



Data-Driven Simulation Calibration with Machine Learning

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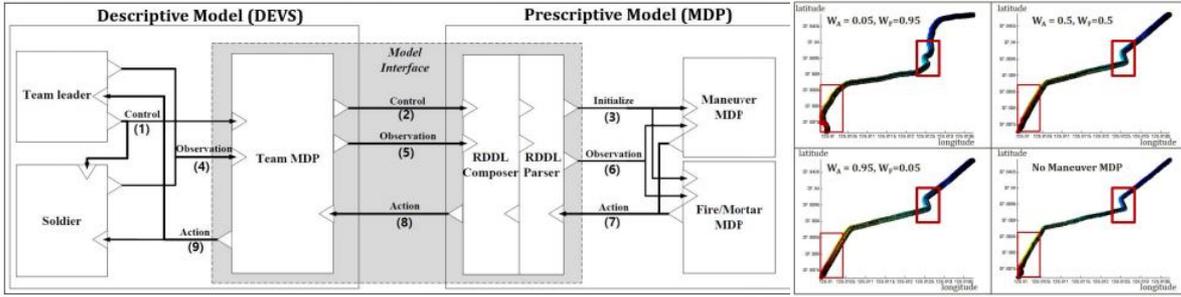
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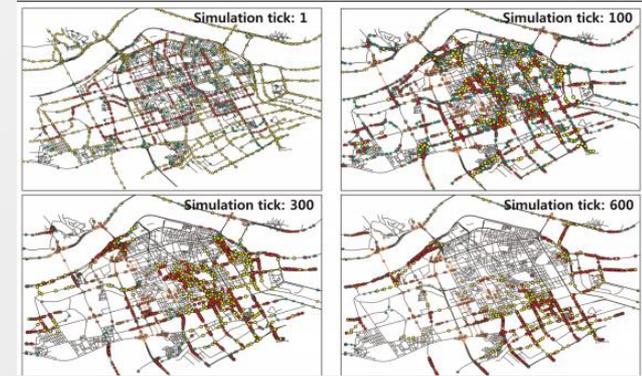
- Short Bio
 - Assistant, Associate Professor (2011-Present)
 - Department of Industrial and Systems Engineering, KAIST
 - PhD in Societal Computing (2008)
 - Institute of Software Research, School of Computer Science, Carnegie Mellon University
- Research Interest
 - Theoretic interests : ABM, M&S Formalism, Model Validation, Deep Generative Models...
 - Application domains : Defense, Recommendations, Profiling, Disaster Management...
- More information : aai.kaist.ac.kr

	Fundamentals	Applications	Fusions	
Modeling and Simulation	M&S Formalims (IEEE T-SMC 2016)	Simulation with Flattened Model Hierarchy (ACM TOMACS 2016)	Social Network Geospace ABM (AAMAS 2007)	Disaster Modeling (IEEE T-SMC 2018)
	Bayesian Nonparametric CF (IJCAI 2016)	VAE+RNN for Health Care (ICDM 2018)	VAE-CF+Tensor Fact. for Political Analysis (AAAI 2018)	Terrorists on Social Net. and Geospace (IEEE Intel. Sys. 2007)
Artificial Intelligence	Adversarial Dropout on CNN (AAAI 2018)	VAE for Collaborative Filtering (CIKM 2017)	Hierarchical Attention for Seq. Recommendation (AAAI 2019)	ABM+MDP (IEEE T-SMC Accepted)
	Adversarial Dropout on RNN (AAAI 2019)	Guided Hierarchical Topic Model (IEEE T-KDE 2017)	Social Network+Text for Email Analysis (KDD 2009)	Emotion Modeling with Brownian ABM (AAMAS 2014)

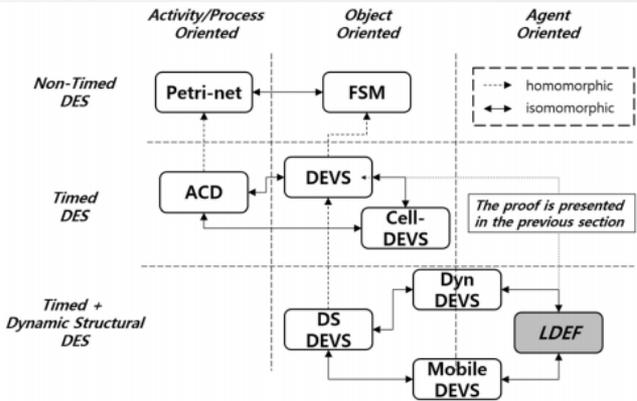
- Modeling and simulation on socio-economic problems
 - Commerce, disaster management, defense
- Theories on modeling and simulation



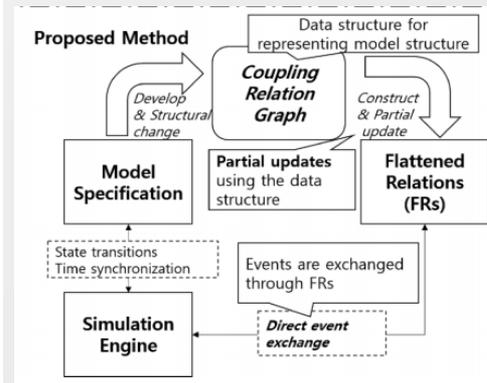
Descriptive-Prescriptive ABM with intelligent behaviors
IEEE T-SMC, Accepted



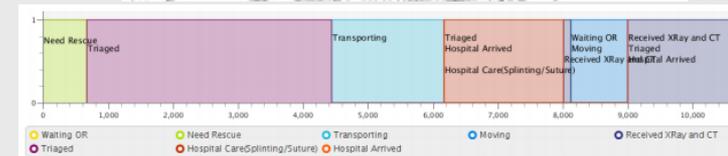
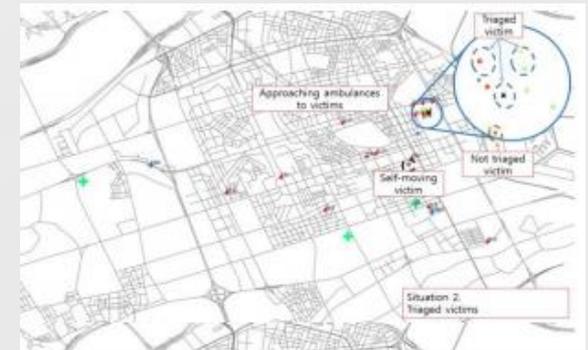
Urban Evacuation with ABM
SIMULATION, 2014



LDEF Formalism:
Formalism on ABM
IEEE T-SMC, 2016

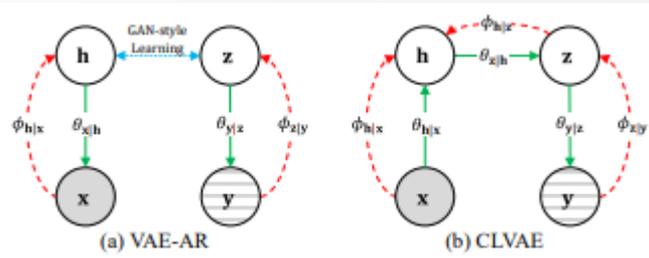


Discrete Event Simulation
Engine Optimization
ACM TOMACS, 2016

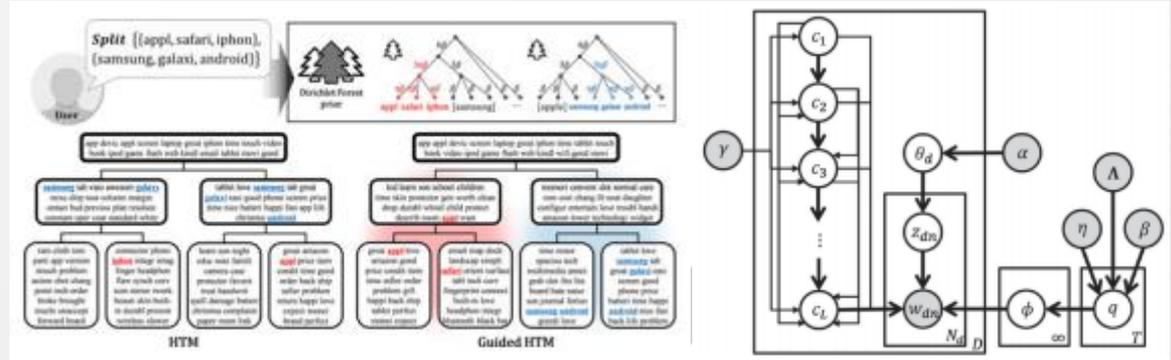


Emergency medical service with ABM
IEEE T-SMC, 2018

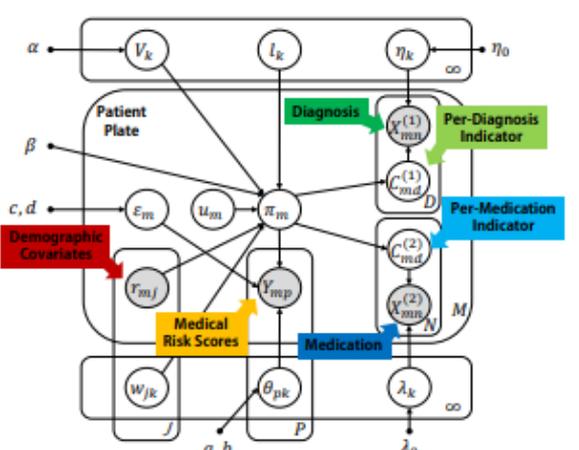
- Modeling and analyzing on socio-economic problems
 - With Probabilistic Graphical Model and Deep Generative Model
- Theories on neural network learning and deep generative models



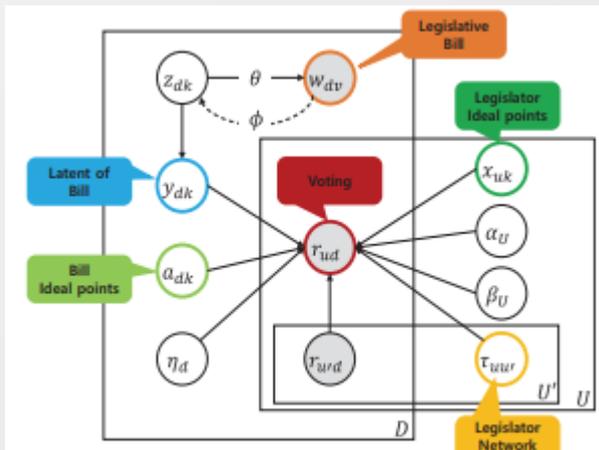
GAN-regularized, Ladder Variational Autoencoder for Collaborative Filtering, CIKM 2017



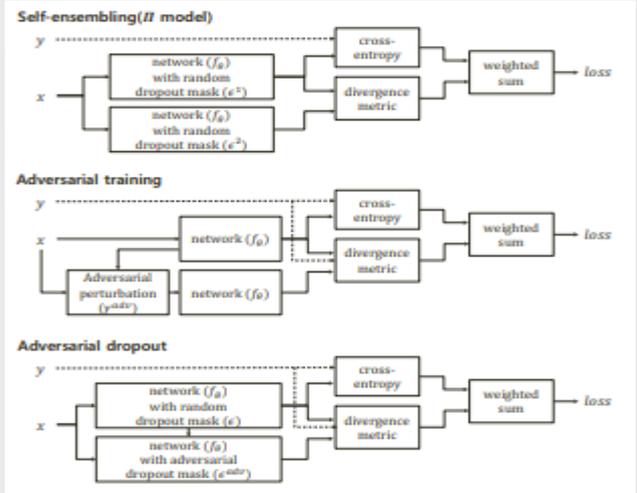
Guided hierarchical topic model, IEEE T-KDE, 2017



Bayesian Nonparametric Collaborative Topic Poisson Factorization For National Health-Care, IJCAI 2016



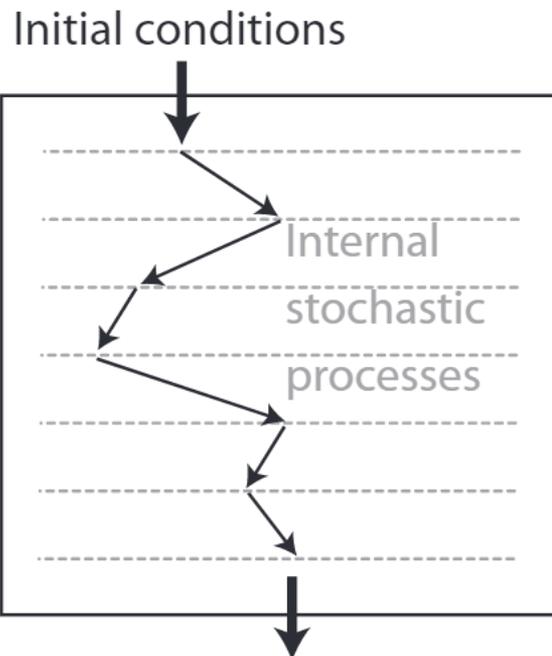
Neural Ideology Point Estimation Network for Law-Makers, AAI 2018



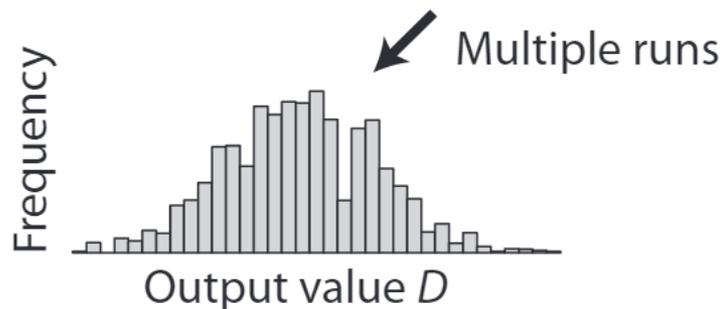
Adversarial Dropout for CNN/RNN, AAI 2018, AAI 2019

SIMULATION AS GENERATIVE MODEL

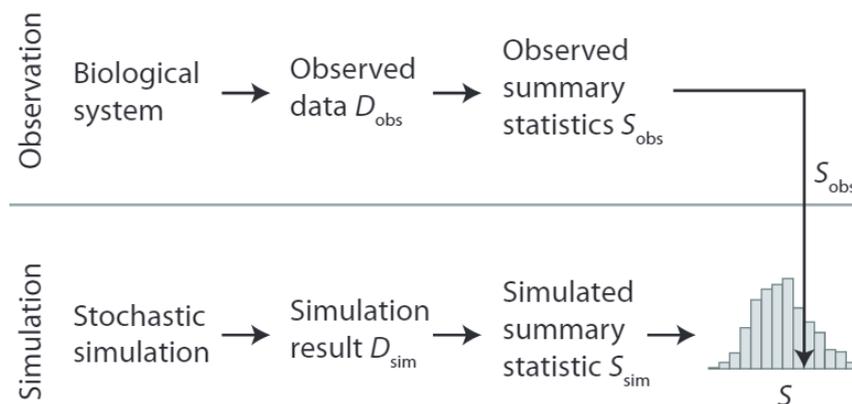
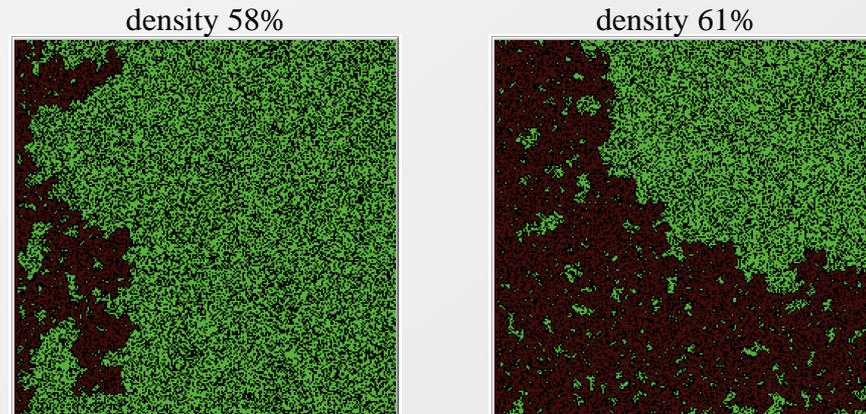
What is a stochastic simulation?



