AAAI-24 / IAAI-24 / EAAI-24

UNIVERSITY OF ALBERTA

Grey-Box Bayesian Optimization for Sensor Placement in Assisted Living Environments

Shadan Golestan
golestan@ualberta.ca

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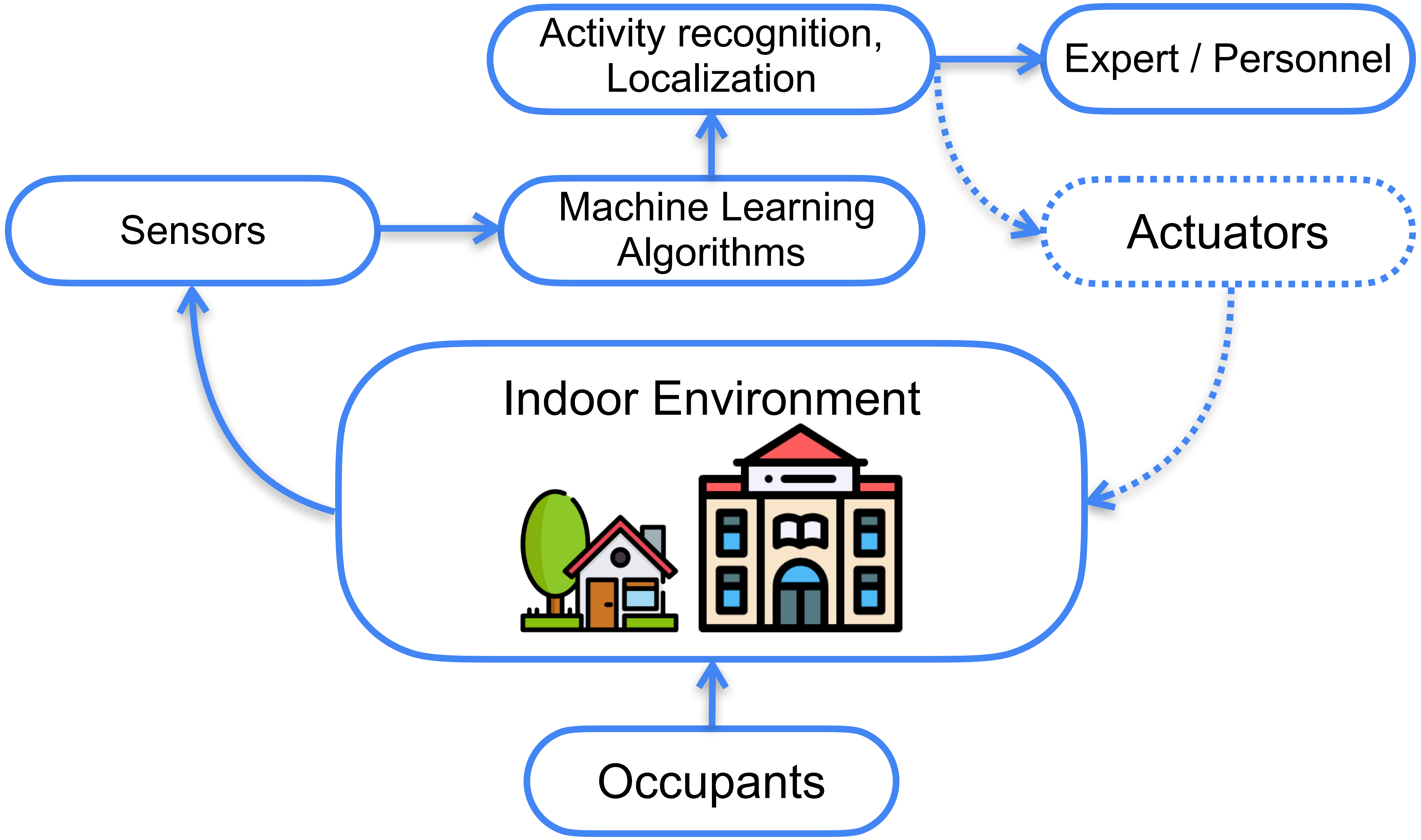
Smart Indoor Spaces

Definition and Problem Statement



Problem:

Finding the best locations for installing sensors

Cost

Privacy

Majumder, S., et al., Smart homes for elderly healthcare—Recent advances and research challenges. *Sensors* **2017**, *17*, 2496.

C. Lee, L., et al. "Securing smart home: Technologies security challenges and security requirements", *Proc. IEEE Conf. Commun. Netw. Secur.*, pp. 67-72, Oct. 2014.

Rocha, P., et al. Improving energy efficiency via smart building energy management systems: A comparison with policy measures. *Energy Build.* **2015**, *88*, 203–213.

Sensor Placement Techniques

Optimize the location of sensors

Given a lower bound on the performance of downstream applications

Evolutionary Algorithm

Genetic Algorithm

Brian L Thomas, Aaron S Crandall, and Diane J Cook. A genetic algorithm approach to motion sensor placement in smart environments. Journal of reliable intelligent environments, 2(1):3–16, 2016.

Greedy

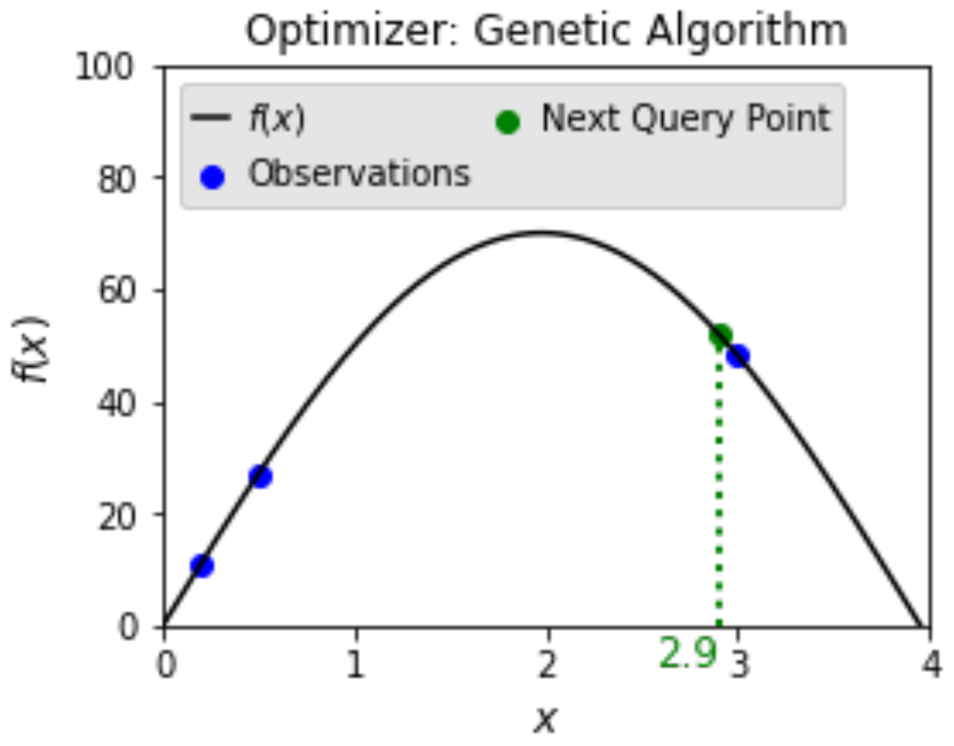
Andreas Krause, Jure Leskovec, Carlos Guestrin, Jeanne VanBriesen, and Christos Faloutsos. Efficient sensor placement optimization for securing large water distribution networks. Journal of Water Resources Planning and Management, 134(6):516–526, 2008.

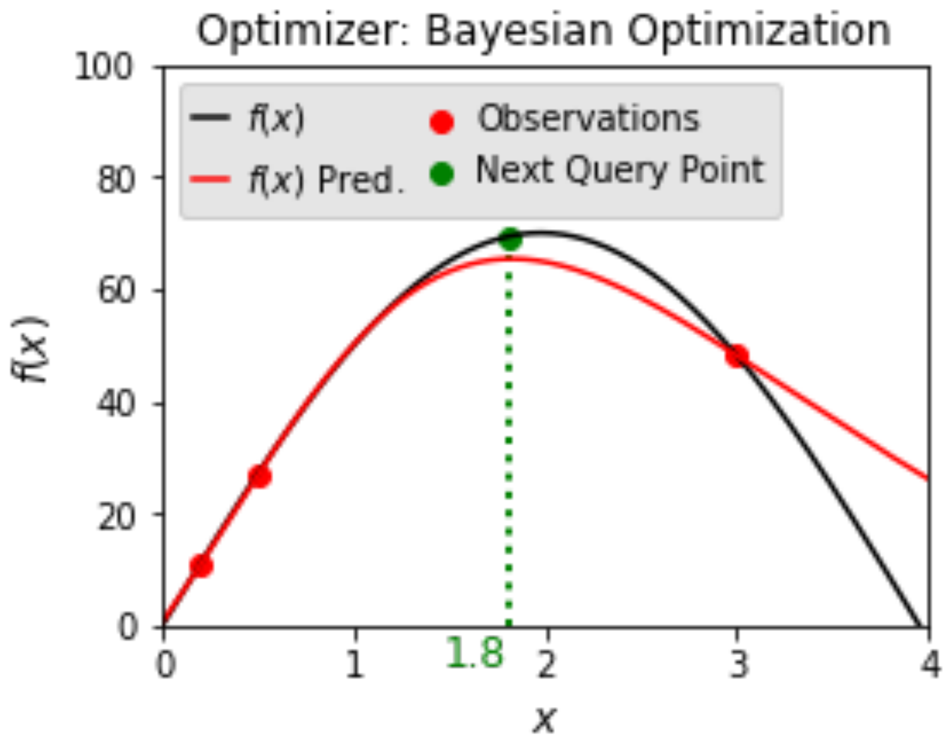
They rely solely on **local information** that samples provide

