψ, τ) for (w, τ) in zip(ws, τs))
end
\end{julieverbatim}
\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}

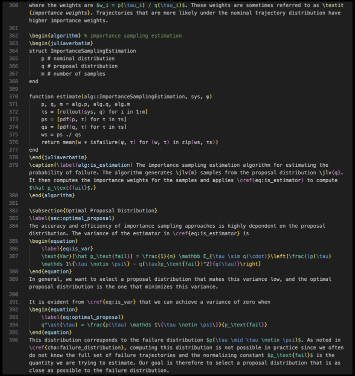
\subsection{Optimal Proposal Distribution}
\label{sec:optimal_proposal}
The accuracy and efficiency of importance sampling approaches is highly dependent on the proposal distribution. The variance of the estimator in \cref{eq:is_estimator} is
\begin{equation}
    \label{eq:is_var}
    \text{Var}\left[\hat p_\text{fail}\right] = \frac{1}{m} \mathbb E_{\tau \sim q}\left[\frac{p(\tau}{\mathbb 𝟙(\tau \notin \pit)} - q(\tau)p_\text{fail}\right]^2
\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} \mathbb 𝟙(\tau \notin \pit)}{p_\text{fail}}
\end{equation}
This distribution corresponds to the failure distribution $p(\tau \mid \tau \notin \pit)$. 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_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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    qs = [pdf(q, τ) for τ in τs]
    ws = ps ./ qs
    return mean(w * isfailure(ψ, τ) for (w, τ) in zip(ws, τs))
end
\end{juliaverbatim}
\caption{\label{alg:is_estimation} The importance sampling estimation algorithm for estimating the
probability of failure. The algorithm generates \jlv{m} samples from the proposal distribution \jlv{q}.
It then computes the importance weights for the samples and applies \cref{eq:is_estimator} to compute
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\end{algorithm}

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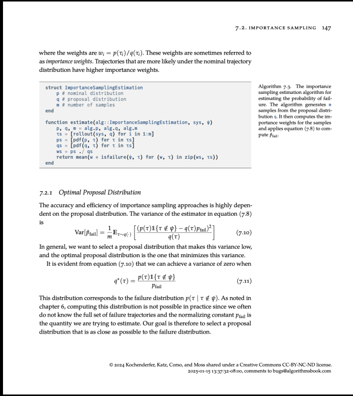
close as possible to the failure distribution.
```

LaTeX code example

Integrated Julia code using pythontex



7.2. IMPORTANCE SAMPLING 147

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

```
struct ImportanceSamplingEstimation
    p # nominal distribution
    q # proposal distribution
    m # number of samples
end

function estimate(alg::ImportanceSamplingEstimation, sys, ψ)
    p, q, m = alg.p, alg.q, alg.m
    τs = [rollout(sys, q) for i in 1:m]
    ps = [pdf(p, τ) for τ in τs]
    qs = [pdf(q, τ) for τ in τs]
    ws = ps ./ qs
    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 m samples from the proposal distribution q. It then computes the importance weights for the samples and applies equation (7.8) 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

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

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

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

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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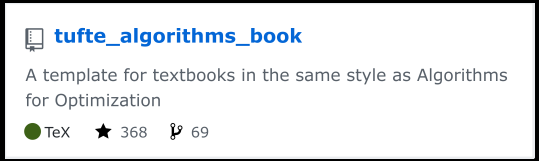

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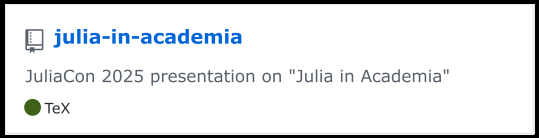

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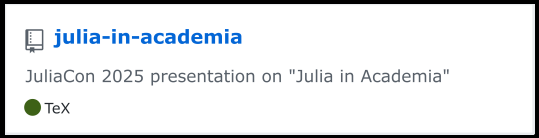

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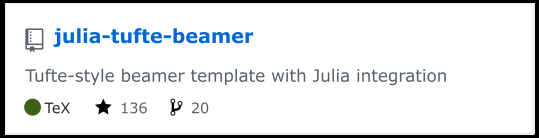

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Integrated Julia Example

We can compute Julia code *directly in the slides/pages*.

