

# **ODEParameterEstimation.jl: Robust Parameter Estimation for ODEs**

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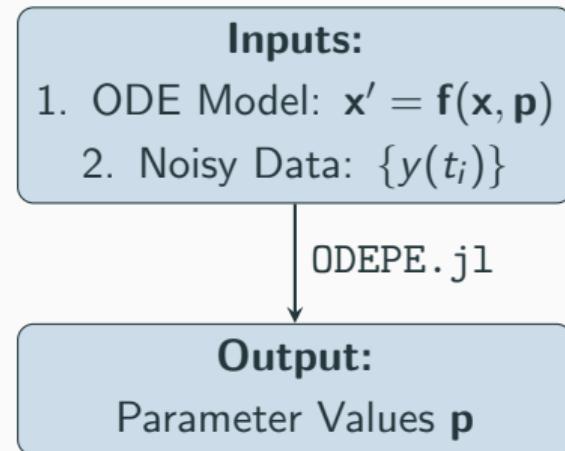
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# The Big Picture: What is ODEParameterEstimation.jl?

Many real-world systems are described by ODEs, but we often don't know the parameters.

`ODEParameterEstimation.jl` is a toolbox for discovering these unknown parameters directly from data.



## A Walkthrough of the Method (1/2)

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2. **Approximate Derivatives from Data:** At a time  $t_i$ , compute numerical values for  $y(t_i), y'(t_i), \dots$  from measurements. This is the critical step where GPR is used.

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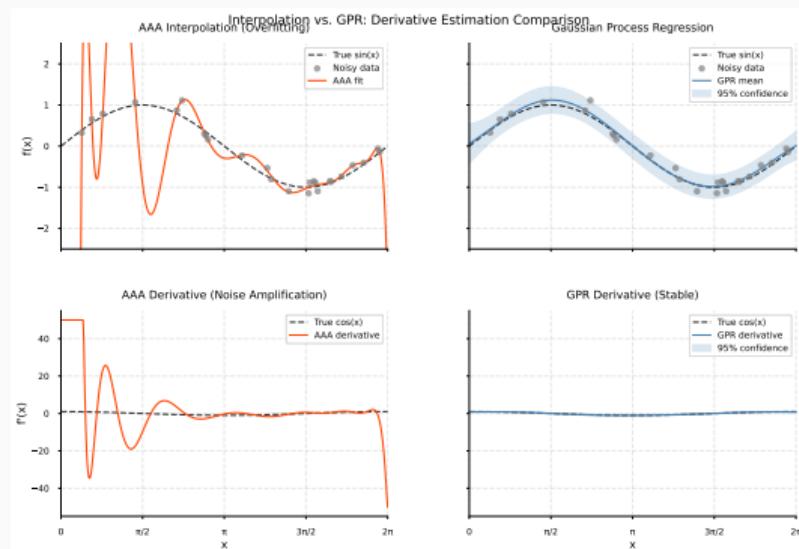
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4. **Solve:** Use a numerical polynomial solver to find all sets of solutions for the parameters ( $a, b$ ) and states ( $x(t_i)$ ).
5. **Filter & Validate:** Use forward simulation to find the best-fitting parameter set.

# The Challenge: Real-World Data is Noisy

## The Problem

The original method, based on AAA baryrational interpolation, is extremely accurate on clean data but fails catastrophically with noise. Interpolation overfits, leading to unstable derivatives.



**Figure 1:** Interpolation vs. Regression

## The Solution: Taming Noise with Gaussian Process Regression

### Why Gaussian Process Regression (GPR)?

GPR defines a *prior distribution over functions* and updates it based on the data.

- **Principled Smoothing:** A smoothness assumption is encoded in the prior via a kernel function (e.g., RBF).
- **Noise Modeling:** GPR explicitly models measurement noise, learning the noise level from the data itself.
- **Analytic Derivatives:** The posterior mean function is smooth and can be differentiated reliably.

### The Result

Robust and accurate derivative estimation, even with noisy data.

## The Results: Robust and Accurate

### Benchmark on Nonlinear Systems

Noise	Lotka-Volterra			Van der Pol		
	GPR	AAA	SciML	GPR	AAA	SciML
0.0%	0.0%	0.0%	9.1%	0.0%	0.0%	7.6%
1.0%	4.4%	29.0%	7.7%	0.8%	7.8%	13.5%
5.0%	13.7%	> 229%	4.1%	1.3%	64.2%	6.7%

### Key Takeaway

The GPR-enhanced method is robust to noise, making it practical for real-world applications.

## Why Julia?

Julia is the perfect language for this kind of work!

- **Symbolic Manipulation:** Symbolics.jl
- **Numerical Methods:** DifferentialEquations.jl, GaussianProcesses.jl, Groebner.jl, HomotopyContinuation.jl
- **High Performance:** Fast enough for complex systems.
- **Composable:** Easy to combine different tools and packages.

## Get Involved!

`github.com/orebas/ODEParameterEstimation`

(Formerly known as ParameterEstimation.jl)

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# Thank You

Questions?