Calibrating Agent-Based Models with Machine Learning Surrogates

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What is the Problem?

What is our Approach?

Example

Evaluation Times

Empirical Results

Empirical Results

What is the Problem?

(*many*) Macroeconomic Agent-Based Models (ABMs) are

- computationally expensive
- defined by dozens of parameters
- hard to calibrate, estimate, test, explore *

*Due to complex parameter-specific behaviours.

What are we proposing?

Machine Learning *Surrogates*!

Faster

- Agent-Based Model “Calibration” (e.g. Inference)

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- Scenario Stress Testing (e.g. Monte Carlo)

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- Scenario Stress Testing (e.g. Monte Carlo)
- Policy Exercises (e.g. Exploration)

Surrogate(**ABM** + “Calibration” Quality Test)

$$\text{Surrogate}\left(\textbf{Brock \& Hommes}\ \text{ABM} + \begin{array}{c}\text{Kolmogorov–Smirnov}\\ \text{Two Sample Test}\end{array}\right)$$

Brock & Hommes (BH)

Very simple ABM with **10 parameters**

Brock & Hommes

This model is **NOT** representative of complex Macroeconomic Agent-Based Models

Smooth Learning Manifold

but

13.4 quadrillion combinations

Tiny positive region

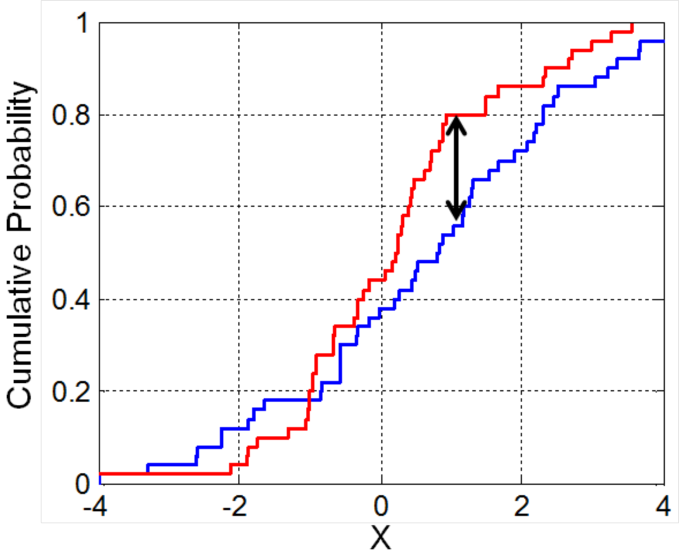
Enormous parameter space!

The Curse of Dimensionality!

How do we measure calibration quality?

Kolmogorov–Smirnov Two Sample Test (KS)

$$D_{n,n'} = \sup_x \left| F_{X^{SP500},n}(x) - F_{X^{BH},n'}(x) \right|$$



Cumulative Probability
1
0.8
0.6
0.4
0.2
0
-4
-2
0
2
4
X

Evaluation Times

Single Evaluation

$$BH + KS = 0.30 seconds$$

Policy Constraint

Security prices are not negative

Policy Constraint

Only run parameters y_i that pass the following constraint (filter),

$$S(T_1 * P + B_1) + (1 - S) * (T_2 * P + B_2) > 0,$$

where S is the share type, P is the initial deviation from the fundamental price, B_1 and B_2 are the bias of agent 1 and 2, and T_1 and T_2 are the trend of agent 1 and 2.

Simulation X

$$\mathrm{BH}(y_i) = X^{\mathrm{BH}}$$

Simulation Objective

y_i that produce 250 Log Returns

An *obvious* Constraint

Length Filter

ABM simulations should produce
250 Log Returns

Length Filter

$$len(X^{\mathsf{BH}}) == 250$$

Length Filter (Density)

3,000 per 100,000[†]

[†] Random Latin Hypercube Sampling[4]

2-Sample KS Test

$$\mathrm{KS}(X^{\mathrm{SP500}}, X^{\mathrm{BH}}) = \{D_{X^{\mathrm{SP500}}, X^{\mathrm{BH}}}, \text{p-value}\}$$

KS Threshold

$$\text{p-value} > 0.05$$
$$D_{X^{\mathrm{SP500}}, X^{\mathrm{BH}}} < 0.20$$

KS Threshold (Density)

55 per 1,000,000‡

‡Random Latin Hypercube Sampling[4]

Dataset

Highly Imbalanced!

Evaluation Time

Evaluation Time

1,000,000 samples $\approx$ 3.5 days

Evaluation Time

100 passing tests $\approx$ 20.4 days

What about a Machine Learning Surrogate?

