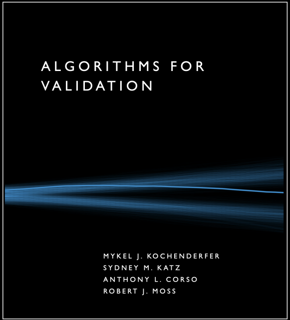
Julia in Academia

Textbooks, Stanford Courses, and the Future



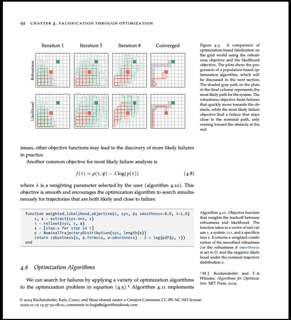

92 CHAPTER 4. FALSIFICATION THROUGH OPTIMIZATION

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.

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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.

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

Robert Moss, PhD
Stanford University | JuliaCon 2025
mossr@cs.stanford.edu

WHOAMI

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Recent Stanford PhD Graduate

Used Julia throughout my research

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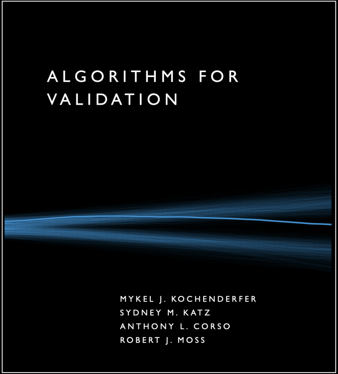
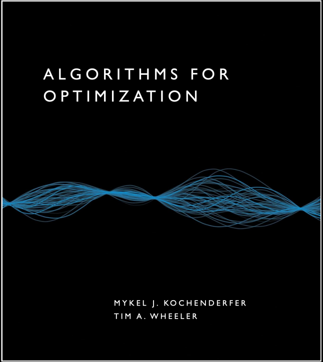


Textbook Co-Author/Head TA
Algorithms written in Julia

Textbooks using Julia

Textbooks using Julia



Algorithms for Optimization
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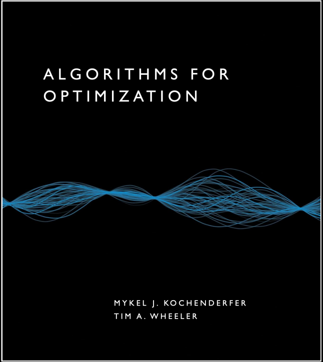

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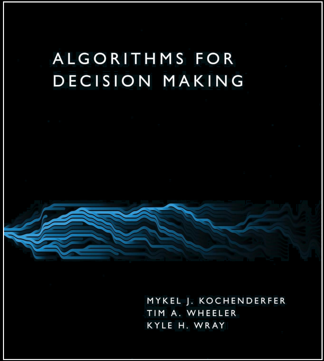

Algorithms for Decision Making
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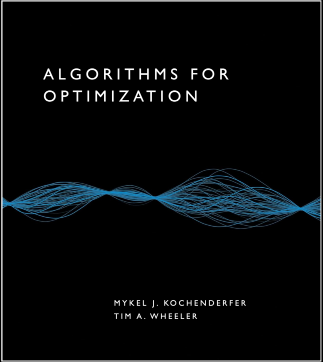

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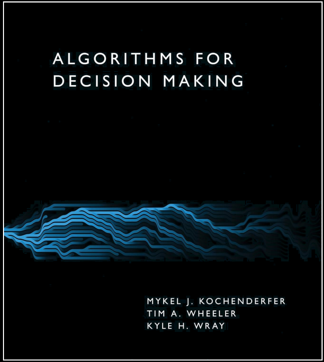

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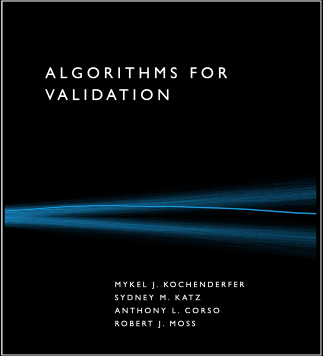

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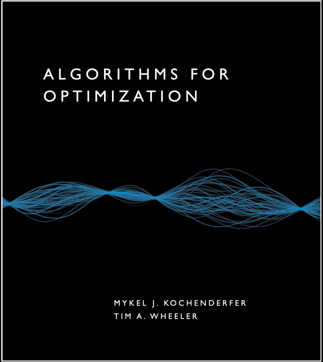