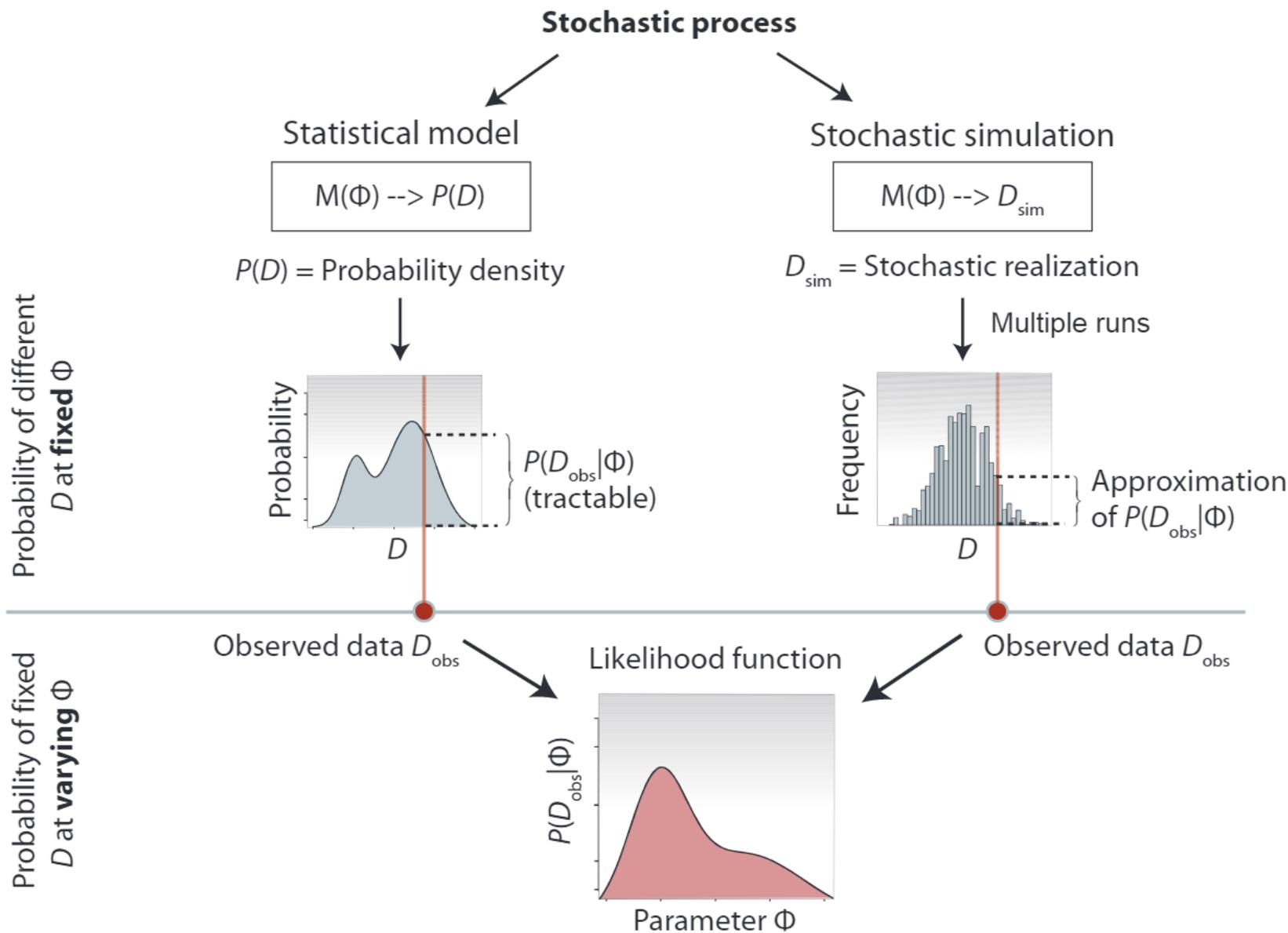
Stochastic realization D_{sim}



<Fire Burning Model>

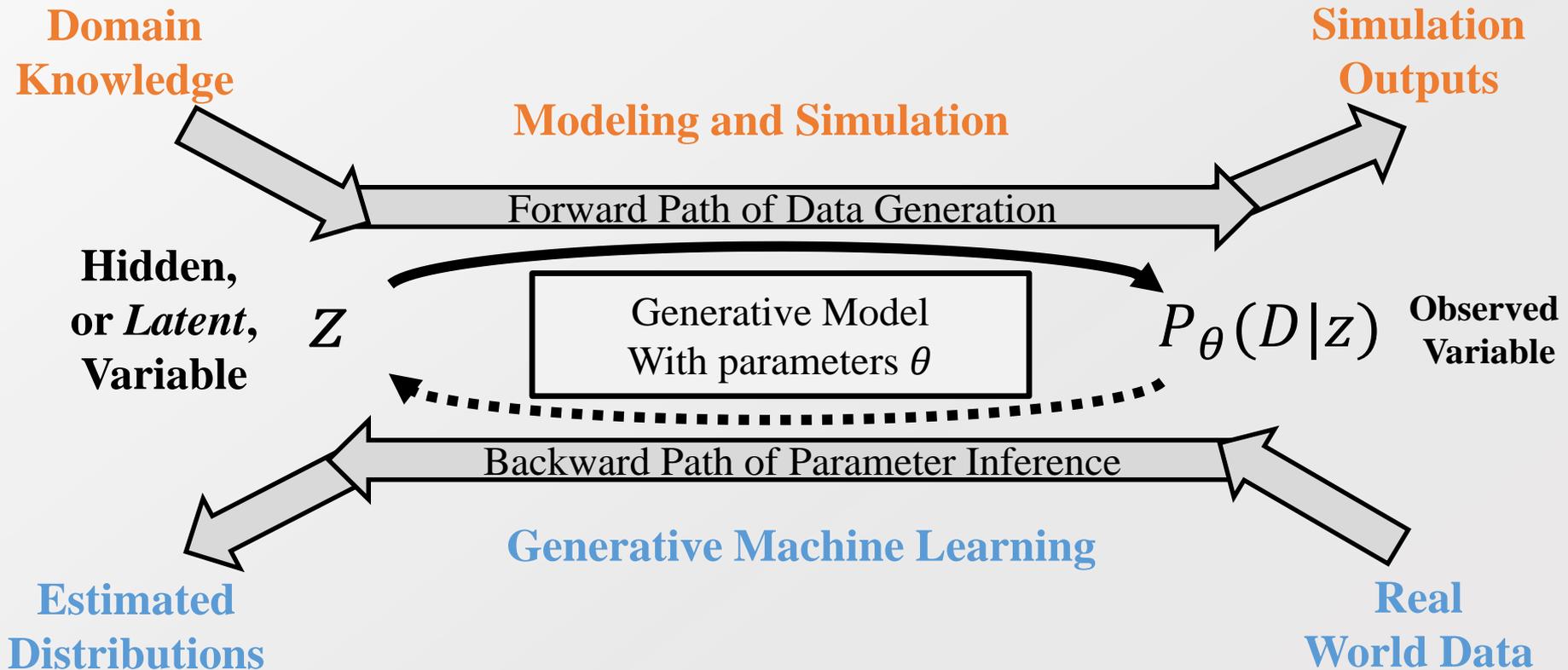


Simulation executes Models with Input Conditions + Parameters to generate Output Distribution

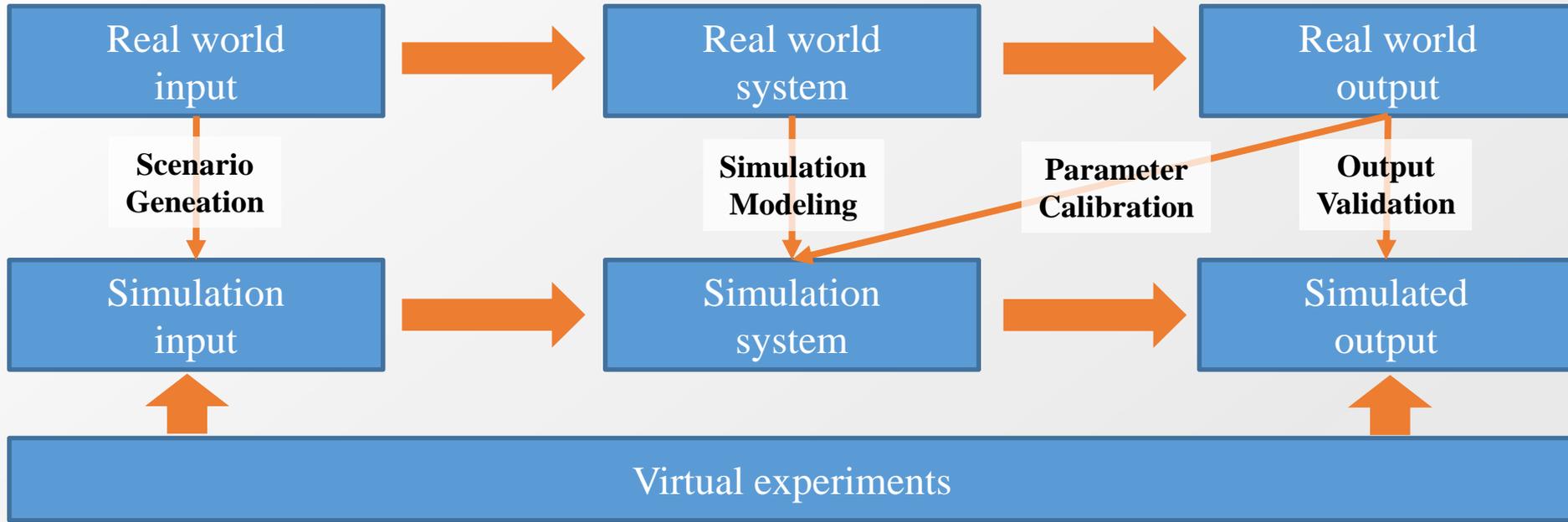


Generative Model in Two Directions

- Simulation expects to generate a **realistic virtual** output
 - Validation ensures the realism of the generated output
- Not all variables in the simulation models are known
 - Some variables are selected by domain experts or modelers



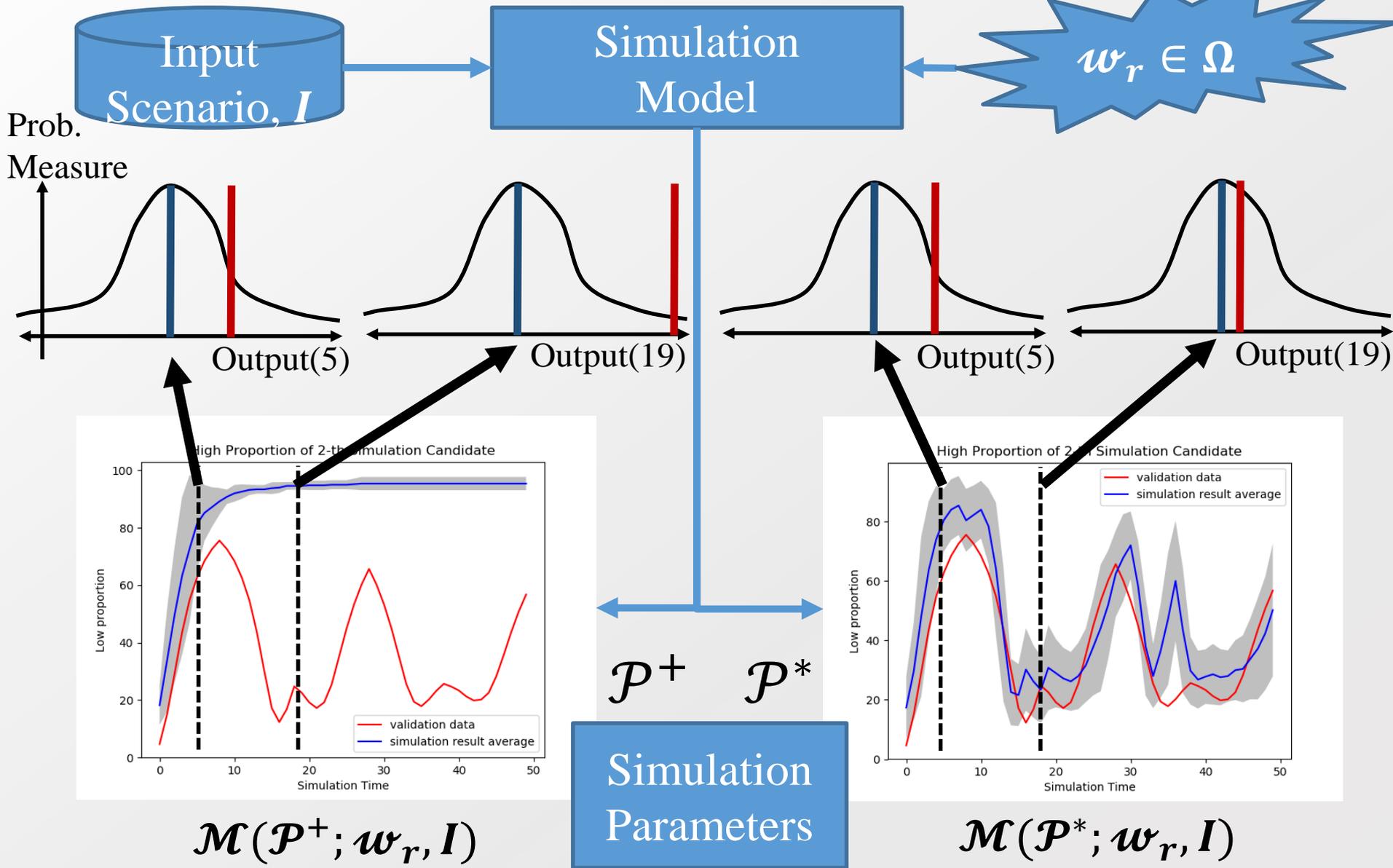
SIMULATION CALIBRATION



- Validation requires

- Realistic input scenario, which can be obtained from past data
- Realistic simulation model, which can be designed by domain experts
- Realistic simulation parameters
 - Some parameters are introduced by abstraction
 - Real world abstraction inevitably introduces approximations on parameters
 - How to well approximate parameters == **Calibration**

Concent of Calibration and Validation



Formal Description of Calibration

$$\mathcal{P}^* = \underset{\mathcal{P}}{\text{arg min}} \underbrace{d\left(E_R \left[\underbrace{\mathcal{S}(\mathcal{M}(\mathcal{P}; w_r, I))}_{\text{Single Simulation Exec.}} \right] \right)}_{\text{Deviation Function i.e. MAPE, MSE, Likelihood}}, \underbrace{\mathcal{D}}_{\text{Real World Validation Target}}$$

Modeler?
Domain Experts?
Users?