$f(x)$

The function being optimized: some performance measure of the ML model

A sensor placement





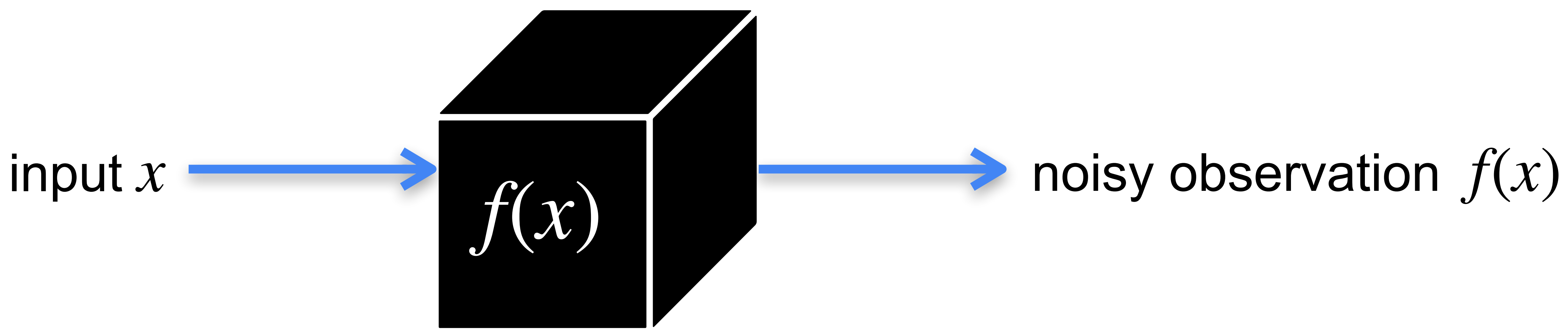
Estimation of Distribution Algorithms

Bayesian Optimization (BO)

Bobak Shahriari, Kevin Swersky, Ziyu Wang, Ryan P Adams, and Nando De Freitas. Taking the human out of the loop: A review of bayesian optimization. *Proceedings of the IEEE*, 104(1):148–175, 2015.

Uses local information to build a probabilistic surrogate model

Bayesian Optimization (BO)



Optimization over permutation spaces

Aryan Deshwal, Syrine Belakaria, Janardhan Rao Doppa, and Dae Hyun Kim. Bayesian opti- mization over permutation spaces. In *Proceedings of the AAAI Conference on Artificial Intel- ligence*, volume 36, pages 6515–6523, 2022.

The main shortcoming:

Disregards any inherent, domain knowledge that might exist about $f(x)$

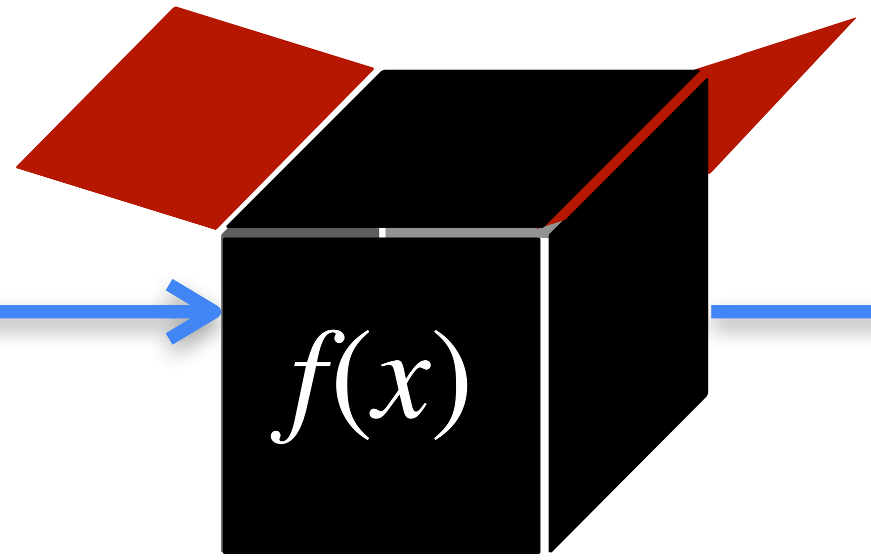
Conference on Artificial Intelligence and Statis- tics, pages 7021–7039. PMLR, 2023.

Active monitoring of air pollution

Sigrid Passano Hellan, Christopher G Lucas, and Nigel H Goddard. Bayesian optimisation for active monitoring of air pollution. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 11908–11916, 2022.

Grey—Box Bayesian Optimization

x : a sensor placement



$f(x)$: performance of an activity recognition model

Raul Astudillo and Peter I Frazier. Thinking inside the box: A tutorial on grey-box bayesian optimization. In *2021 Winter Simulation Conference (WSC)*, pages 1–15. IEEE, 2021.

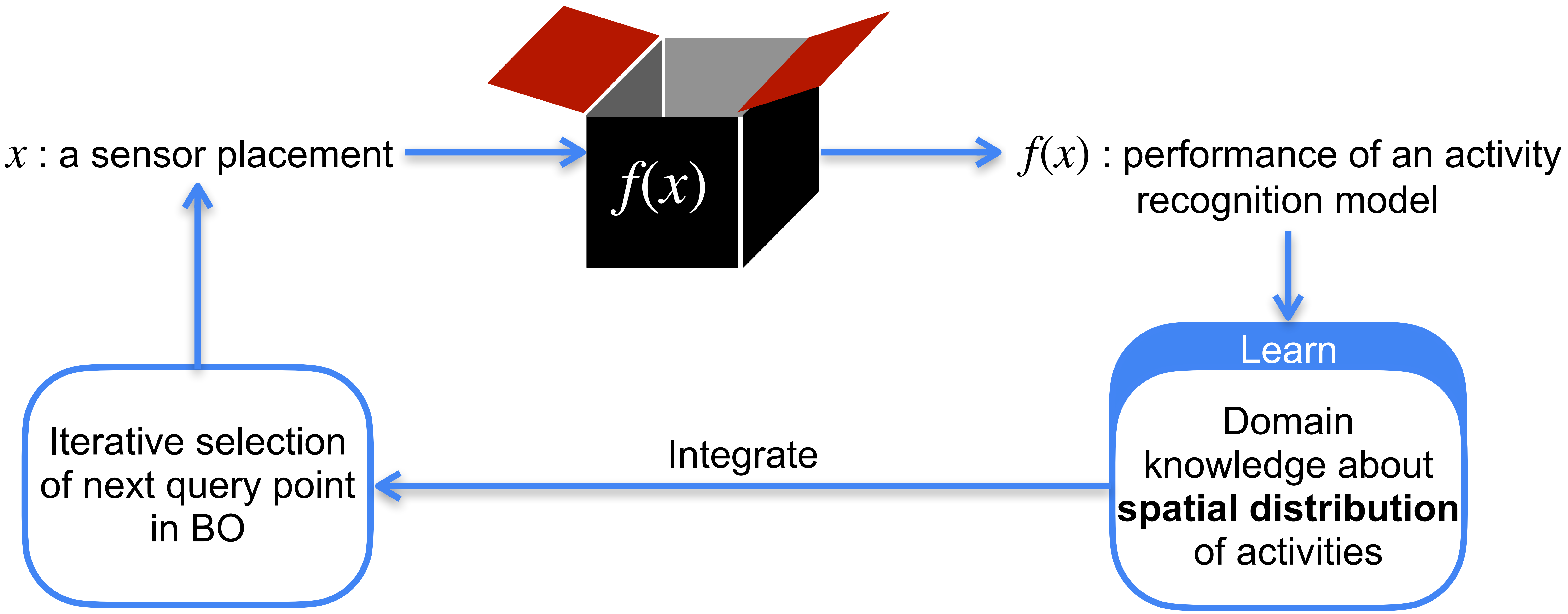
Our hypothesis:

$f(x)$ contains inherent domain knowledge about the **spatial distribution of activities** that could help BO quickly identify important regions in the search space