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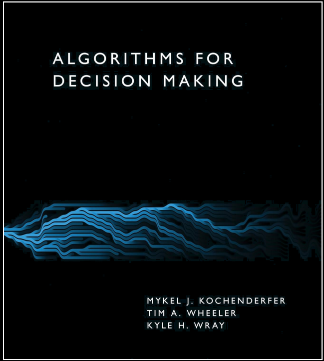

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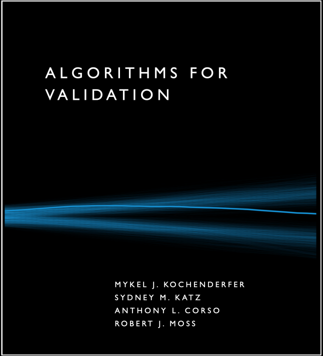

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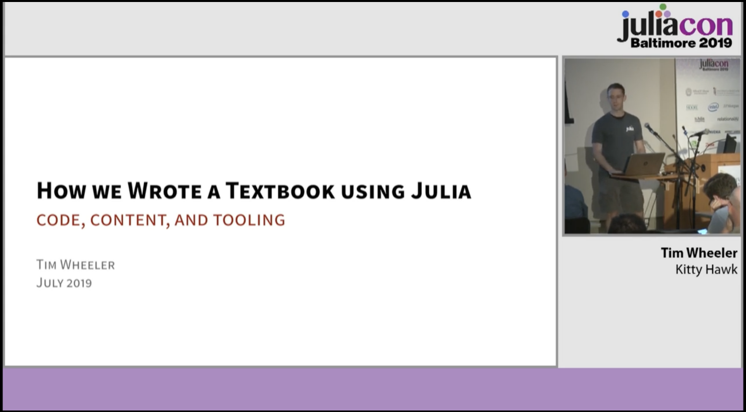
All PDFs available for free at `https://algorithmsbook.com`

JuliaCon 2019



How We Wrote a Textbook using Julia
Tim Wheeler, JuliaCon 2019

Textbooks with integrated Julia

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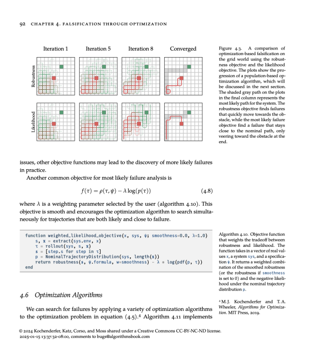

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Algorithms for Validation

Figures and Julia code

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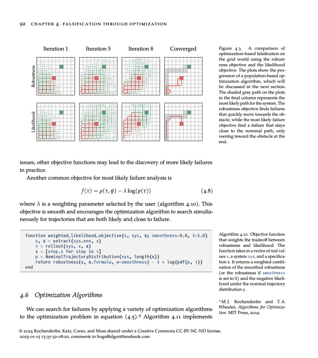

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Algorithms for Validation

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end
```

Example algorithm

Importance sampling estimation of failure probability

Julia integrated into LaTeX code

```latex
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.

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\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}[\hat p_\text{fail}] = \frac{1}{m} \mathbb E_{\tau \sim q(\cdot)}\left[\frac{(p(\tau) \mathds 1\{\tau \notin \psi\} - q(\tau)p_\text{fail})^2}{q(\tau)}\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) \mathds 1\{\tau \notin \psi\}}{p_\text{fail}}
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This distribution corresponds to the failure distribution $p(\tau \mid \tau \notin \psi)$. As noted in \cref{cha: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.
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LaTeX code example

Integrated Julia code using `pythontex`

Julia integrated into $\LaTeX$ code

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$\LaTeX$ code example

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7.2.1 *Optimal Proposal Distribution*

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Compiled $\LaTeX$ PDF

Julia algorithms and $\LaTeX$ math

Open-Source Textbook Template Repository

Open-Source Textbook Template Repository

tufte_algorithms_book

A template for textbooks in the same style as Algorithms for Optimization

TeX ★ 368 69

github.com/sisl/tufte_algorithms_book

Open-Source Slides Repo (beamer + pythontex)

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julia-in-academia

JuliaCon 2025 presentation on "Julia in Academia"

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julia-tufte-beamer

Tufte-style beamer template with Julia integration

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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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- Potential obscure idioms: broadcasting, anonymous functions, multiple dispatch
- Textbook tooling: Needed to be built out from scratch