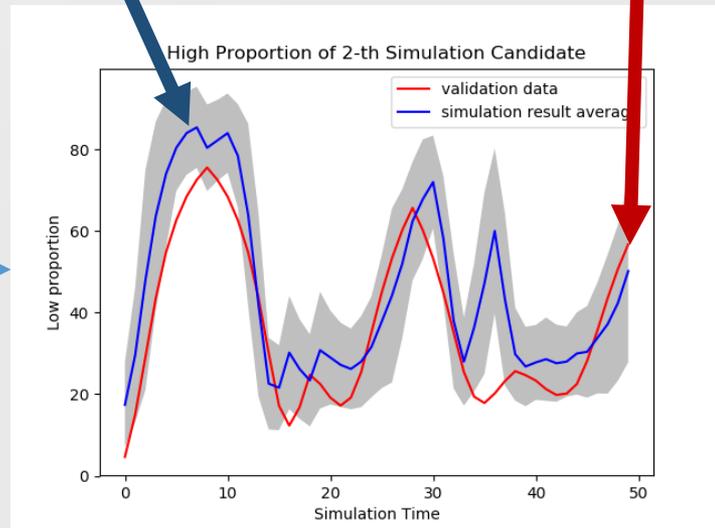
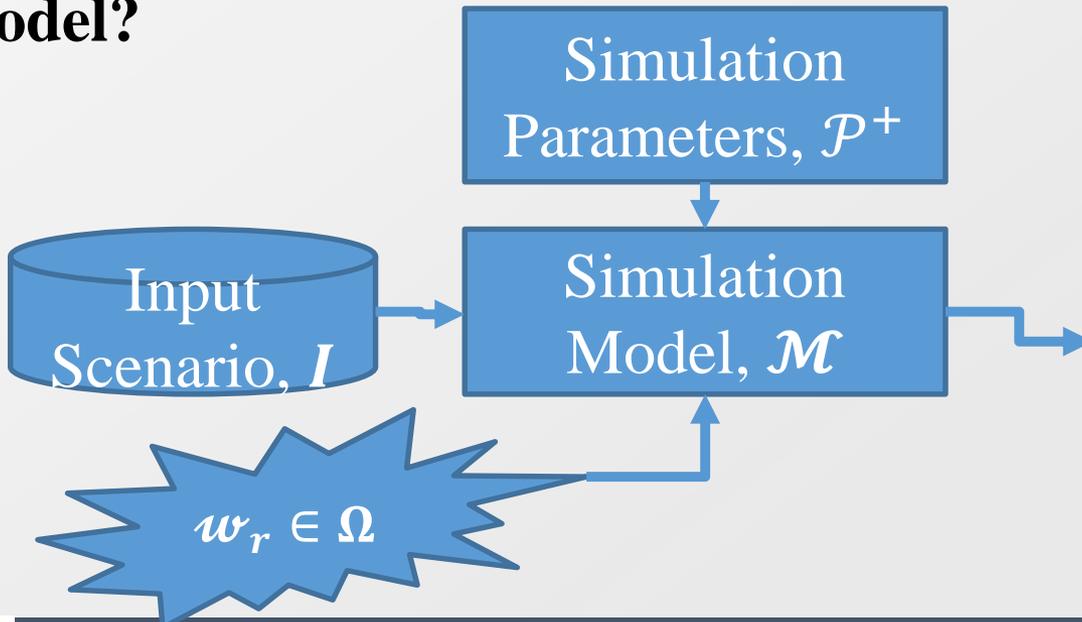
OR

Machine Learning Model?

Deviation Function
 i.e. MAPE,
 MSE,
 Likelihood

Single Simulation Exec.
 Summary Statistics from Single Run
 Replication for Expected Values

Real World
 Validation
 Target



CALIBRATION FRAMEWORK AND PROCEDURE

- \mathcal{P}, ω_r, I by simulation types
 - Initial parameter setup, \mathcal{P}
 - Dynamic parameter adaptation, \mathcal{P}_{dyn}
 - Heterogeneous parameter for instantiated sub-models, \mathcal{P}_{het}

i.e. Agent-Based Model
and Simulations

1. Set the summary statistics
 1. Collect validation data \mathcal{D}
 2. Set the summary statistics function \mathcal{S}
2. Select the simulation performance measure d
 1. d could be a likelihood, MAPE, MSE, etc.
3. Optimize the simulation parameter
 1. Static Calibration: $\mathcal{P}^* = \arg \min_{\mathcal{P}} d(E_R[\mathcal{S}(\mathcal{M}(\mathcal{P}; \omega_r, I))], \mathcal{D})$
 2. Dynamic Calibration: $\mathcal{P}_{dyn}^* = \arg \min_{\mathcal{P}_{dyn}} d_{dyn}(E_R[\mathcal{S}_{dyn}(\mathcal{M}(\mathcal{P}_{dyn}; \omega_r, I))], \mathcal{D}_{dyn})$
 3. Heterogeneous Calibration: $\mathcal{P}_{het}^* = \arg \min_{\mathcal{P}_{het}} d_{het}(E_R[\mathcal{S}_{het}(\mathcal{M}(\mathcal{P}_{het}; \omega_r, I))], \mathcal{D}_{het})$

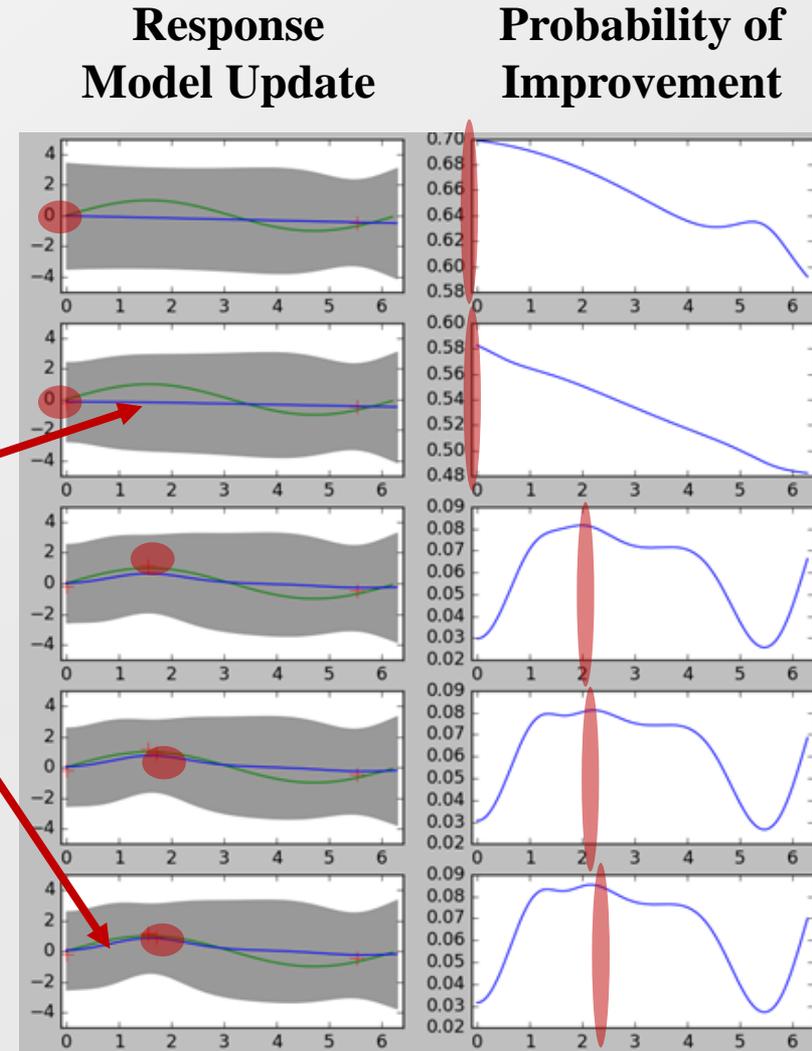
Concept of Calibration on \mathcal{P}

- Traditional methodology of data-driven calibration on \mathcal{P}
- Response surface methodology
 - Response surface model from data
 - Gaussian Process, Piece-wise Linear Regression, Meta-Modeling...
 - Experimental design
 - Latin Hypercube, Full Factorial, Daguchi method...
 - Acquisition function
 - Probability of Improvement...

Validation Quality

Parameter Value

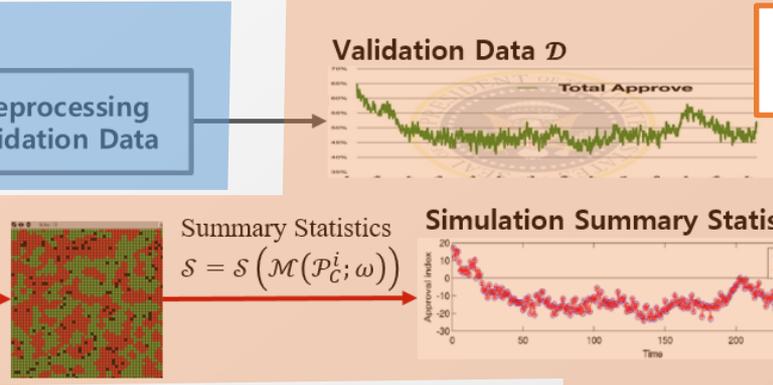
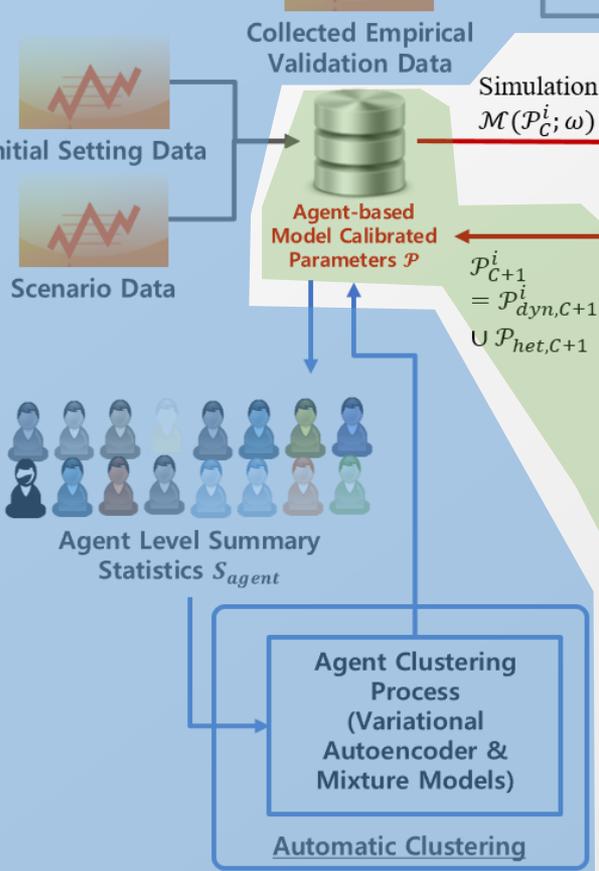
Response Surface Model



Overview on Data-Driven Simulation Calibration

1. Preprocessing before simulation runs

2. Simulation run and calculate divergence

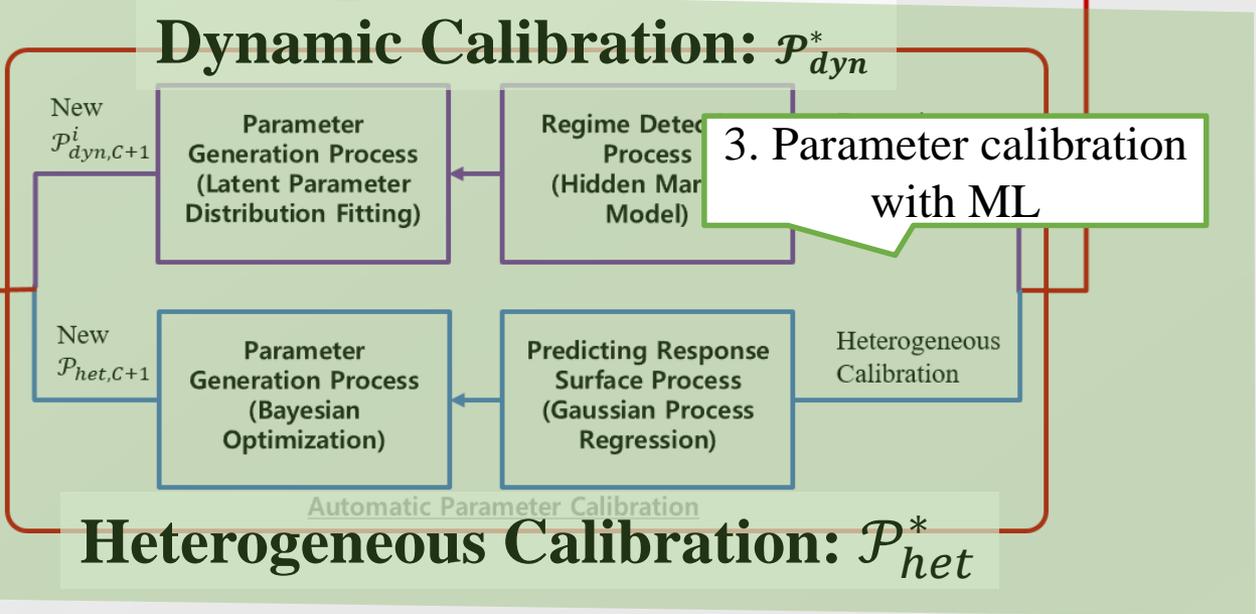


Simulation Performance Error

$$d(\mathcal{S}, \mathcal{D}) = \sum_{s=1}^S \sum_{t=1}^T \frac{|\mu_{s,t} - Real_{s,t}|}{Real_{s,t}}$$