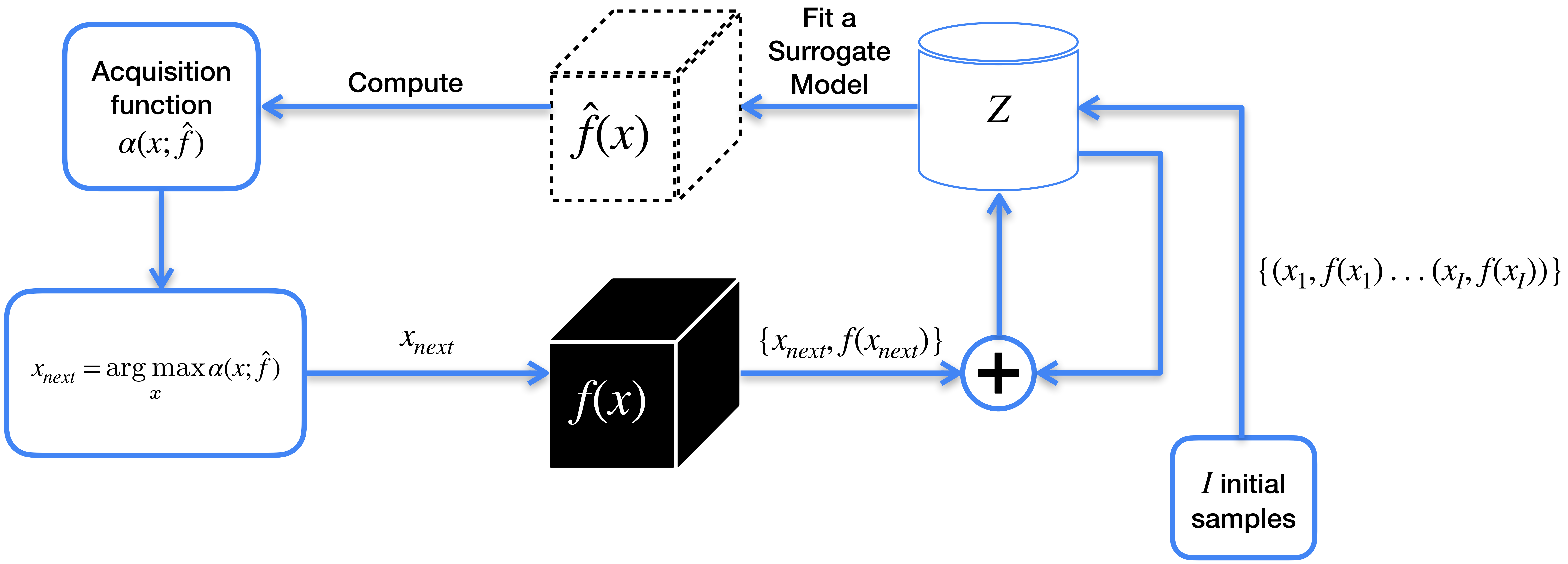
Research Question:

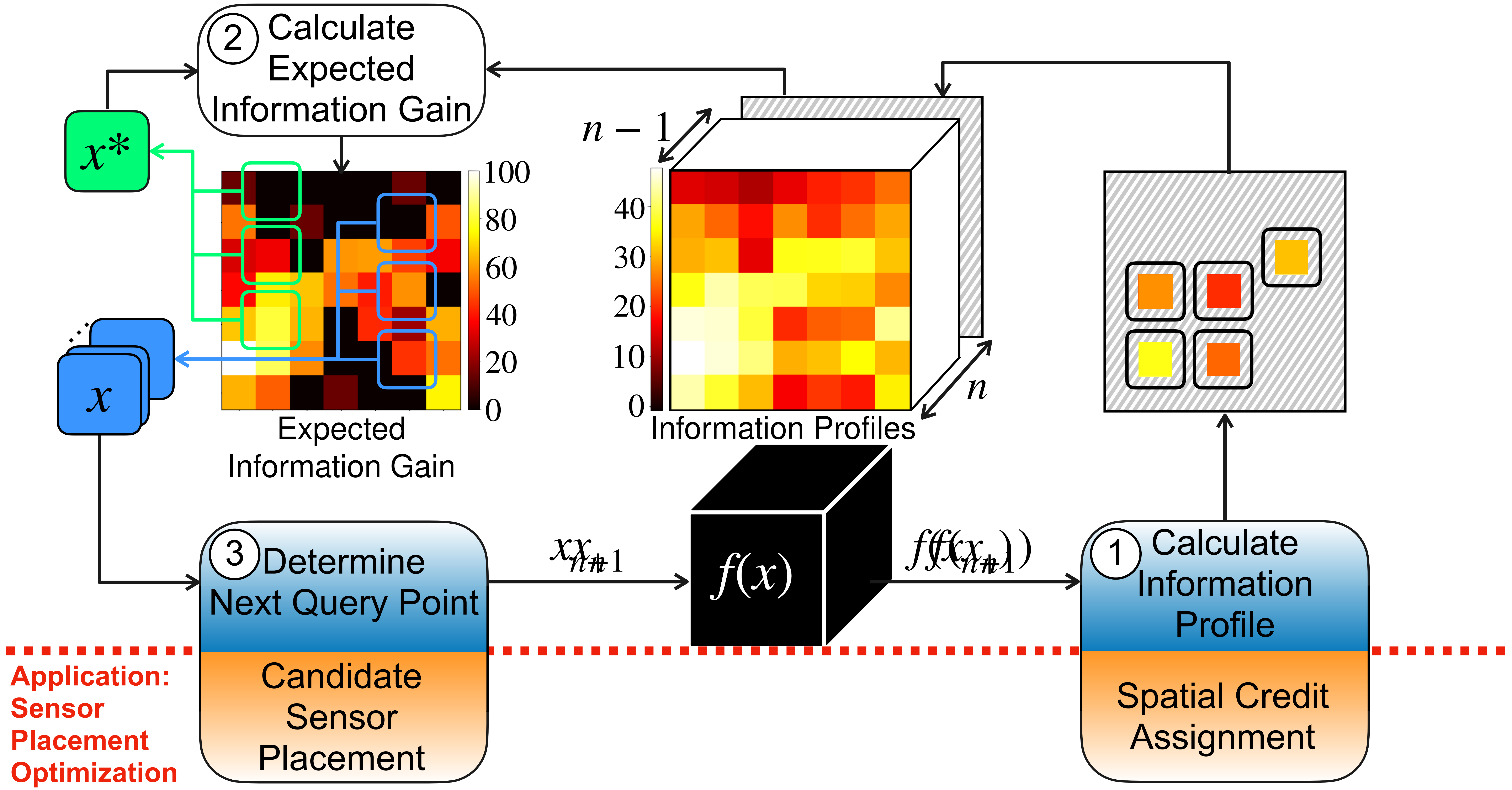
How to **reduce** the number of queries and **improve** the quality of solution found by BO

Distribution—Guided BO (DGBO)