Julia in the Classroom

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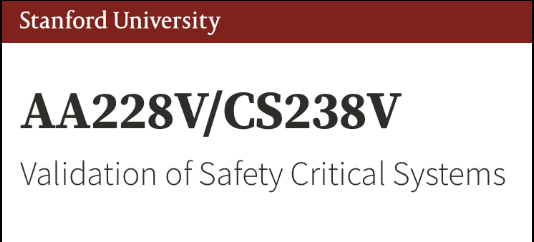


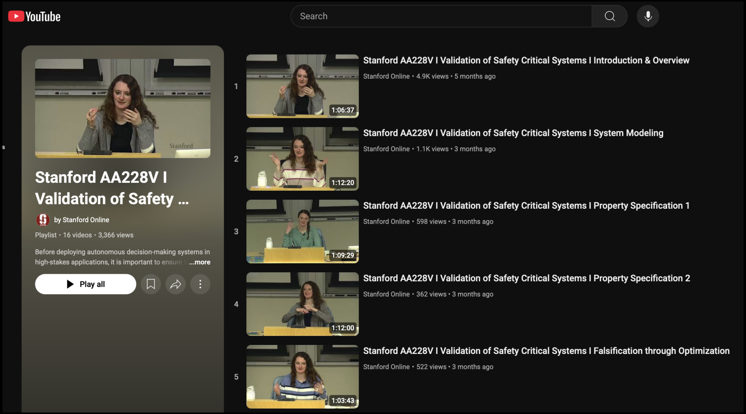
Grad-level course at Stanford

Follows *Algorithms for Validation* textbook

First offered in Winter 2025

Lectures

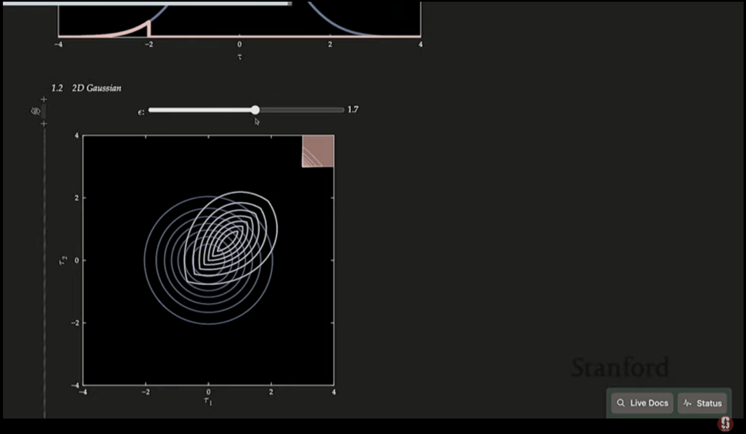
Lectures



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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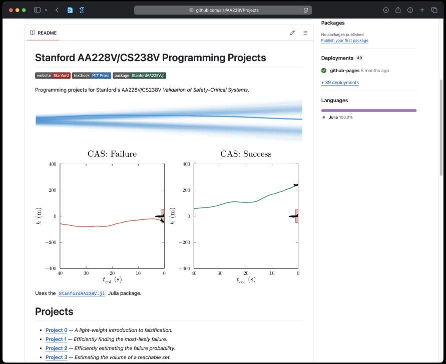
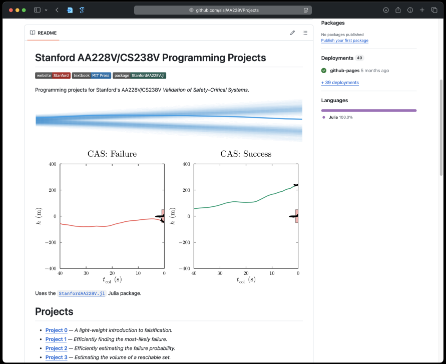


Assignments repository

Student-facing code

Assignments in Julia



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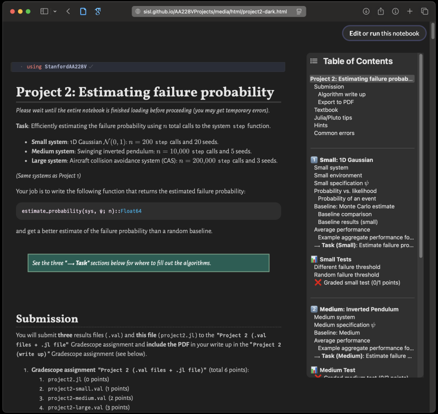
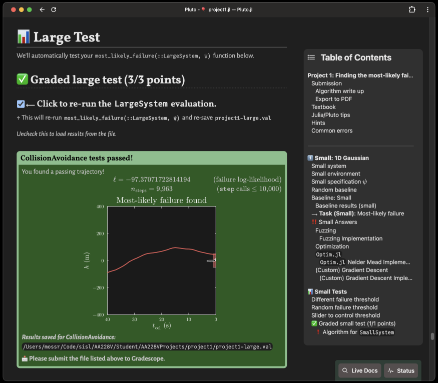