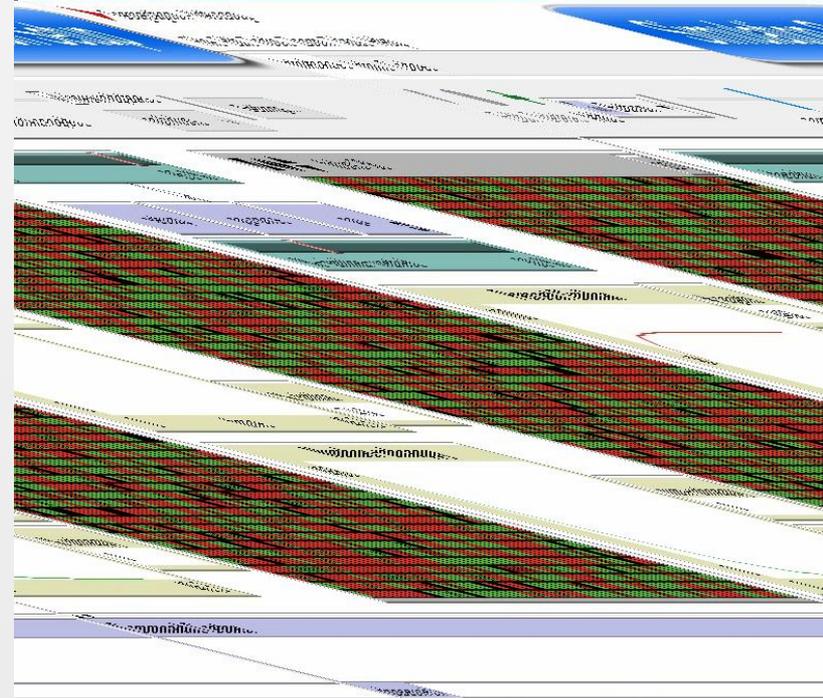
Parameter Calibration Cycle

3. Parameter calibration with ML

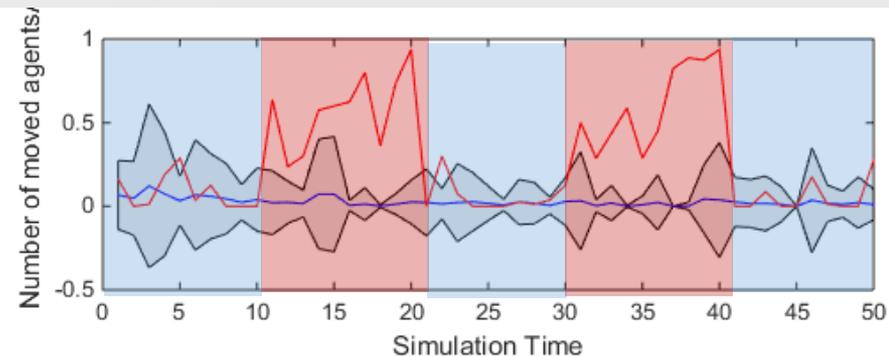
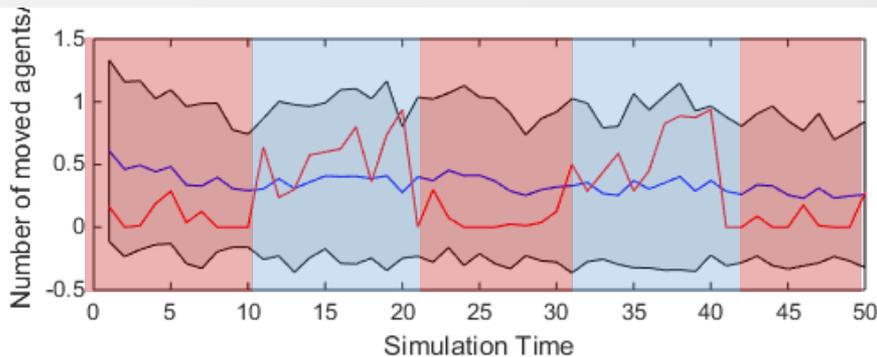


Concept of Calibration on \mathcal{P}_{dyn}

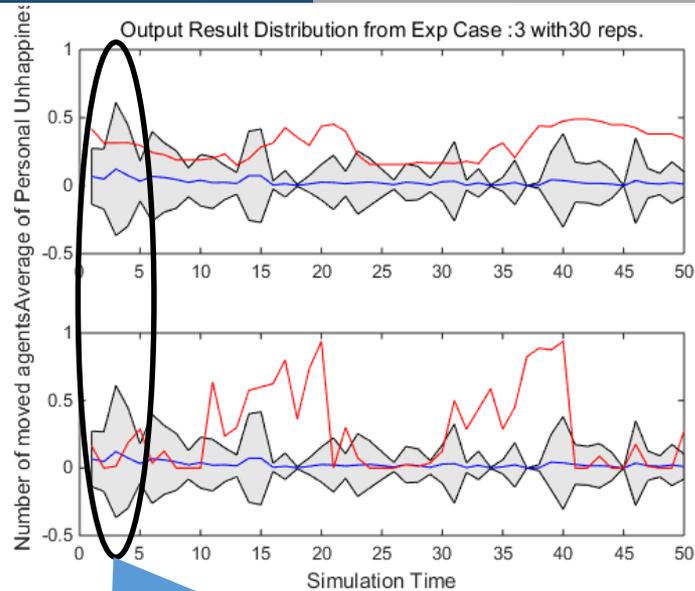
- \mathcal{P}_{dyn} assumes parameter to be varied by t
- $t \in [1..T]$ requires too much separate setting
- Pseudo Code
 - Divide and Calibrate for cycle \mathcal{C}
 - Suggest $\mathcal{P}_{dyn,\mathcal{C}}$ with multiple candidates
 - Identify the **temporal regime** with better validation with a candidate
 - Selectively update $\mathcal{P}_{dyn,\mathcal{C}+1}$ with well-fitted temporal regime
- Regime Detection
 - Hidden Markov Model....



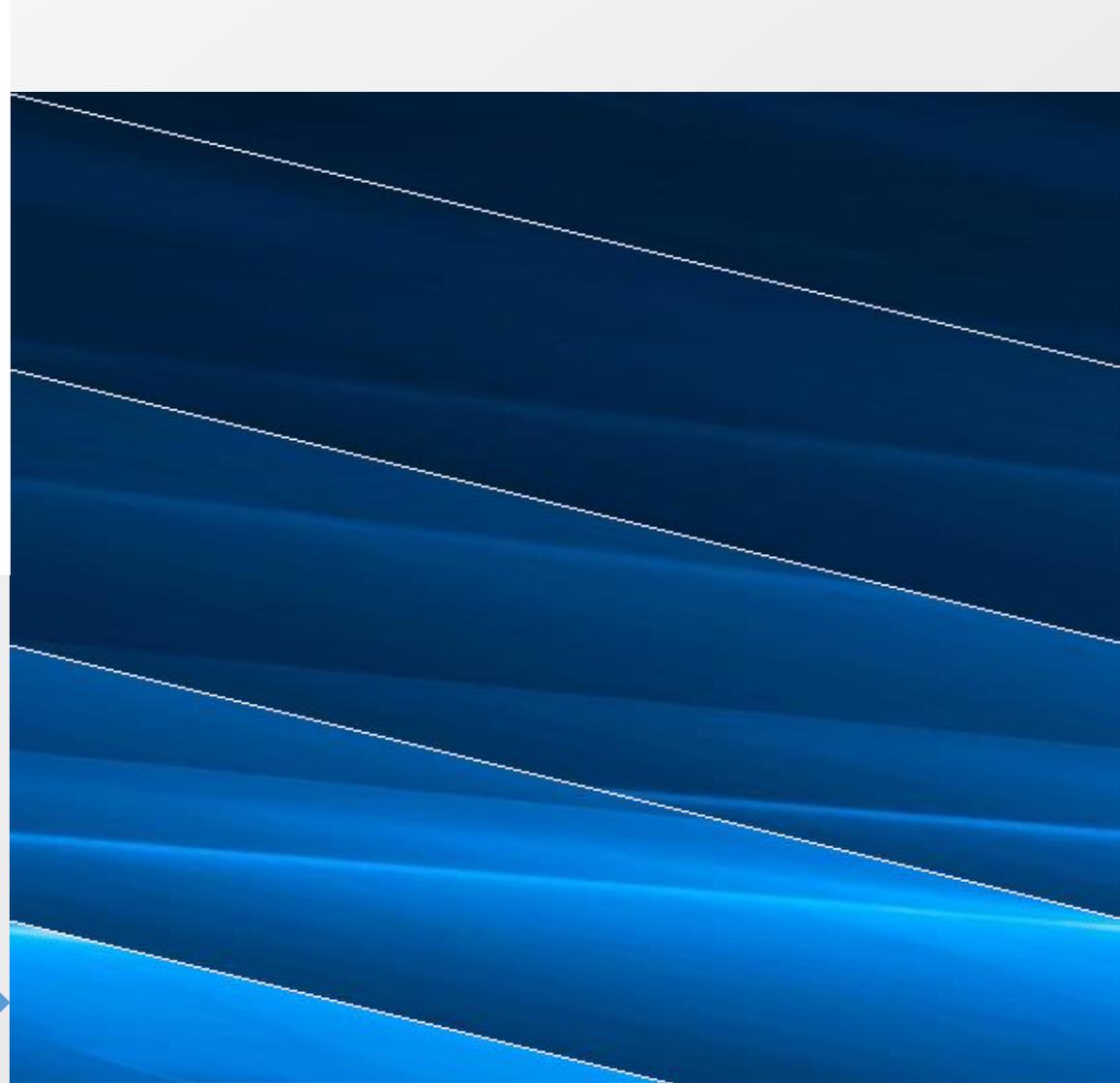
**Dynamically Changed
Simulation Parameter**



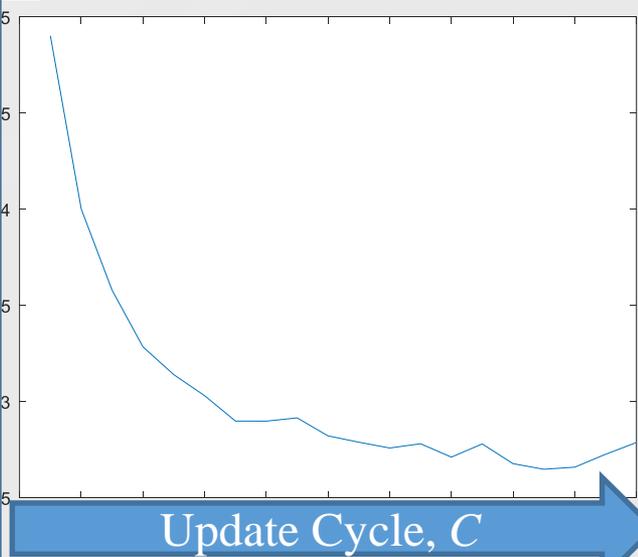
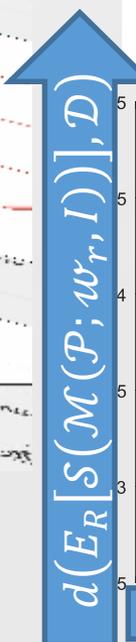
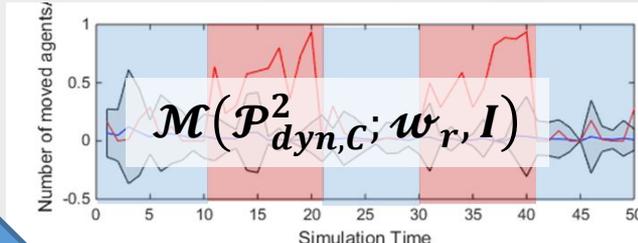
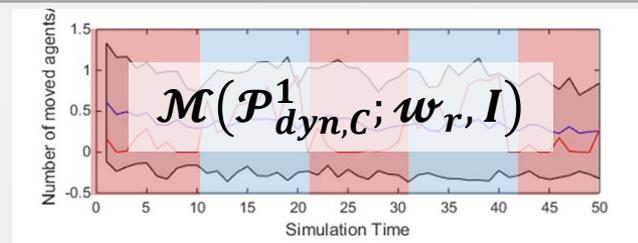
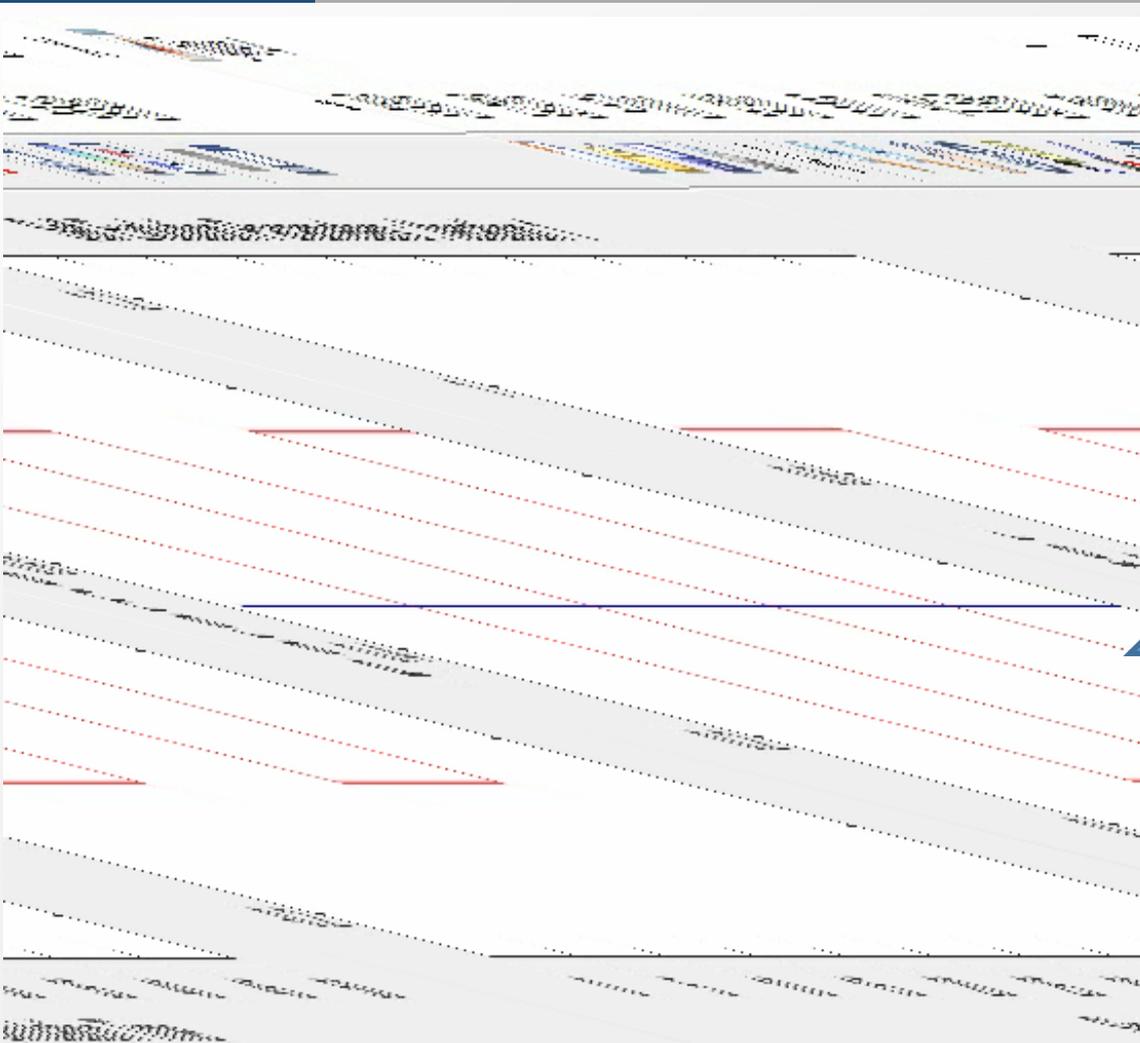
Sample Case of Temporal Regime Detection