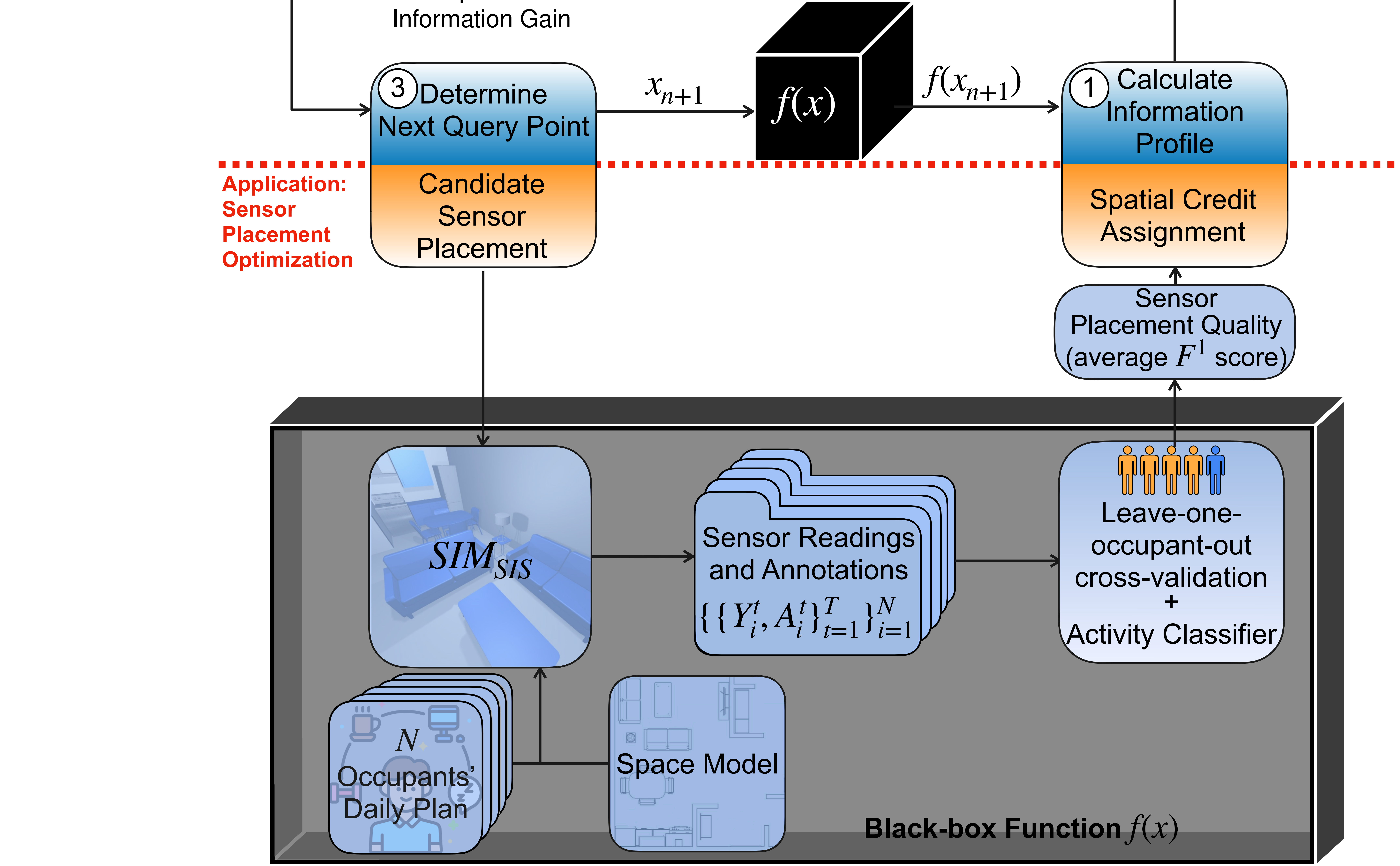


Vanilla BO


Acquisition function $\alpha(x;\hat{f})$
Compute
$\hat{f}(x)$
Fit a Surrogate Model
Z
$\{(x_1, f(x_1) \dots (x_I, f(x_I))\}$
$x_{next} = \arg\max_x \alpha(x;\hat{f})$
x_{next}
$f(x)$
$\{x_{next}, f(x_{next})\}$
I initial samples



2 Calculate Expected Information Gain
x*
x
100
80
60
40
20
0
Expected Information Gain
n − 1
n
40
30
20
10
0
Information Profiles
3 Determine Next Query Point
x_{n+1}
$f(x)$
$f(x_{n+1})$
1 Calculate Information Profile
Application: Sensor Placement Optimization
Candidate Sensor Placement
Spatial Credit Assignment



Information Gain
3 Determine Next Query Point
x_{n+1}
$f(x)$
$f(x_{n+1})$
1 Calculate Information Profile
Application: Sensor Placement Optimization
Candidate Sensor Placement
Spatial Credit Assignment
Sensor Placement Quality (average F^1 score)
SIM_{SIS}
Sensor Readings and Annotations
$\{\{Y_i^t, A_i^t\}_{t=1}^{T}\}_{i=1}^{N}$
Leave-one-occupant-out cross-validation + Activity Classifier
N Occupants' Daily Plan
Space Model
Black-box Function $f(x)$

Experiments

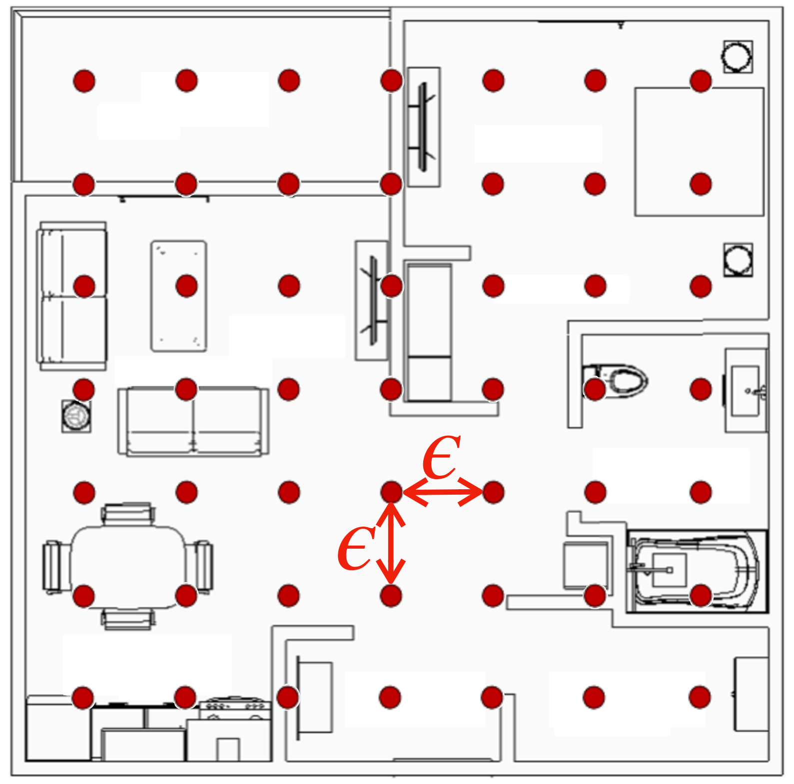
Case Study

Lifestyle Options Retirement Communities - Terra Losa

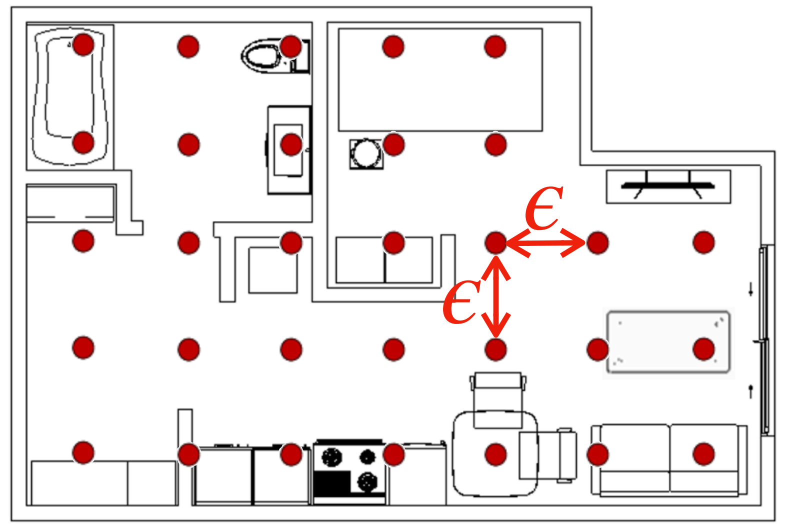
17203 99 Ave NW,
Edmonton, AB T5T 6S5

Simulation Case Study

T1



T2



23 activities

activities with the same superscript can be shuffled

Bathing [a]

1 Undress
2 Shower
3 Dress

Hygiene [a]

1 Use toilet
2 Wash hands

Other [a]

Work w/ Tablet [b]
Exercise [b]
Watch TV [b]
Iron [b]
Sleep [b]

Dining routine [a]

Make tea
Grab ingredients
Fry eggs
Toast breads
Grab utensils
Eat
Take medicine
Wipe dining table
Wash dishes
Clean kitchen

Brooming [a]

Grab broom
Broom
Return broom

Experiments

Case Study

Center of Advanced Studies In Adaptive System

https://casas.wsu.edu/

Real-World Case Study

Aruba

From in 219 days
11 activities
from an adult living alone

- Meal preparation
- Eat
- Enter home
- Wash dishes
- Respirate
- Housekeeping
- Relax
- Work
- Hygiene
- Sleep
- Leave home

Experiments

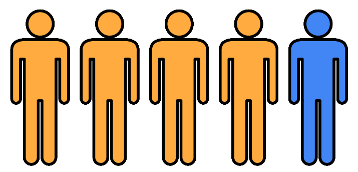
Activity Classifier and Model Performance

Simulation Case Study

Sensor Readings and Annotations

$\{ \{ R^t , A^t \}_{t=1}^{T} \}_{i=1}^{N}$

LOO



Random Forest

Thomas, Brian L., Aaron S. Crandall, and Diane J. Cook. "A Genetic Algorithm approach to motion sensor placement in smart environments." *Journal of reliable intelligent environments* 2.1 (2016): 3-16.