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```
julia> using SignalTemporalLogic
```

Integrated Julia Example

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```
julia> using SignalTemporalLogic
julia> τ = [-1.0, -3.2, 2.0, 1.5, 3.0, 0.5, -0.5, -2.0, -4.0, -1.5];
julia> ψ₁ = @formula ◊(s_t → s_t > 0);
```

```
τ  # \tau<TAB>
ψ₁ # \psi<TAB>\_1<TAB>
◊  # \lozenge<TAB>
```

Integrated Julia Example

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julia> ρ₁ = ρ(τ, ψ₁)
3.0
```

```
τ  # \tau<TAB>
ψ₁ # \psi<TAB>\_1<TAB>
◊  # \lozenge<TAB>
ρ  # \rho<TAB>
```

Integrated Julia Example

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julia> ψ₁ = @formula ◊(sₜ → sₜ > 0);
julia> ρ₁ = ρ(τ, ψ₁)
3.0
julia> ψ₂ = @formula □(sₜ → sₜ > 0);
```

```
τ  # \tau<TAB>
ψ₁ # \psi<TAB>\_1<TAB>
◊  # \lozenge<TAB>
ρ  # \rho<TAB>
□  # \square<TAB>
```

Integrated Julia Example

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julia> ψ₁ = @formula ◊(sₜ → sₜ > 0);
julia> ρ₁ = ρ(τ, ψ₁)
3.0
julia> ψ₂ = @formula □(sₜ → sₜ > 0);
julia> ρ₂ = ρ(τ, ψ₂)
-4.0
```

```
τ  # \tau<TAB>
ψ₁ # \psi<TAB>\_1<TAB>
◊  # \lozenge<TAB>
ρ  # \rho<TAB>
□  # \square<TAB>
```

Integrated Julia Example

We can compute Julia code *directly in the slides/pages*.

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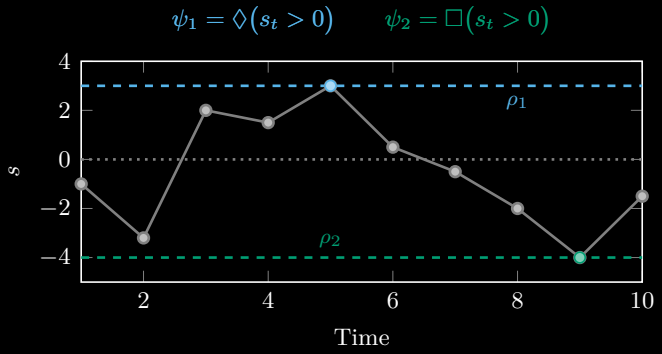

Julia for Textbooks: The Good

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- Concise algorithm descriptions (fits within single page)

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

Showcase: `IntervalArithmetic.jl` and `LazySets.jl`

Showcase: IntervalArithmetic.jl and LazySets.jl

```
struct NaturalInclusion <: ReachabilityAlgorithm
    h # time horizon
end

function r(sys, x)
    s, x = extract(sys.env, x)
    τ = rollout(sys, s, x)
    return τ[end].s
end

to_hyperrectangle(I) = Hyperrectangle(low=[i.lo for i in I],
                                      high=[i.hi for i in I])

function reachable(alg::NaturalInclusion, sys)
    I′s = []
    for d in 1:alg.h
        I = intervals(sys, d)
        push!(I′s, r(sys, I))
    end
    return UnionSetArray([to_hyperrectangle(I′) for I′ in I′s])
end
```

Showcase: IntervalArithmetic.jl and LazySets.jl

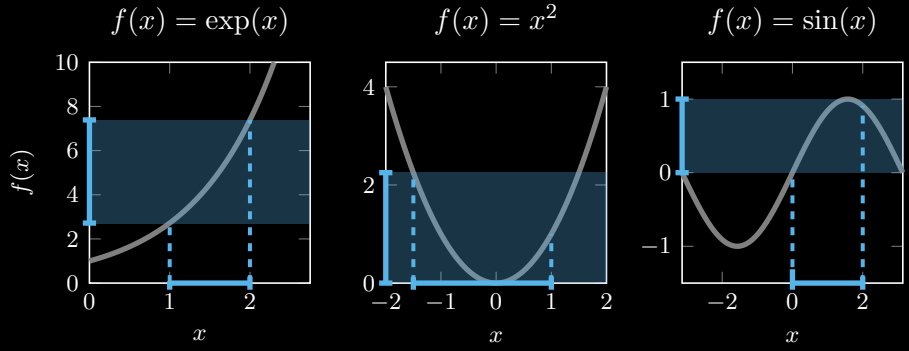

Figure: Example of the interval counterparts for the exp, square, and sin functions.

Showcase: IntervalArithmetic.jl and LazySets.jl