Pluto assignments

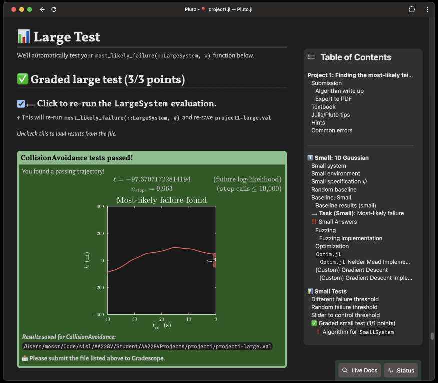
Includes local tests

Assignments in Julia



Interactive Pluto tests
Get feedback instantly

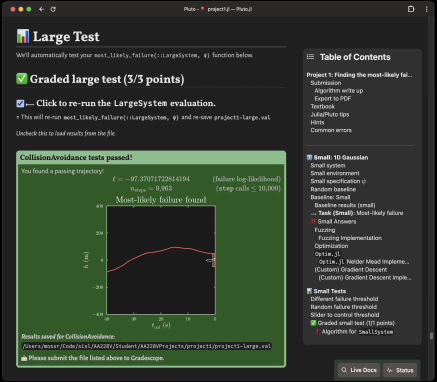
Assignments in Julia



Interactive Pluto tests
Get feedback instantly

- Separated assignment code from core library (`StanfordAA228V.jl`)

Assignments in Julia



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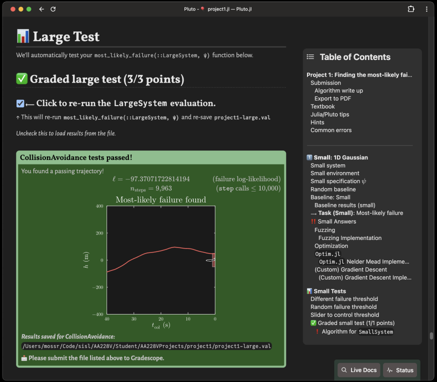

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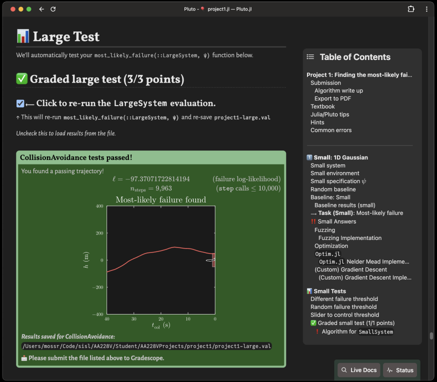

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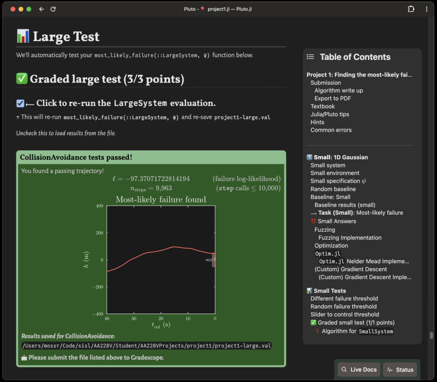
- Interactive nature allows students to play with their algorithms
- No "hidden state" that may confuse students

Assignments in Julia



Interactive Pluto tests
Get feedback instantly

- Separated assignment code from core library (`StanfordAA228V.jl`)
- Local tests exactly match graded tests
- Interactive nature allows students to play with their algorithms
- No "hidden state" that may confuse students
- Open-source nature requires clever obfuscation of solution code