Surrogate Modeling

- Function Approximation [3]
- Meta-Modeling [1]
- “Response Surface” Methodology [2, 5]
- Experimental Design
- Model Emulation
- “Model of a Model”

Surrogate Solution

- Draw $1,000,000$ parameters using RLH
- Policy Constraint $\approx 500,000$
- Time to compute $y_i^{\text{PC}} \approx 0.25$ secs

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- Length Constraint $\approx 3,000$ $y_i^{\text{PC,len}}$: 5 min

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- $\text{KS}(X^{SP500}, X_i^{\text{PC,len}}) = \{D_{X^{\text{SP500}}, X_i^{\text{PC,len}}}, \text{p-value}_i^{\text{PC,len}}\}$: 800 min

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- $\mathrm{KS}(X^{SP500}, X_i^{\mathrm{PC,len}}) = \{D_{X^{\mathrm{SP500}}, X_i^{\mathrm{PC,len}}}, \text{p-value}_i^{\mathrm{PC,len}}\}$: 800 min
- Threshold Constraint ≈ 55 $y_i^{\mathrm{PC,len},\mathit{Thresholded}}$: 1 min

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- $\text{KS}(X^{SP500}, X_i^{\text{PC,len}}) = \{D_{X^{\text{SP500}}, X_i^{\text{PC,len}}}, \text{p-value}_i^{\text{PC,len}}\}$: $4,000$ min
- Threshold Constraint ≈ 55 $y_i^{\text{PC,len,}\mathit{Thresholded}}$: 1 min

Total Time

BH+KS: $6,508\frac{1}{4}$min

Out of Sample

$100,000,000$ out of sample y_i[§] ≈ 2 min

[§] using RLH

$$1,000 \times 6,508\tfrac{1}{4}\text{min} = 6,508,250 \text{ min}$$

- (*naive*) Budgeted Model Search[¶]: 60 min

[¶] https://github.com/hyperopt/hyperopt-sklearn

Machine Learning Surrogate

Filter OOS using Learned Model $\approx$ 12 min

Speedup (OOS Only)

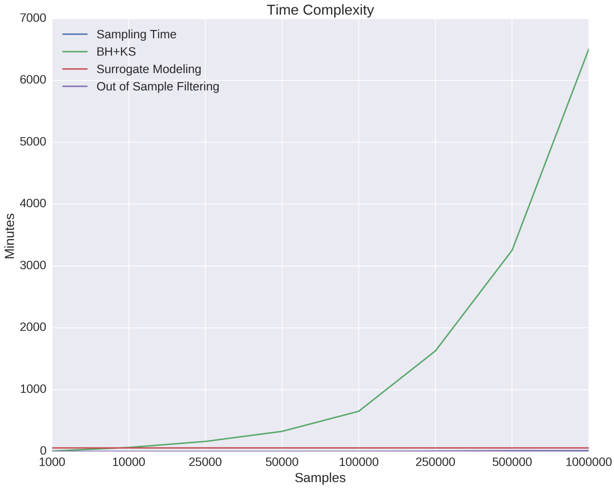
$$\text{BH+KS: } 1,000 \times 6,508\tfrac{1}{4}\text{min} = 6,508,250 \text{ min}$$

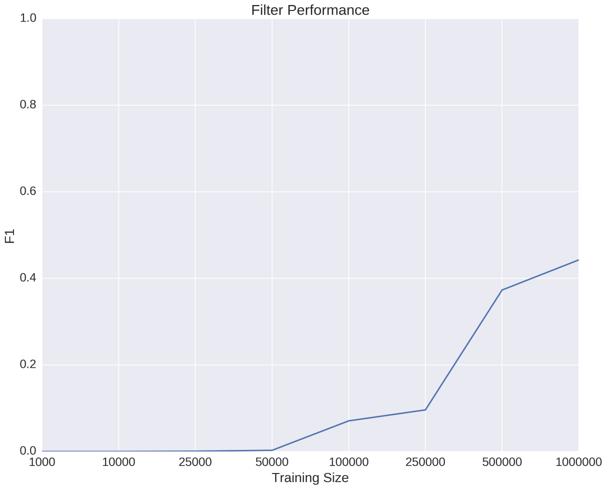
$$\text{Machine Learning Surrogate: } 72 \text{ min}$$

$$\approx 90,392\tfrac{1}{3}\times \text{ Speedup!}$$

Advantage

Reusable Machine Learning Surrogate Model


Time Complexity
Sampling Time
BH+KS
Surrogate Modeling
Out of Sample Filtering
Minutes
7000
6000
5000
4000
3000
2000
1000
0
1000
10000
25000
50000
100000
250000
500000
1000000
Samples


Filter Performance
F1
Training Size
1.0
0.8
0.6
0.4
0.2
0.0
1000
10000
25000
50000
100000
250000
500000
1000000

Thank you!

References

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[6] The Art of Software. *Derivation of Bias-Variance Decomposition*, September 2012. `http://artofsoftware.org/2012/09/13/derivation-of-bias-variance-decomposition/`.