```
function (env::InvertedPendulum)(s, a)
    θ, ω = s[1], s[2]
    dt, g, m, l = env.dt, env.g, env.m, env.l
    ω = ω + (3g / (2 * l) * sin(θ) + 3 * a / (m * l^2)) * dt
    θ = θ + ω * dt
    return [θ, ω]
end
```

Showcase: IntervalArithmetic.jl and LazySets.jl

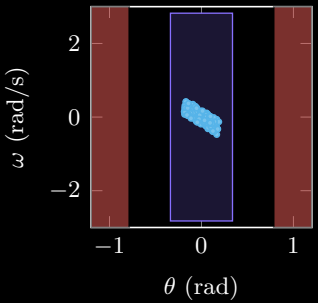

Figure: Inverted pendulum reachable set using IntervalArithmetic.jl and LazySets.jl.

Julia for Textbooks: The Not-So-Good

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- Textbook tooling: Needed to be built out from scratch

Julia in the Classroom

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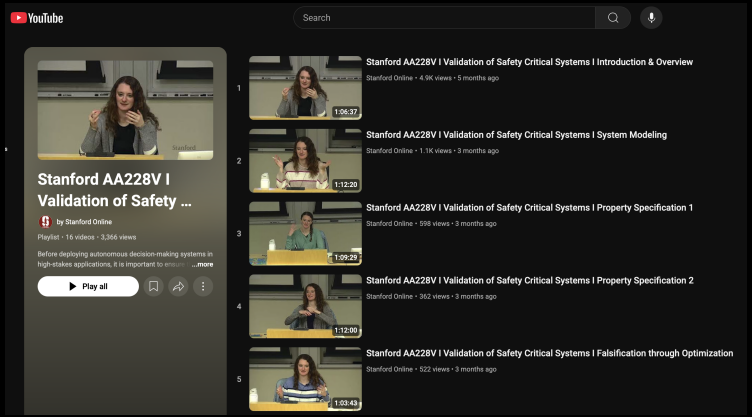
Grad-level course at Stanford

Follows *Algorithms for Validation* textbook

First offered in Winter 2025

Lectures

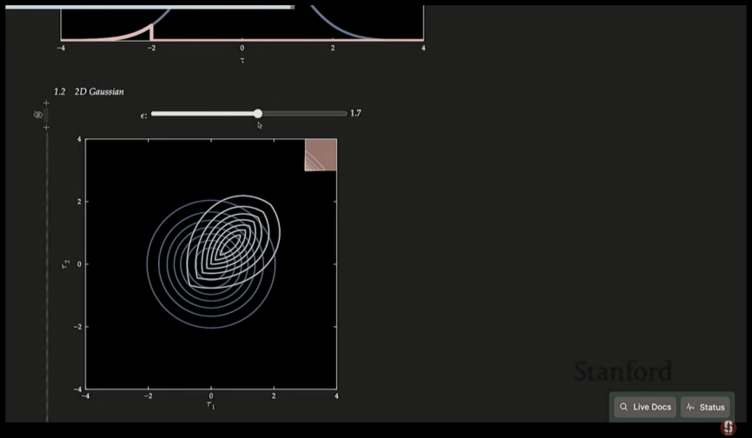
Lectures