Two simulation outputs
 $d(E_R[\mathcal{S}(\mathcal{M}(\mathcal{P}; w_r, I))], \mathcal{D})$
→ 2D Temporal Data



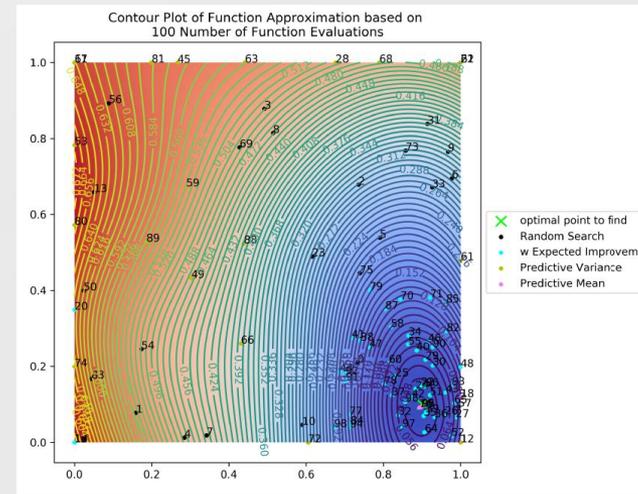
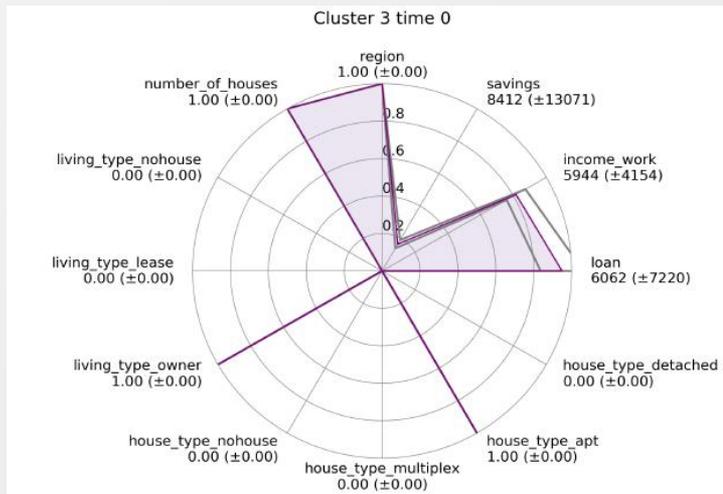
Matching Well-Fitted Regime and \mathcal{P}_{dyn}



\mathcal{P}_{dyn} update over the cycle, C

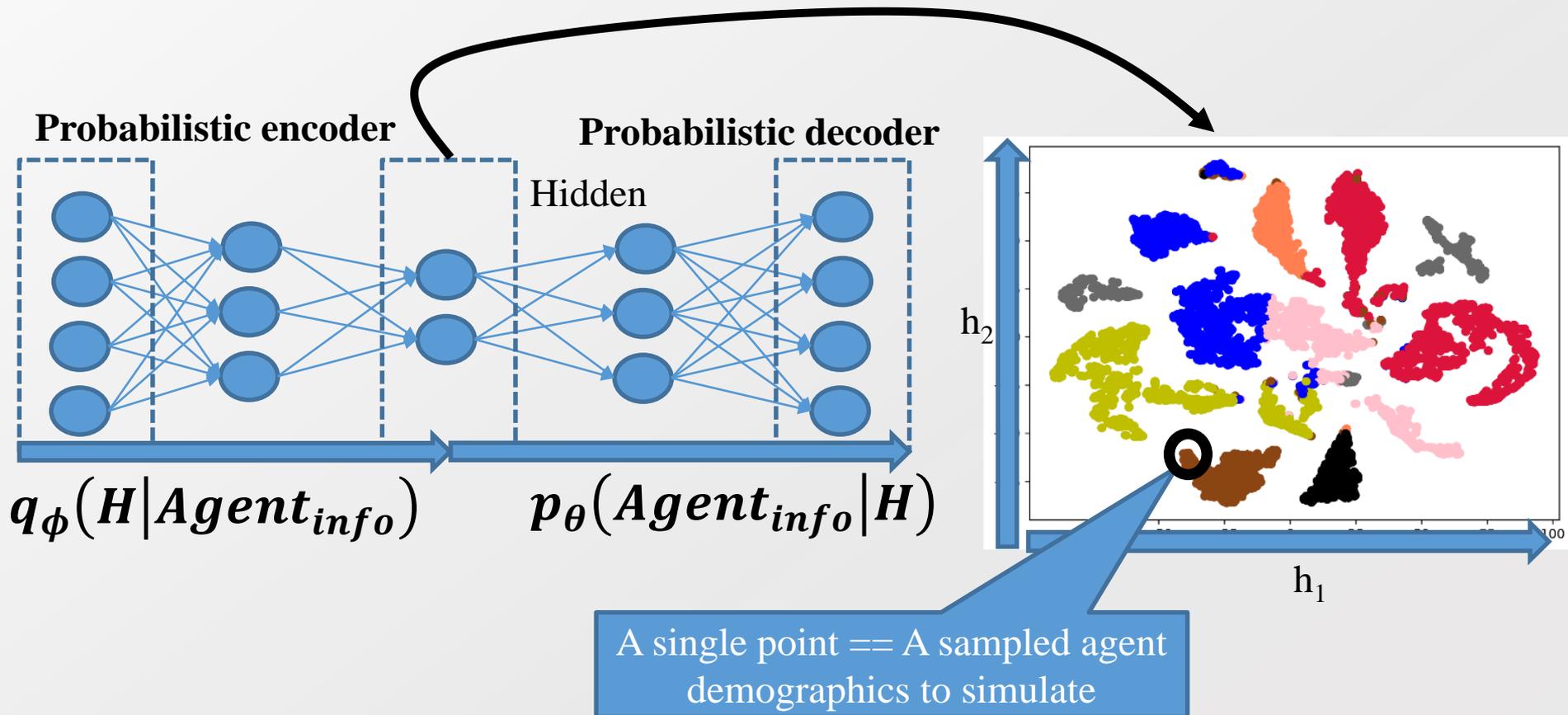
Concept of Calibration on \mathcal{P}_{het}

- \mathcal{P}_{het} assumes parameter to be varied by agents
- $i \in [1..N]$ requires too much separate setting
- Pseudo Code
 - Clustering with agent demographics
 - Calibrate for cycle C
 - For each agent cluster, i
 - Update response surface curve by Gaussian Process
 - Suggest $\mathcal{P}_{het,C+1}^i$ with expected improvement acquisition function on GP
- Agent Cluster Detection
 - Variational Autoencoder, Gaussian Mixture Model, Gaussian Process...



Agent Embedding with VAE

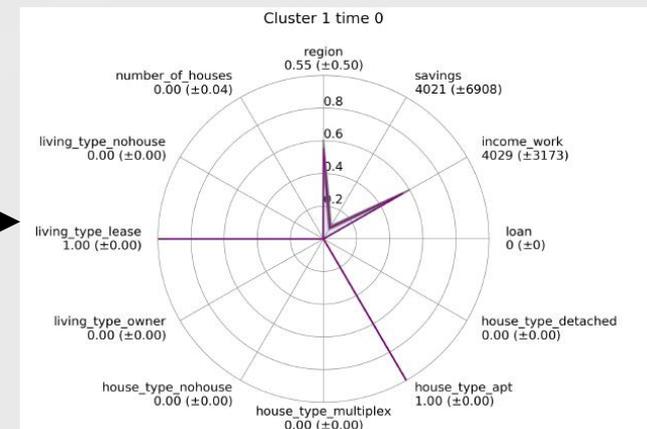
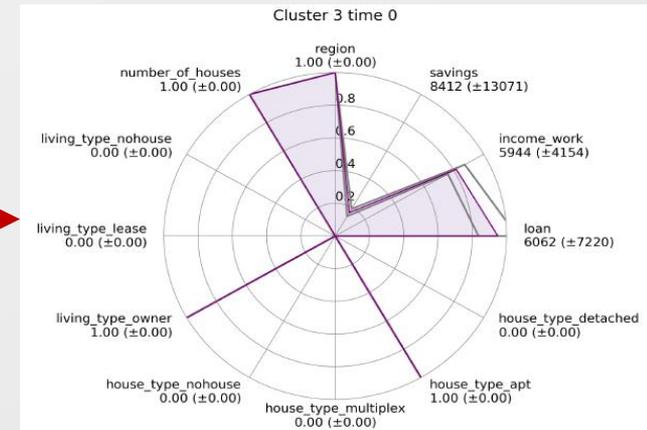
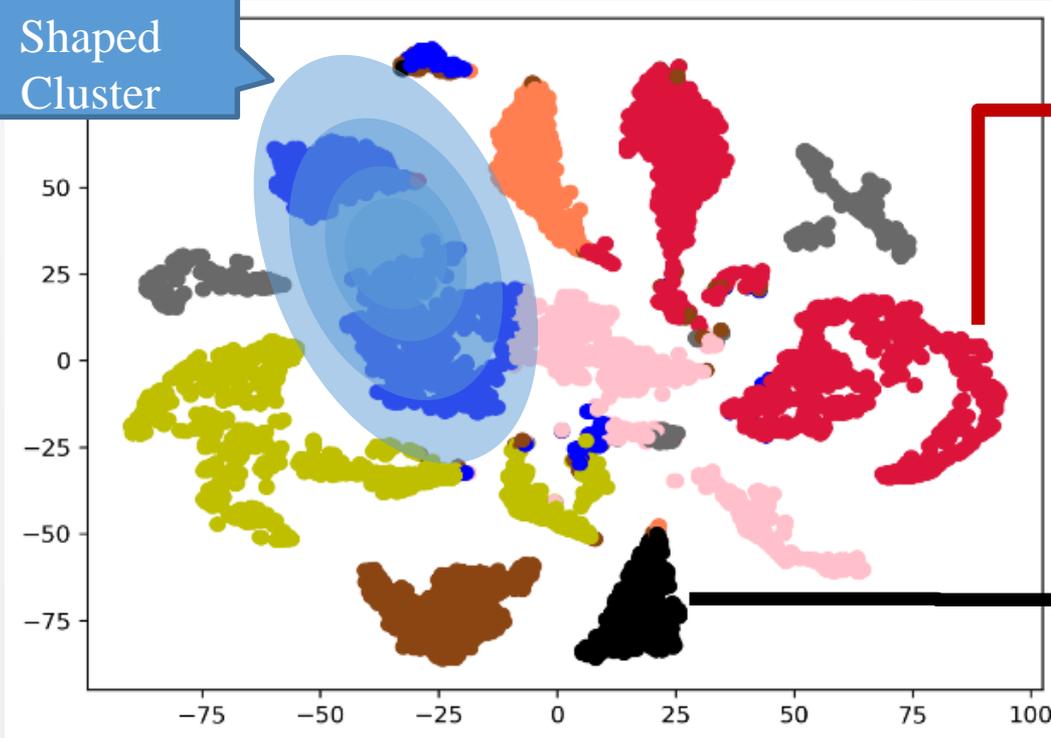
- Agent demographic information can be high-dimensional
 - Need to embed the agent information into the low dimensions
 - Use Autoencoder, and we use the variational autoencoder (VAE)
- Clustering requires further operation by Gaussian Mixture Model