$$F^1 = \Sigma_{i=1}^{N} (\text{Macro avg f1-score})/N$$

Real-World Case Study

219 days

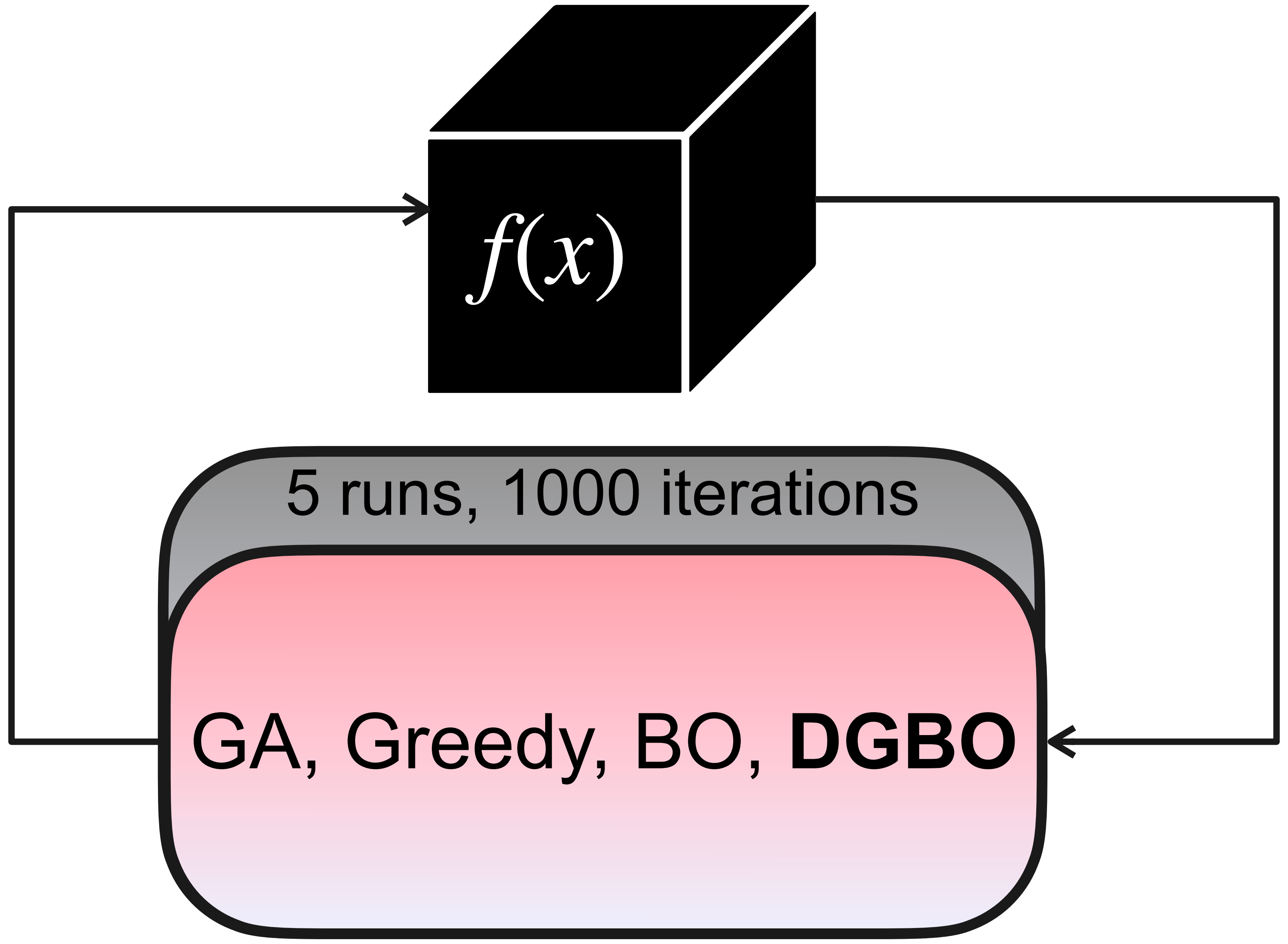
70% 30%

Random Forest

Thomas, Brian L., Aaron S. Crandall, and Diane J. Cook. "A Genetic Algorithm approach to motion sensor placement in smart environments." *Journal of reliable intelligent environments* 2.1 (2016): 3-16.