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

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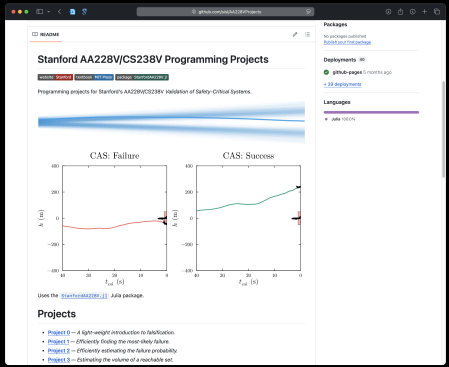
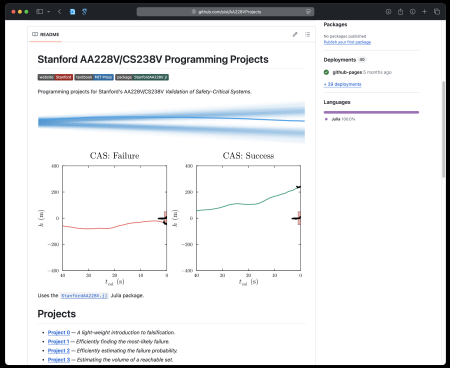


Assignments repository

Student-facing code

Assignments in Julia



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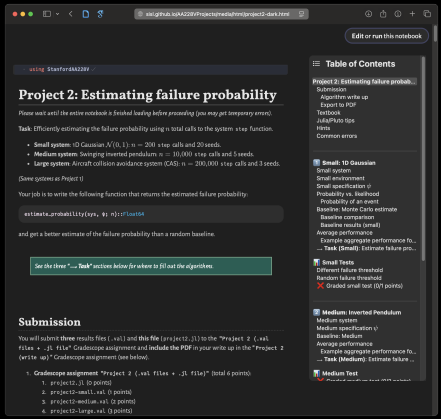
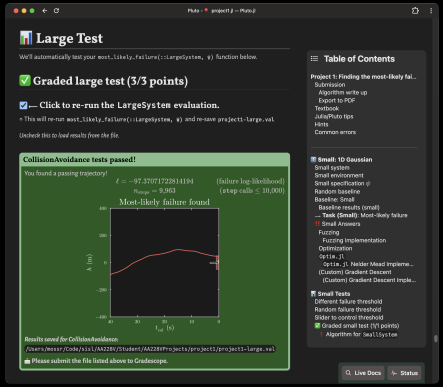


Pluto assignments

Includes local tests

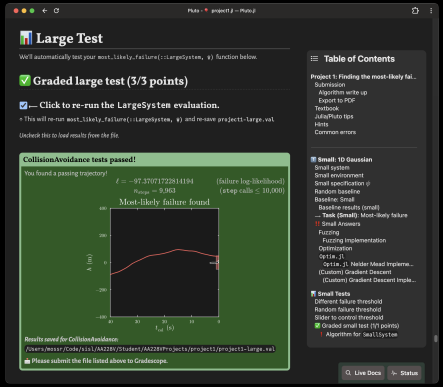
Assignments in Julia



Interactive Pluto tests

Get feedback instantly

Assignments in Julia



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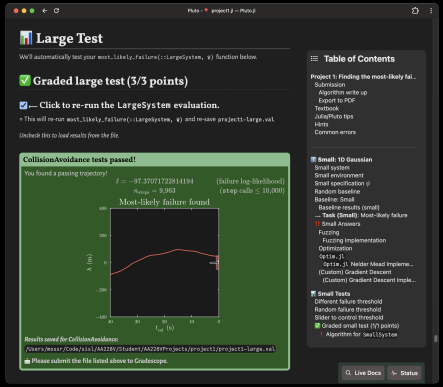

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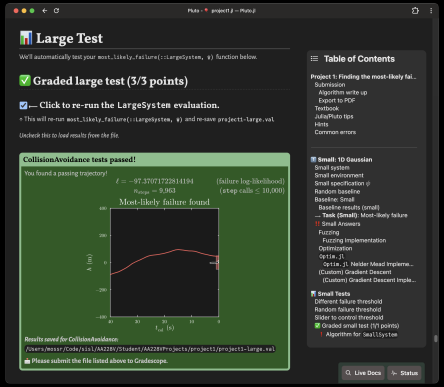

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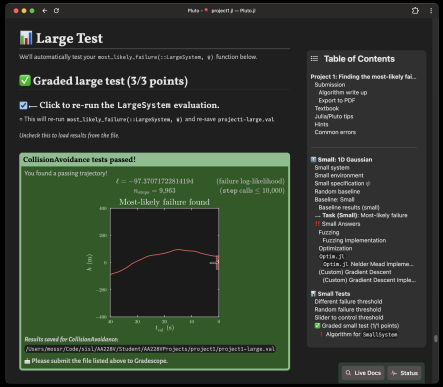