Agent Clustering with GMM

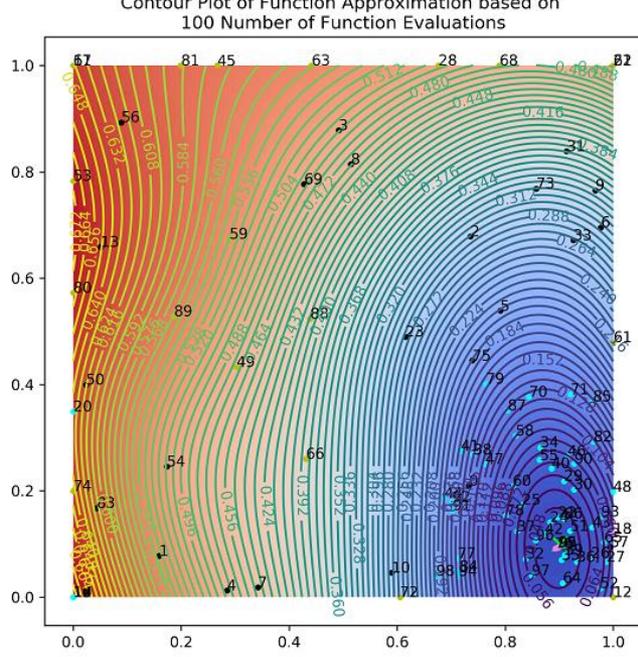
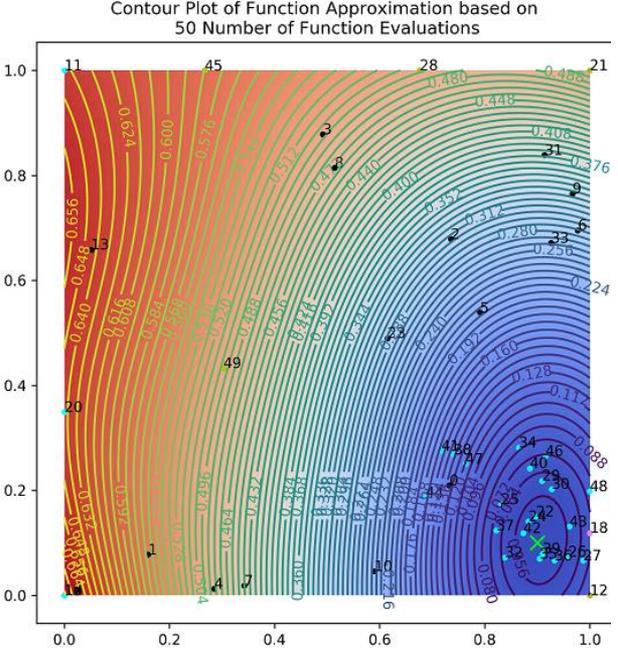
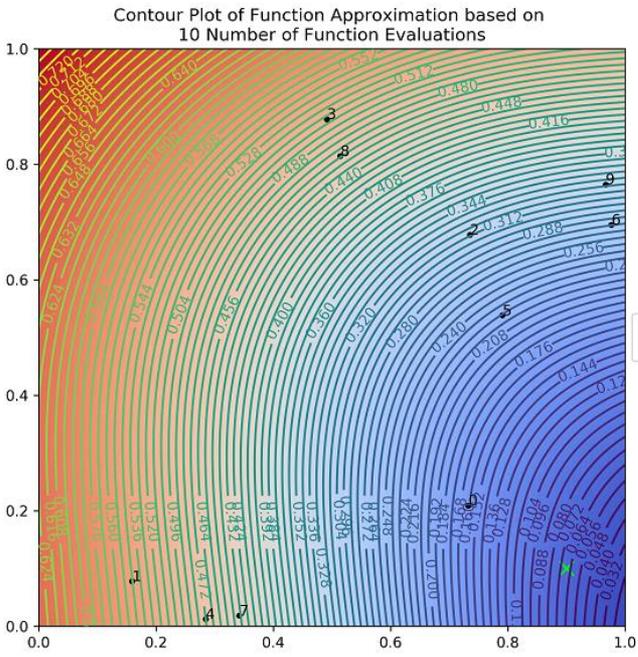
- Low dimension agent demographics embedding
 - Closeness between two embedded points == similarity between two agents
 - Use clustering algorithm to finalize agent clusters
 - We use the Gaussian Mixture Model (GMM)

Gaussian Shaped Cluster

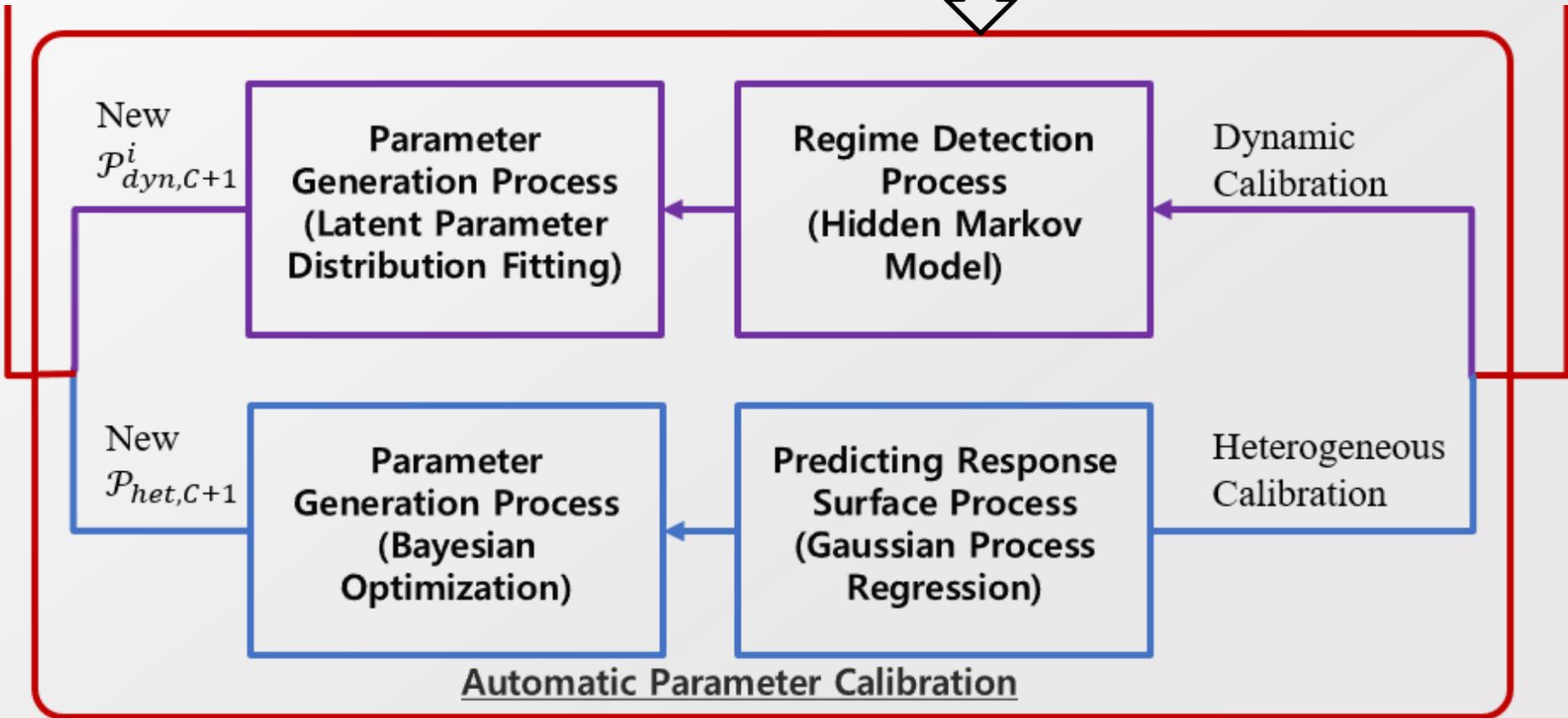
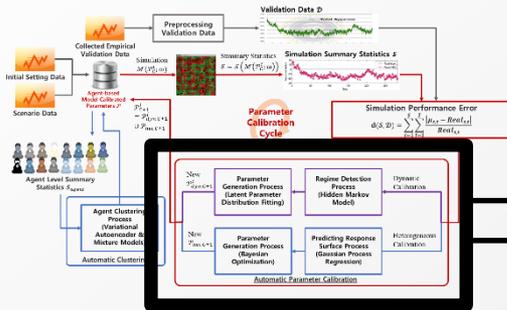


- Multiple cycle of calibration iterations
 - Multiple points of $\langle d_{het}(E_R[\mathcal{S}_{het}(\mathcal{M}(\mathcal{P}_{het}; w_r, I))], \mathcal{D}_{het}), \mathcal{P}_{het,C}^i \rangle$
 - Gaussian Process approximation on the collection of parameter points
 - Acquisition functions with expected improvement

Response surface learning with Gaussian Process



Highlighted on Data-Driven Simulation Calibration



Algorithm 1: Calibration Framework Algorithm

input : Input parameter combination $\mathcal{P}^{in} = \mathcal{P}_{dyn}^{in} \cup \mathcal{P}_{het}^{in}$
output: Calibrated parameter combination $\mathcal{P}^{out} = \mathcal{P}_{dyn}^{out} \cup \mathcal{P}_{het}^{out}$