Macro avg f1-score

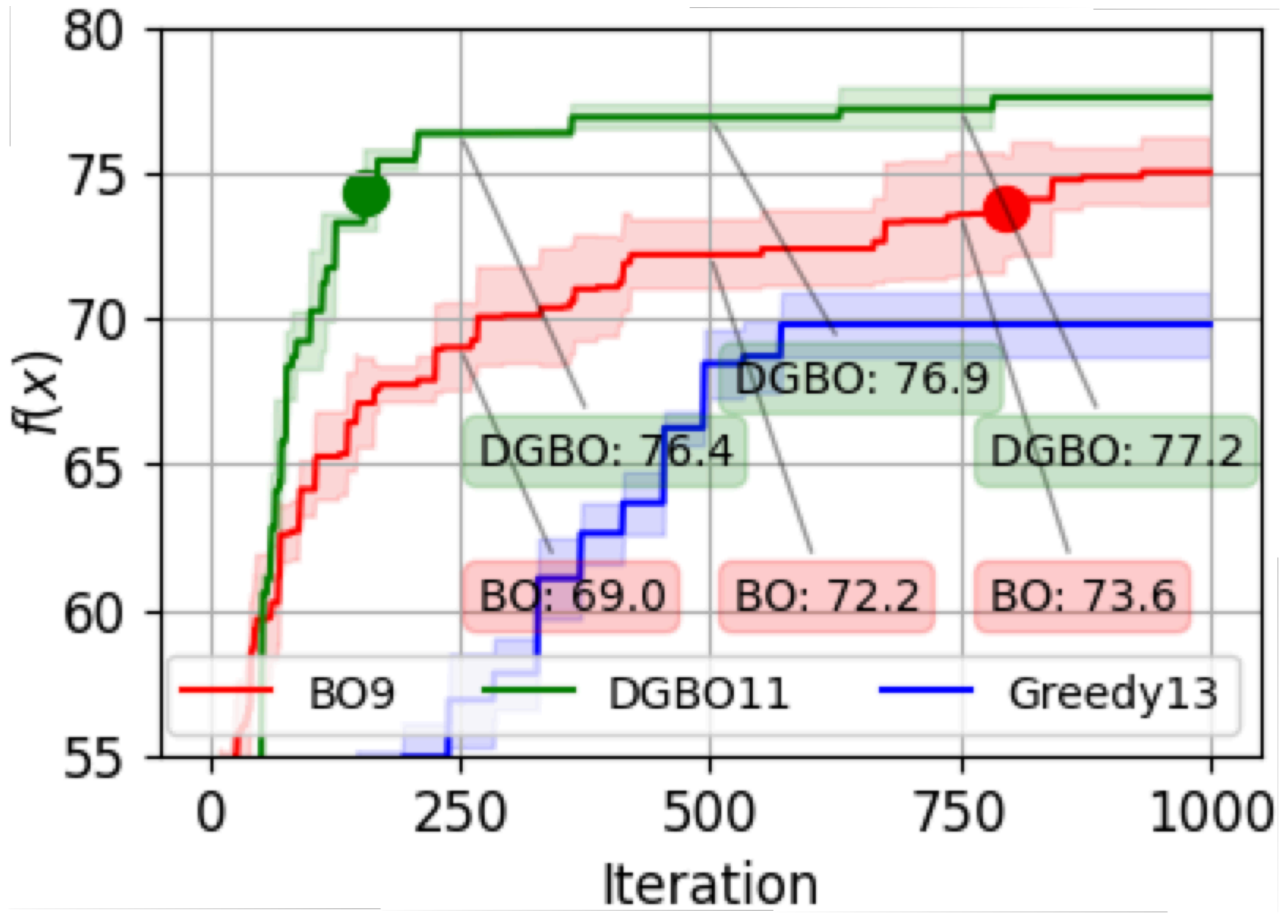
Experiments
Comparison



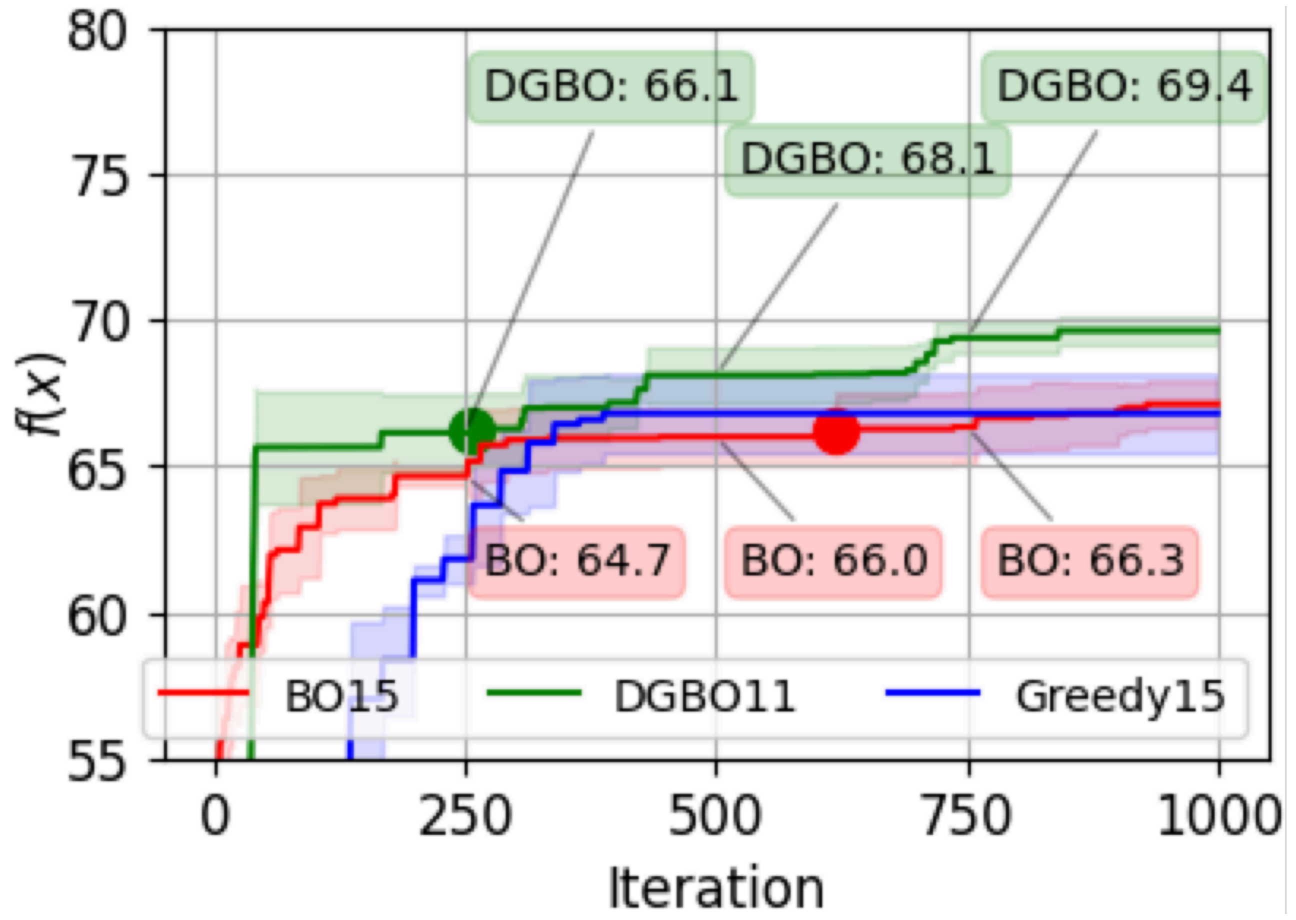
Experiments

Results

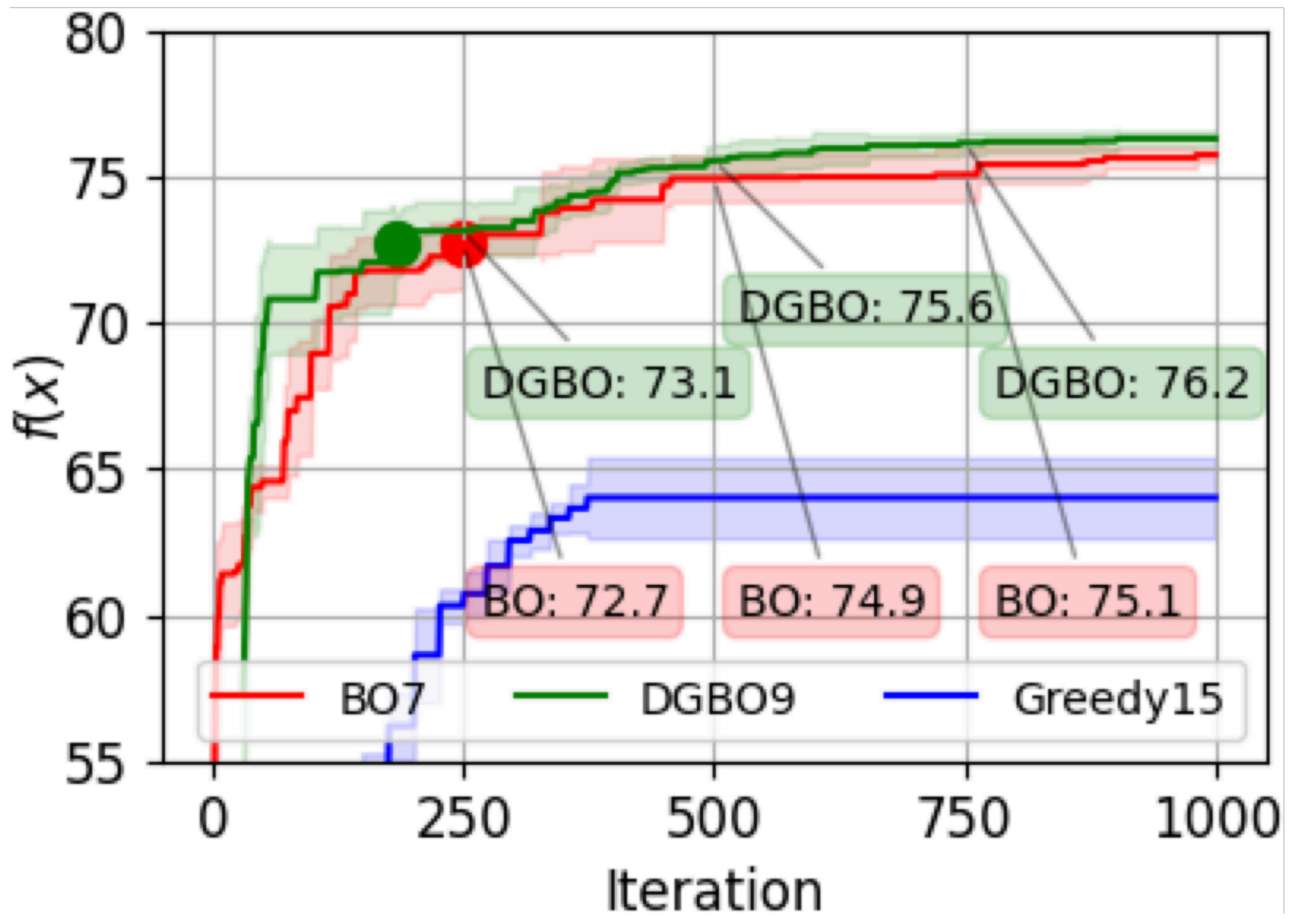
T1 with $\epsilon = 1$



T2 with $\epsilon = 1$



Aruba



Testbed		$100\times\frac{\bullet-\bullet}{\bullet}$	avg.
T1	ϵ=**0.25**(**m**)	-17.9%	-55.4%
	ϵ=**0.5**(**m**)	-61.8%	
	ϵ=**1**(**m**)	-86.6%	
T2	ϵ=**0.25**(**m**)	-41.0%	-58.9%
	ϵ=**0.5**(**m**)	-71.7%	
	ϵ=**1**(**m**)	-64.1%	
Aruba		-39.6%	-39.6%

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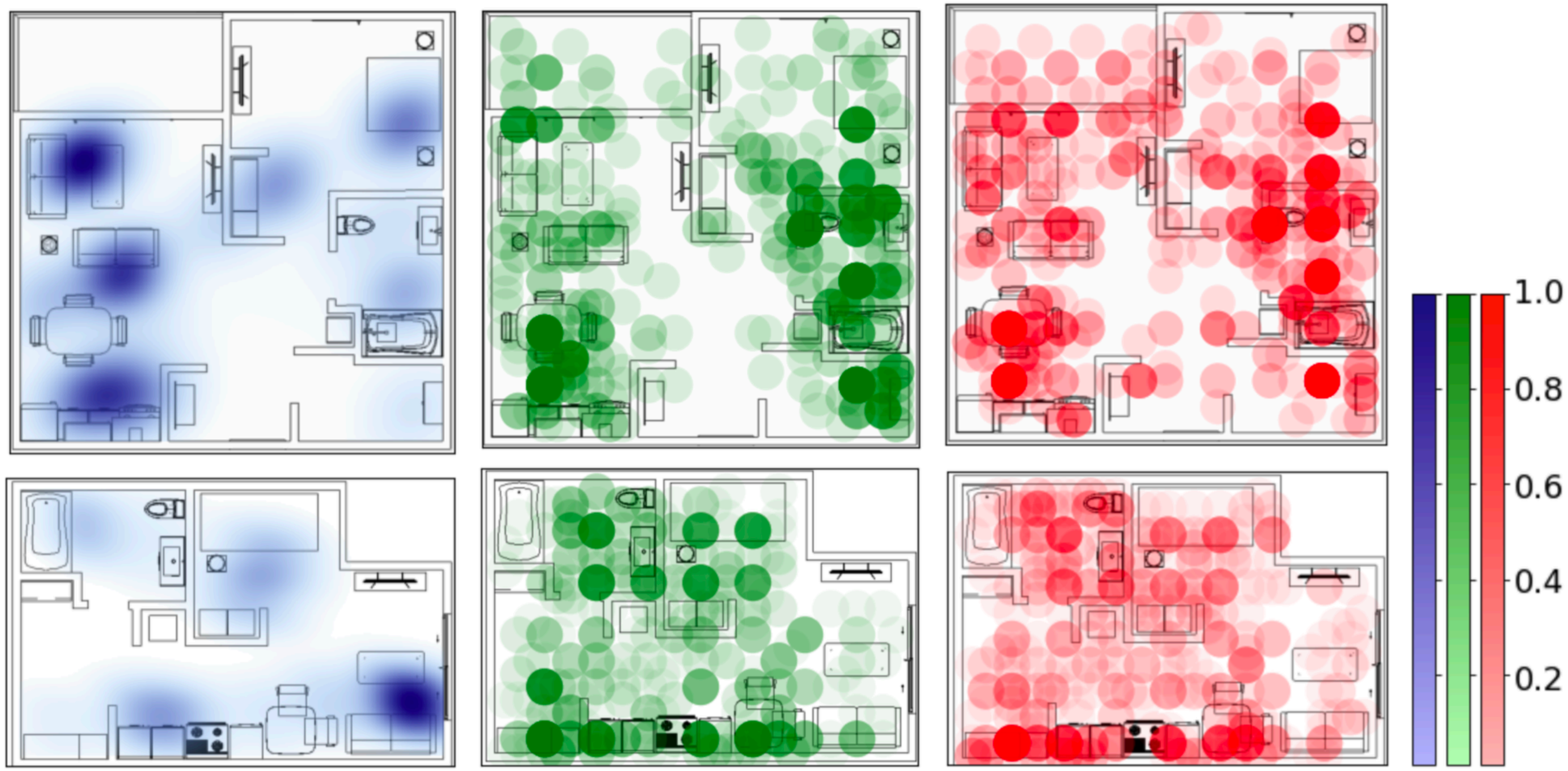
Experiments