Grading Assignments

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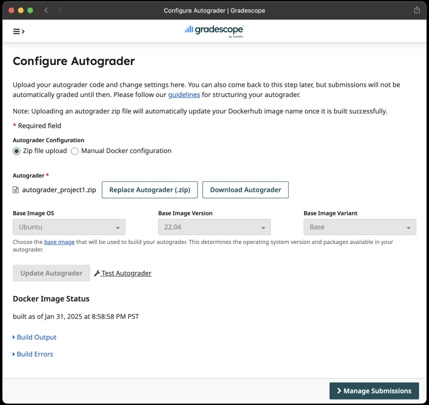
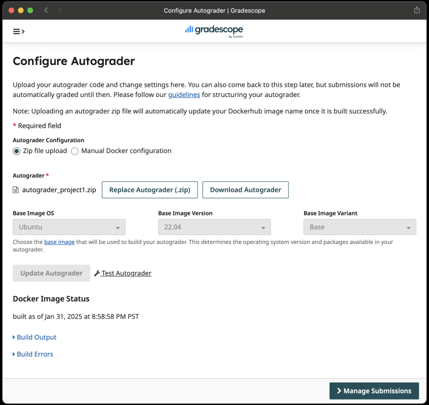


Autograde via Gradescope

Students upload Pluto notebook

Grading Assignments



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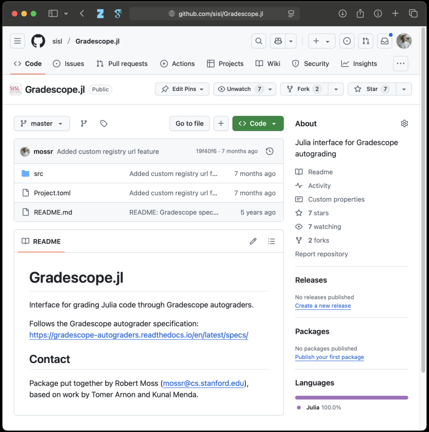

Light-weight `Gradescope.jl` package

Manage deps and create autograders

Future use of Julia in Academia

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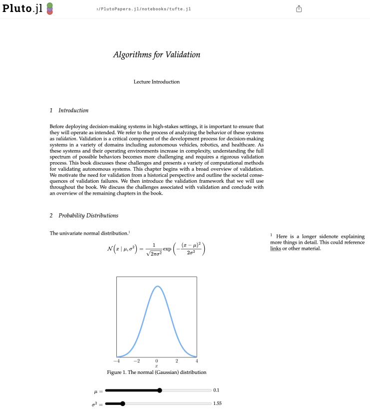
- Compile Julia code to binaries to avoid obfuscation
- Write interactive research papers in Julia/Pluto

PlutoPapers.jl

PlutoPapers.jl

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

PlutoPapers.jl



Pluto.jl

/PlutoPapers.jl/notebooks/tufte.jl

Algorithms for Validation

Lecture Introduction

1 *Introduction*

Before deploying decision-making systems in high-stakes settings, it is important to ensure that they will operate as intended. We refer to the process of analyzing the behavior of these systems as *validation*. Validation is a critical component of the development process for decision-making systems in a variety of domains including autonomous vehicles, robotics, and healthcare. As these systems and their operating environments increase in complexity, understanding the full spectrum of possible behaviors becomes more challenging and requires a rigorous validation process. This book discusses these challenges and presents a variety of computational methods for validating autonomous systems. This chapter begins with a broad overview of validation. We motivate the need for validation from a historical perspective and outline the societal consequences of validation failures. We then introduce the validation framework that we will use throughout the book. We discuss the challenges associated with validation and conclude with an overview of the remaining chapters in the book.

2 *Probability Distributions*

The univariate normal distribution.[1]

$$\mathcal{N}\left(x \mid \mu, \sigma^2\right) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

[1] Here is a longer sidenote explaining more things in detail. This could reference links or other material.

Figure 1. The normal (Gaussian) distribution

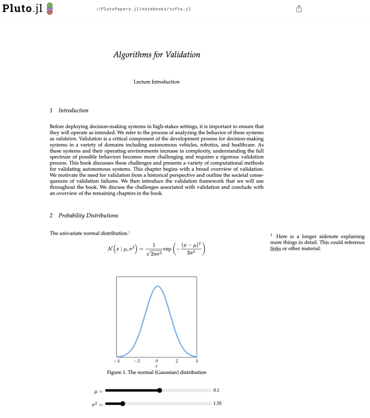
$\mu =$ 0.1

$\sigma^2 =$ 1.55

Interactive research papers

Run code directly in the paper

PlutoPapers.jl


Pluto.jl ⁄PlutoPapers.jl/notebooks/tufte.jl

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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