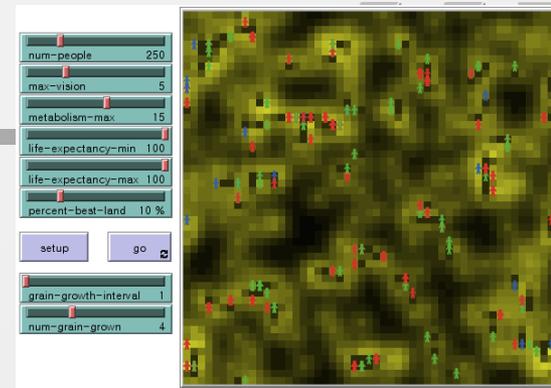
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1 Function CalibrationFramework( $\mathcal{P}_{dyn}^{in} \cup \mathcal{P}_{het}^{in}$ ):
2    $\mathcal{P}_{dyn,0} = \mathcal{P}_{dyn}^{in}$ 
3    $\mathcal{P}_{het,0} = \text{AgentClustering}(\mathcal{P}_{dyn}^{in} \cup \mathcal{P}_{het}^{in})$  (see Algorithm 3)
4   for  $c$  in range( $C_{cal}$ ) do
5     if  $0 \leq c - \left\lfloor \frac{c}{C_{dyn} + C_{het}} \right\rfloor (C_{dyn} + C_{het}) < C_{dyn}$  then
6        $\mathcal{P}_{dyn,c+1} = \text{DYNAMICCALIBRATION}(\mathcal{P}_{dyn,c} \cup \mathcal{P}_{het,c})$  (see Algorithm 2)
7        $\mathcal{P}_{het,c+1} = \mathcal{P}_{het,c}$ 
8     else if  $C_{dyn} \leq c - \left\lfloor \frac{c}{C_{dyn} + C_{het}} \right\rfloor (C_{dyn} + C_{het}) < C_{dyn} + C_{het}$  then
9        $\mathcal{P}_{het,c+1} = \text{HETEROGENEOUSCALIBRATION}(\mathcal{P}_{dyn,c} \cup \mathcal{P}_{het,c})$  (see Algorithm 3)
10       $\mathcal{P}_{dyn,c+1} = \mathcal{P}_{dyn,c}$ 
11   Set  $\mathcal{P}^{out} = \mathcal{P}_{dyn}^{opt} \cup \mathcal{P}_{het}^{opt}$  to have the lowest simulation error
12   return  $\mathcal{P}_{dyn}^{out} \cup \mathcal{P}_{het}^{out}$ 
```

EXPERIMENTS

Test Case 1

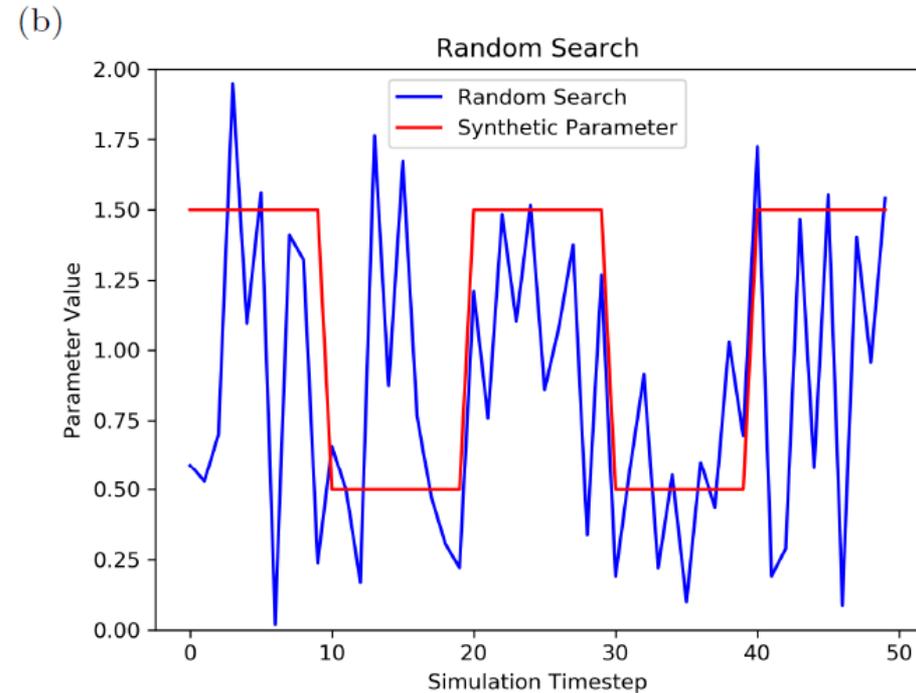
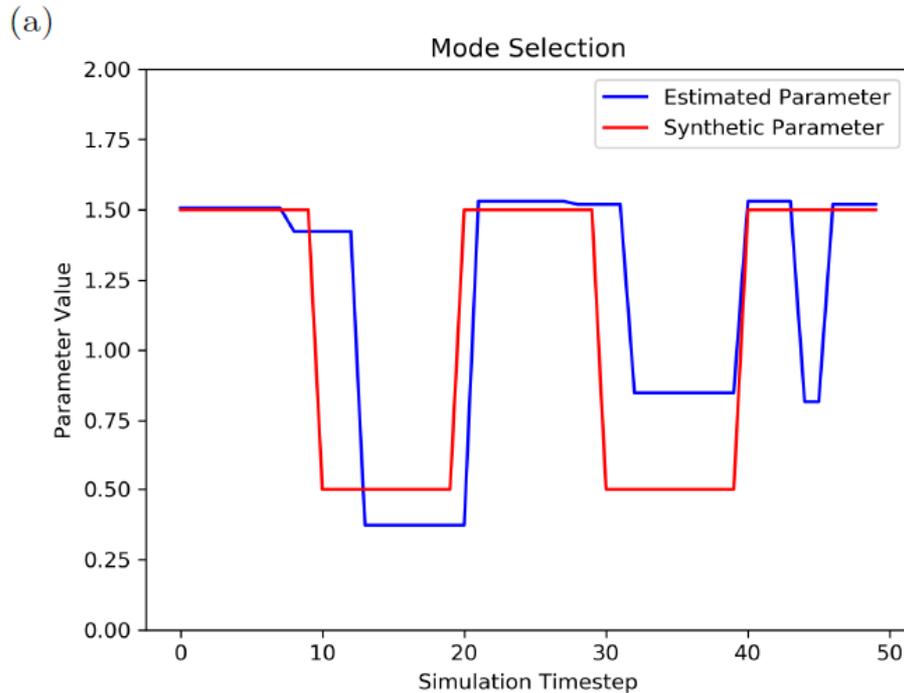
- [Model Description] Wealth Distribution ABM

- Sugarscape Model
- Agent seek wealth to maximize the wealth savings
- Grid provides its wealth to the agents located at the grid
- Agent consumes the wealth

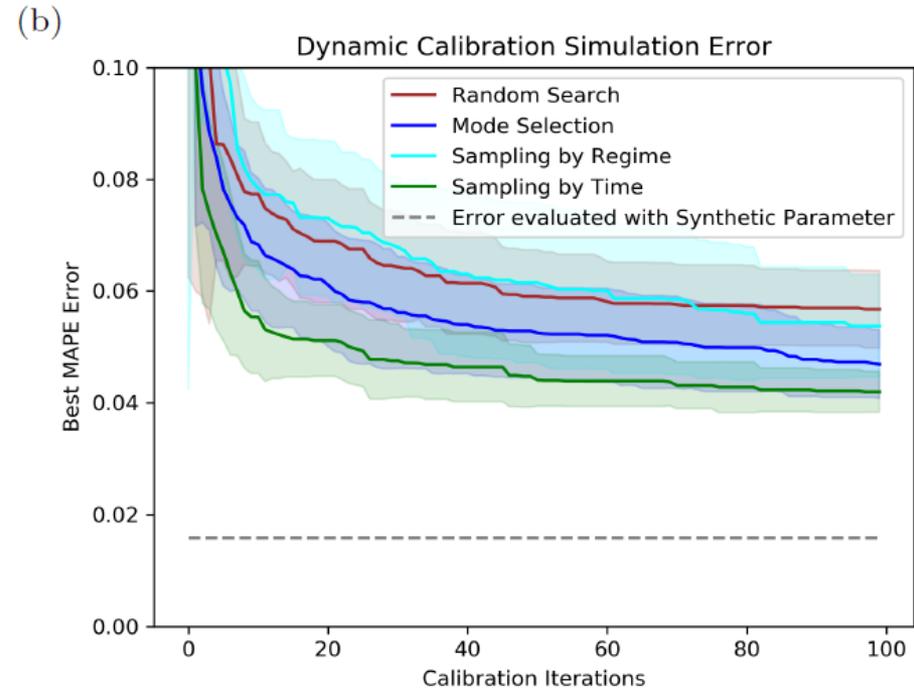
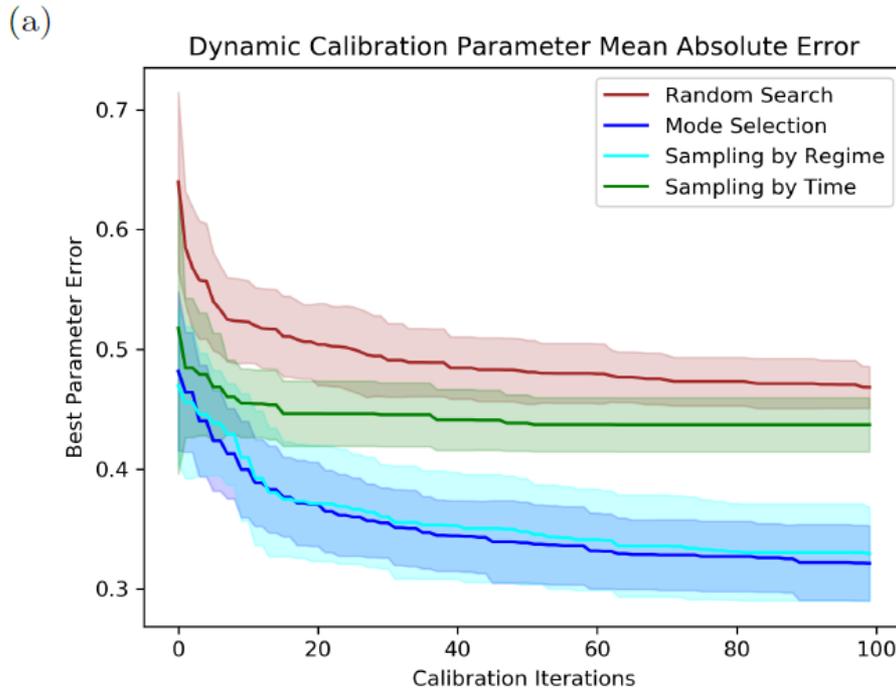


Parameters	Parameter Type	Parameter Range	Synthetic Parameter Setting	
			Value	Time or Cluster
<i>Wealth Income</i>	Dynamic	0-2	1.5	1-10,21-30,41-50
			0.5	11-20,31-40
<i>Wealth Consumption</i>	Heterogeneous	0-1	0.9	Top 50% in Initial Wealth
			0.1	Bottom 50% in Initial Wealth

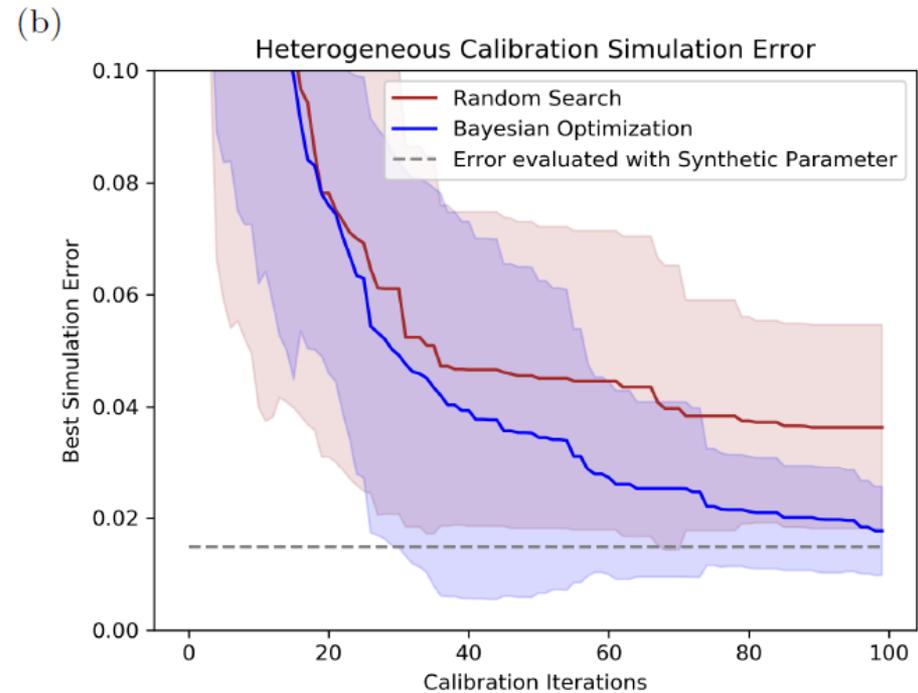
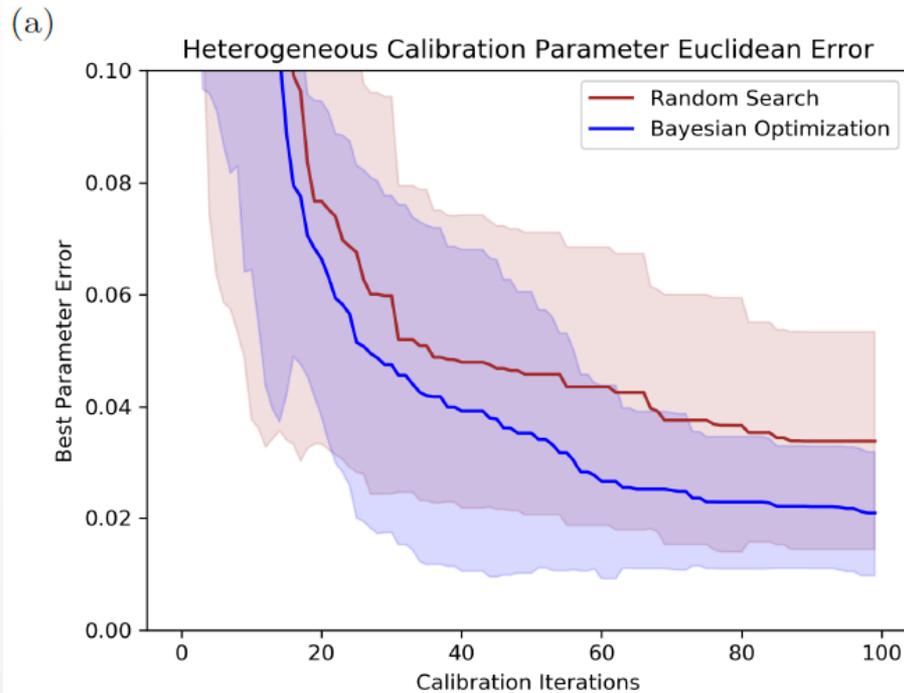
Type of Summary Statistics	Name of Summary Statistics	Variable Description
Validation Summary Statistics	HIGH CLASS WEALTH AVERAGE	Average wealth of top 1/3 agents
	MIDDLE CLASS WEALTH AVERAGE	Average wealth of middle 1/3 agents
	LOW CLASS WEALTH AVERAGE	Average wealth of bottom 1/3 agents
	GINI INDEX	The area ratio of the Lorenz curve to measure the wealth inequality



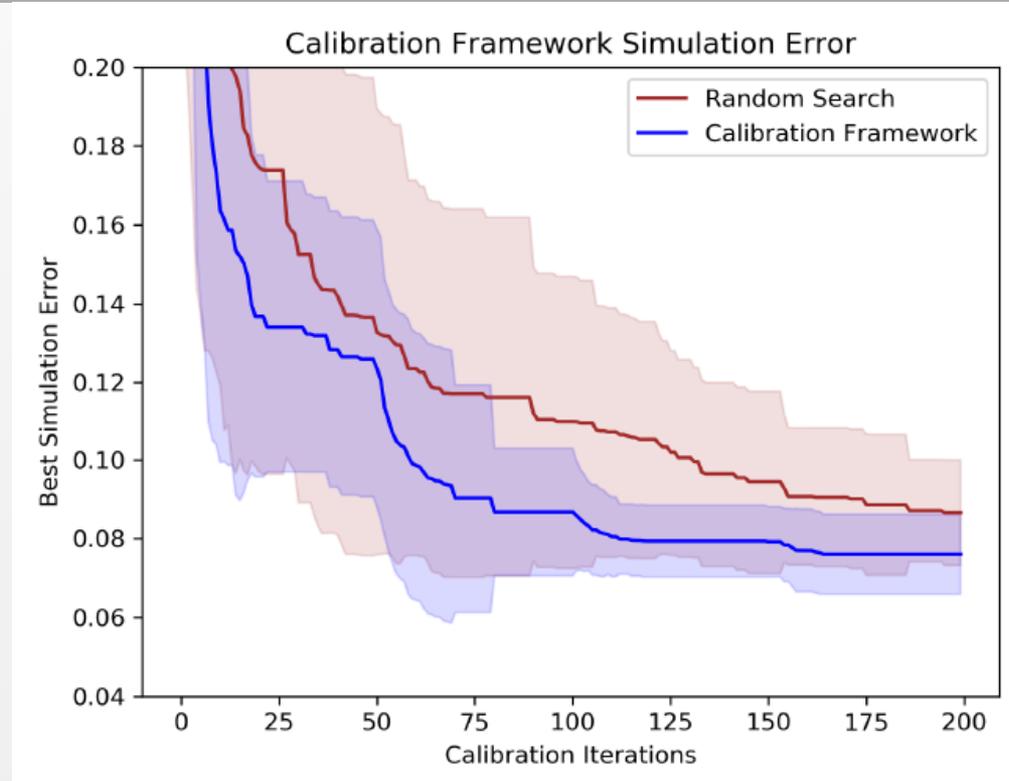
- Dynamic calibration finds a dynamic parameter by regime to avoid overfitting.
 - Red line is the synthetic parameter
 - Blue line is the estimated dynamic parameter.
- Random Search finds an overfitted dynamic parameter, which only fits the given validation data without matching with the given synthetic parameter.



- (a) Parameter Mean Absolute Error of dynamic calibration
 - Parameter generation methods Sampling by Regime and Mode Selection find parameters closer to the synthetic parameter than the other methods.
- (b) Dynamic calibration simulation error
 - Parameter generation method Sampling by Time performs the best in terms of simulation MAPE.



- (a) Parameter Euclidean Error of Heterogeneous calibration
- (b) Heterogeneous calibration simulation MAPE
 - Suggested Bayesian optimization converges to the optimal lower bound, which is not 0 because of the stochasticity.



- The suggested calibration framework simulation MAPE
 - Four cycles of the calibration framework is replicated
 - Each cycle includes
 - Dynamic calibration for the first 20 iterations