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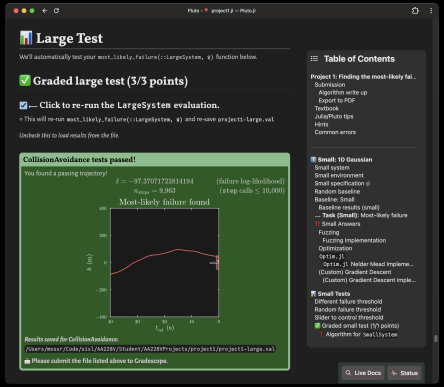

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Grading Assignments

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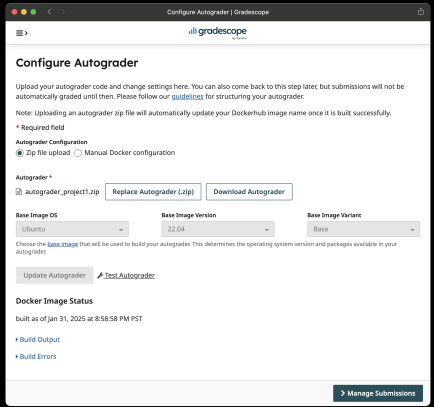
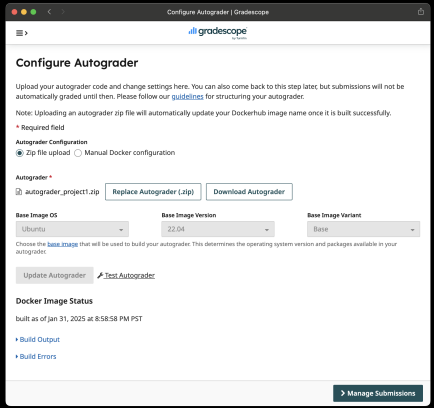


Autograde via Gradescope

Students upload Pluto notebook

Grading Assignments



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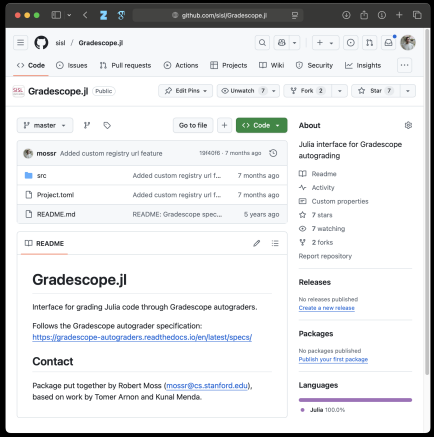

Light-weight `Gradescope.jl` package

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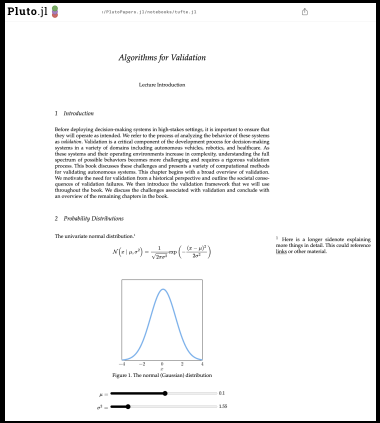
What if we could interact directly with the code in research papers?

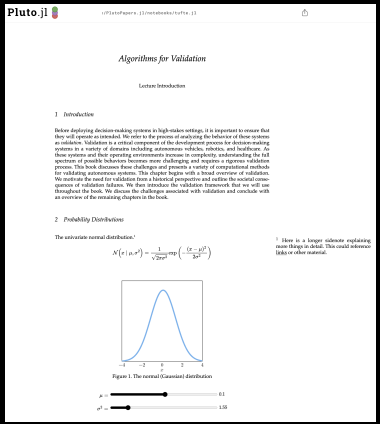
PlutoPapers.jl



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