Results

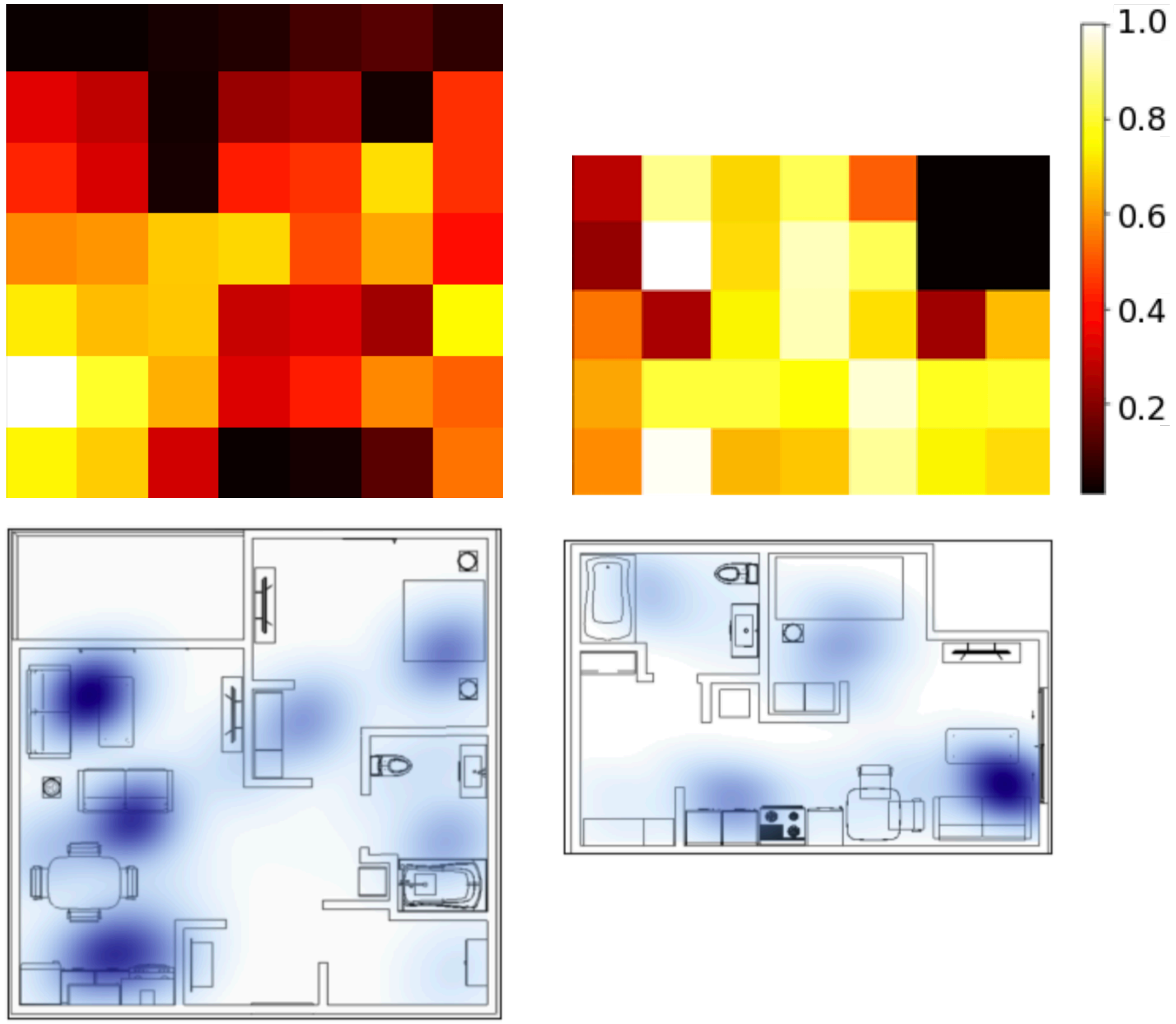


Discussion

DGBO learns the **spatial distribution of activities**,
that results in:

- High quality sensor placement
- Significantly fewer queries

Expected Information Gain Convergence (after 50 iterations)



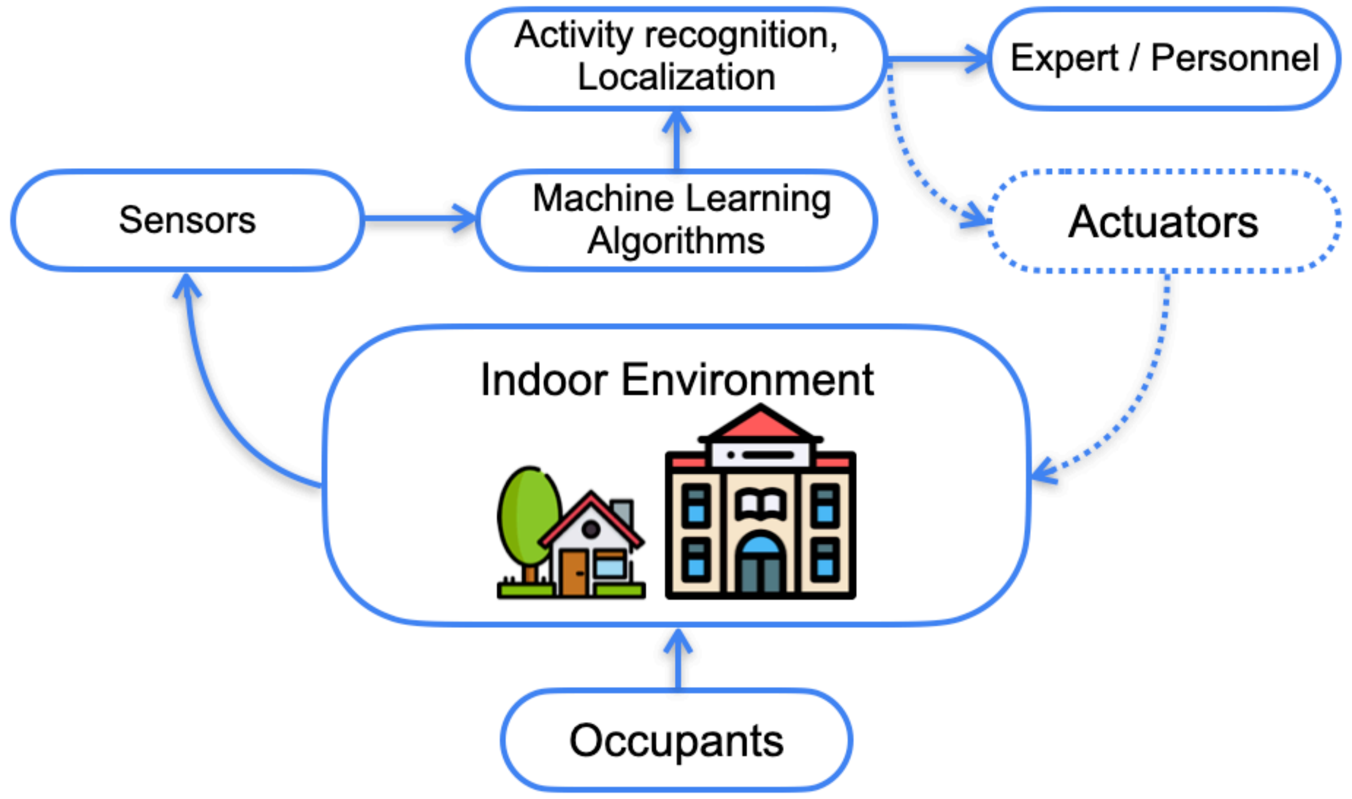
DGBO in other domains:

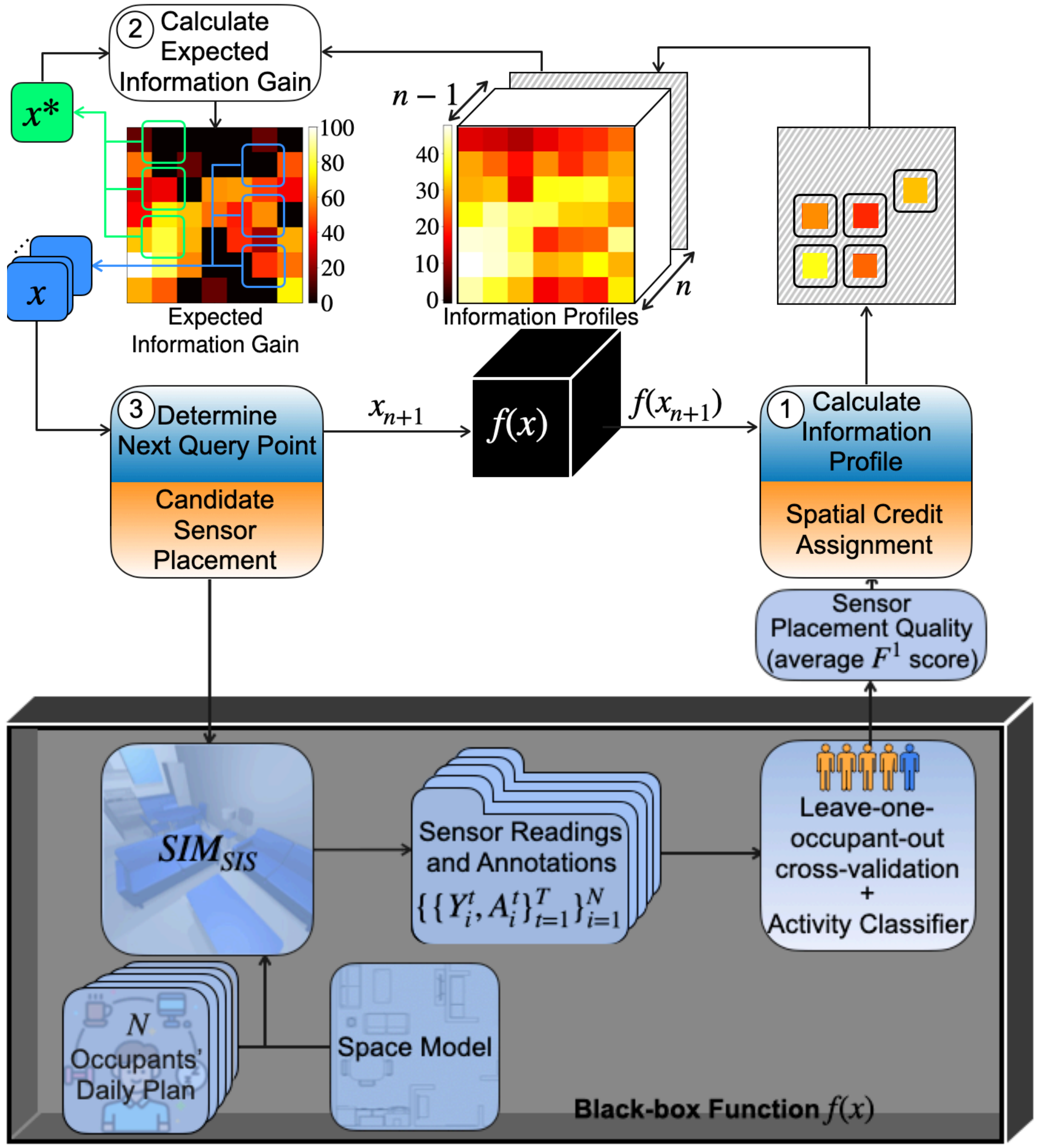
Air pollution

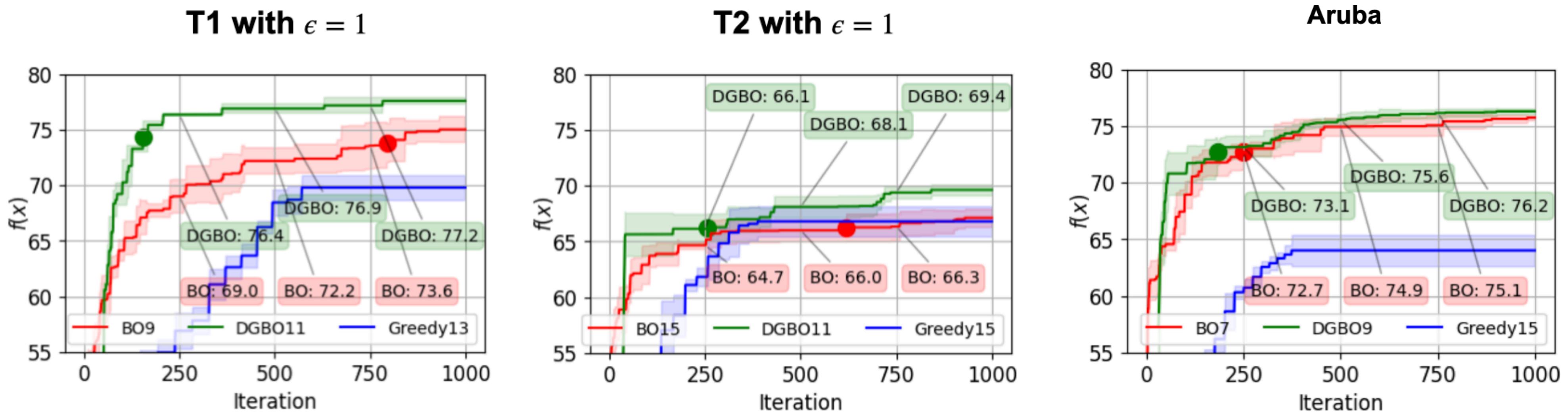
Wildfire

Emergency response

Conclusion







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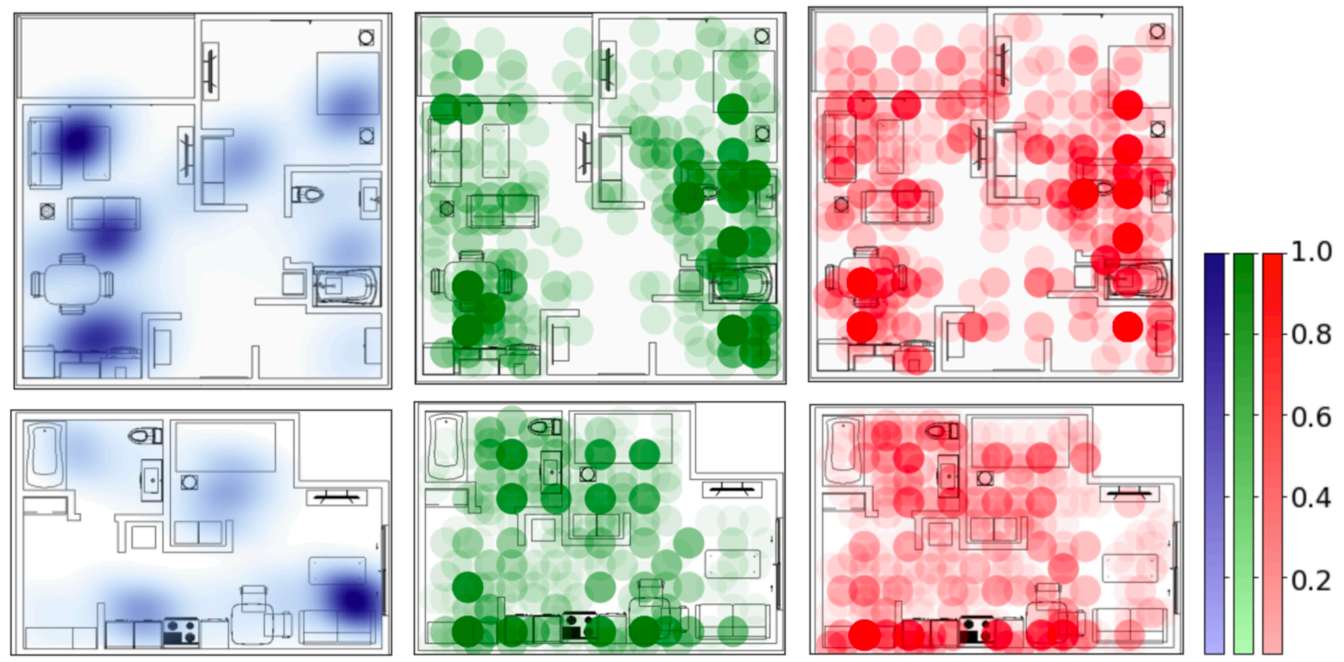

Thanks!