 - Heterogeneous calibration for the next 30 iterations.

- [Model Description] Real Estate Market Agent-based Model
 - Agent buy and sell/lease either house/apartment/condo
 - House price is increased when the same typed houses are popular
 - House price is decreased if the house is not sold, while the house is listed in the housing market
- Housing Transaction Number
 - Market Participation Rate → [Dynamic] Demand change due to the up and down of the economic trends is modeled in the dynamic parameter
 - Willing to Pay
 - Purchase Rate } → [Heterogeneity] Household investment portfolio is modeled in the heterogeneous parameter
- Housing Price
 - Market Price Increase Rate
 - Market Price Decrease Rate

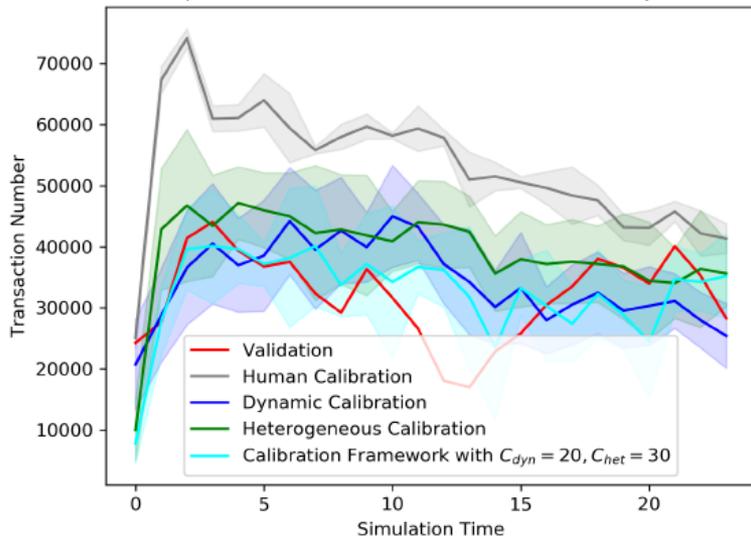
Parameter	Parameter Type	Parameter Range
<i>Market Participation Rate</i>	Dynamic	0-0.05
<i>Market Price Increase Rate</i>	Dynamic	0-0.1
<i>Market Price Decrease Rate</i>	Dynamic	0-0.1
<i>Willing to Pay</i>	Heterogeneous	0.3-0.9
<i>Purchase Rate</i>	Heterogeneous	0.3-0.9

Summary Statistics

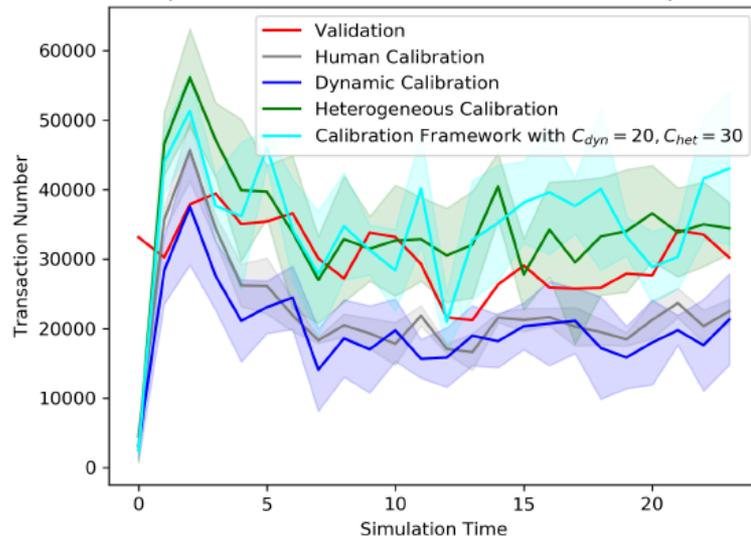
Types of Summary Statistics	Name of Summary Statistics	Variable Description	Variable Value	
Validation-level Summary Statistics	APARTMENT SALES PRICE INDEX IN CAPITAL	Jevons price index of Apartment sales price	Housing Price is converted into a percentage, with base value as 100 at the initial timestep.	
	APARTMENT SALES PRICE INDEX IN NONCAPITAL			
	APARTMENT LEASE PRICE INDEX IN CAPITAL	Jevons price index of Apartment lease price.		
	APARTMENT LEASE PRICE INDEX IN NONCAPITAL			
	APARTMENT SALES TRANSACTION NUMBER IN CAPITAL	Transaction numbers of Apartment sales.		Simulation transaction number is scaled up to be compatible with the validation transaction number.
	APARTMENT SALES TRANSACTION NUMBER IN NON-CAPITAL			
	APARTMENT LEASE TRANSACTION NUMBER IN CAPITAL	Transaction numbers of Apartment lease.		
APARTMENT LEASE TRANSACTION NUMBER IN NON-CAPITAL				
Agent-level Summary Statistics	LIVING REGION	Agent living region between capital/noncapital area.	1: Capital, 0: Noncapital	
	SAVINGS	Total savings.	1 unit/1000 KRW	
	INCOME	Sum of the labor income and transfer income.	1 unit/1000 KRW	
	LOAN	Total amount of money agent have borrowed from bank.	1 unit/1000 KRW	
	HOUSE TYPE	Type of house where an agent lives.	1: Detached House, 2: Apartment, 3: Multiplex House, 4: No House	
	LIVING TYPE	Type of living where an agent lives	1: Owner, 2: Lease, 3: No House	
	NUMBER OF OWN HOUSES	Number of houses agent owns	1 unit/1 House	

Calibrated Apartment Transaction Numbers

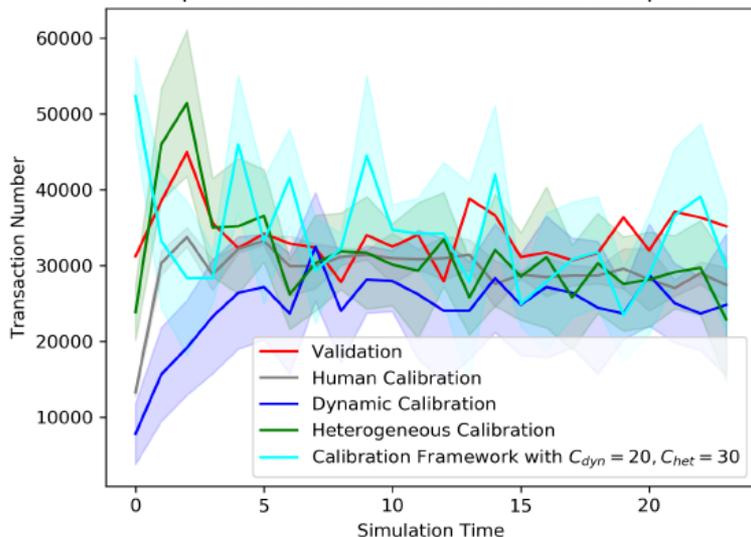
Apartment Sales Transaction Number in Capital



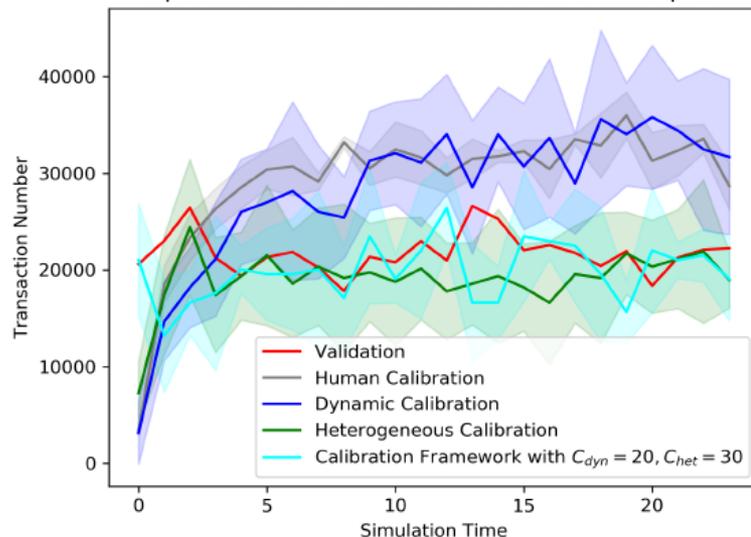
Apartment Sales Transaction Number in Noncapital

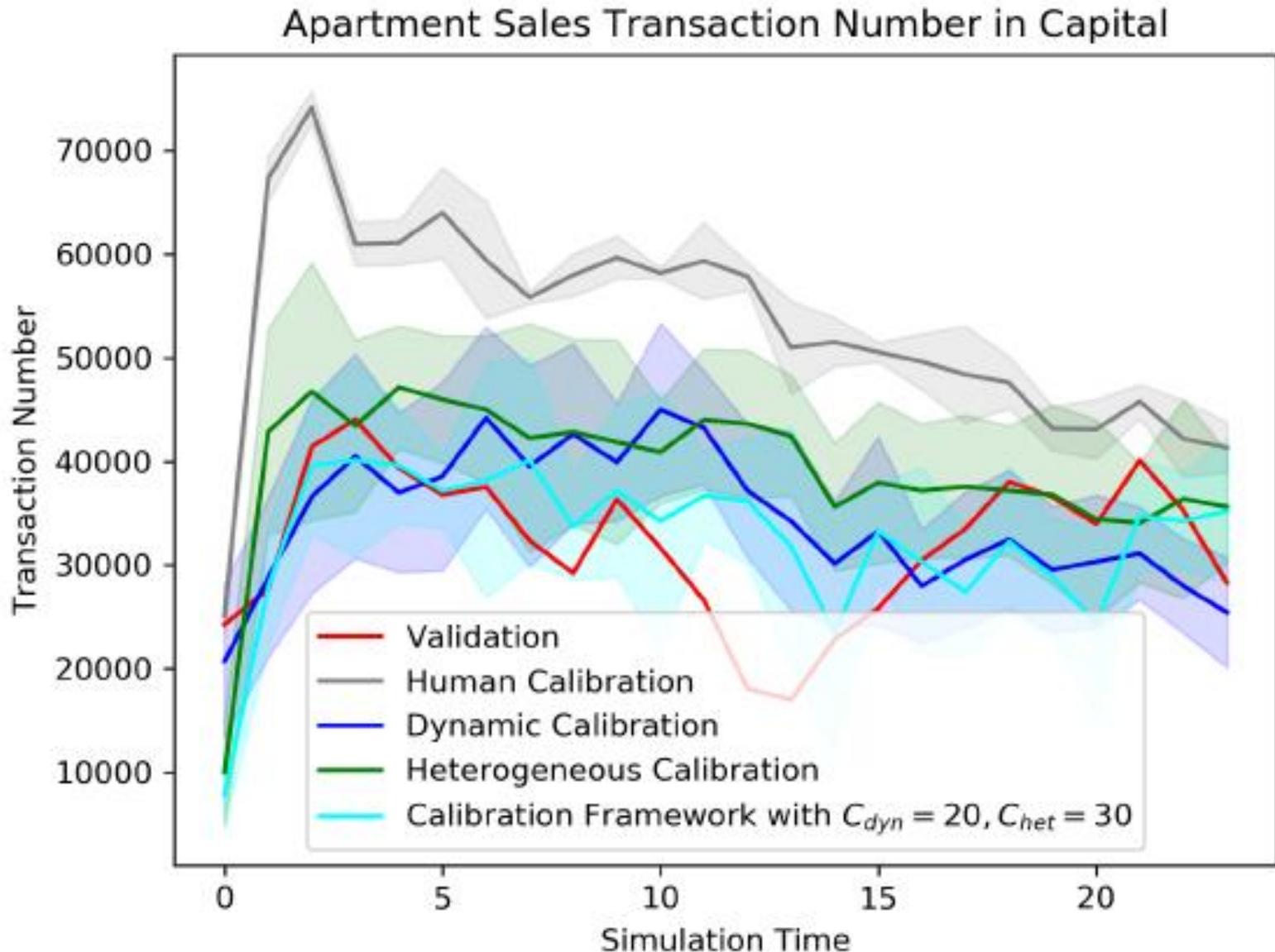


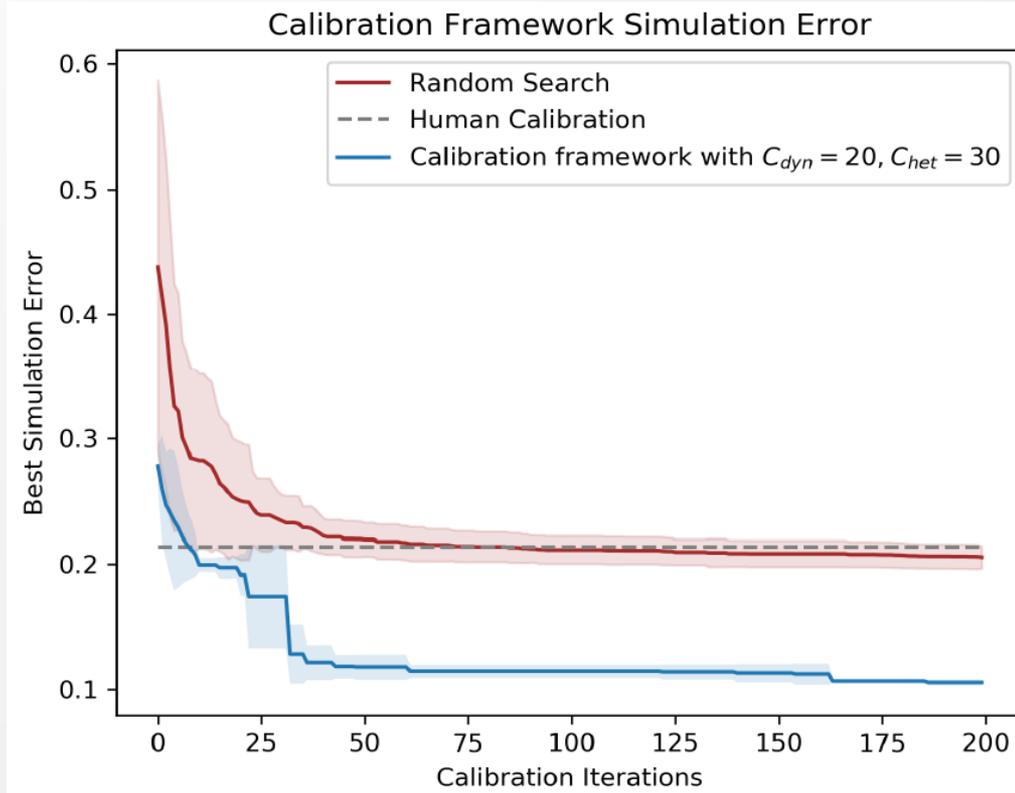
Apartment Lease Transaction Number in Capital



Apartment Lease Transaction Number in Noncapital







- Suggested calibration framework simulation MAPE
 - Blue line is a experimental result where the calibration framework is executed with $C_{dyn} = 20$ and $C_{het} = 30$.
 - Red line is a random search experimental result.
 - Dotted line is the human calibration result.

- We propose the new calibration framework, using Dynamic Calibration, and Heterogeneous Calibration.
 - Dynamic Calibration estimates an optimal set of dynamic parameters, using two components
 - Heterogeneous Calibration estimates an optimal set of heterogeneous parameters using three components

