

# PySensors 2.0: A Python Package for Sparse Sensor Placement

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## Software

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## Summary

PySensors is a Python package for the optimization of sparse sensor placement for reconstruction and classification tasks. This major update to PySensors introduces novel spatial constraints for sensor placement, including the enforcement of maximum or exact sensor counts in specific regions, predetermined sensor locations, and minimum distances between sensors. This functionality is extended to support custom basis inputs, enabling integration of any data-driven or spectral basis. We also propose a thermodynamic approach that goes beyond a single “optimal” sensor configuration and maps the complete landscape of sensor interactions induced by the training data. This comprehensive view facilitates integration with external selection criteria and enables assessment of sensor replacement impacts. The new optimization technique also accounts for over- and under-sampling of sensors, utilizing a regularized least squares approach for robust reconstruction. Additionally, we implement noise-induced uncertainty quantification of the estimation error and provide pointwise uncertainty heat maps to guide deployment decisions. To highlight these additions, we outline the mathematical algorithms and theory underlying these new capabilities. The usage of these new features is illustrated with code examples and practical advice for implementation across multiple application domains. Finally, we outline a roadmap of potential extensions to further strengthen the package's functionality and applicability to emerging sensing challenges.

## Statement of need

The scalable optimization of sensor placement is critical for efficient monitoring, control, and decision-making in complex engineering systems. Sensor measurements are necessary for real-time estimation of high-dimensional fluid flows (Erichson et al., 2020), large-scale flexible structures (Manohar, Hogan, et al., 2018), temperature fields and pressure fields across geophysical (Alonso et al., 2010) and nuclear energy systems (Karnik et al., 2024). Accurate real-time tracking of key system variables depends sensitively on the locations of sensors deployed within the system, which have to be optimized for the desired task. In general, the selection of an optimal subset of sensors among candidate locations is NP-hard, necessitating heuristic or greedy approaches such as compressed sensing (Donoho, 2006) or greedy algorithms that exploit submodularity (Krause et al., 2008).

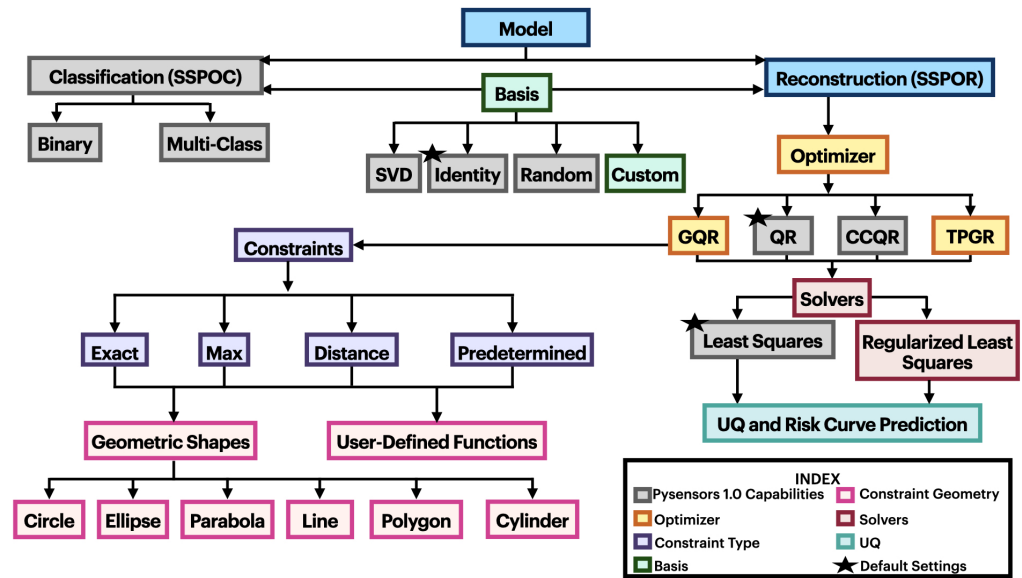


Figure 1: An overview image of capabilities of PySensors

PySensors is a Python package (Silva et al., 2021) dedicated to solving the complex challenge of optimal sensor placement in data-driven systems. It implements advanced sparse optimization algorithms that use dimensionality reduction techniques to identify the most informative measurement locations with remarkable efficiency (Brunton et al., 2016; Clark et al., 2020; Manohar, Brunton, et al., 2018). It helps users identify the best locations for sensors when working with complex high dimensional data, focusing on both reconstruction (Manohar, Brunton, et al., 2018) and classification (Brunton et al., 2016) tasks. The package follows scikit-learn conventions for user-friendly access while offering advanced customization options for experienced users. Other sensor placement packages such as Chama (Klise et al., 2017), Polire (Narayanan et al., 2020), and OSPS toolbox (Yi et al., 2011), focus primarily on event detection, Gaussian process modeling, and structural health monitoring respectively, while PySensors specifically targets signal reconstruction and classification applications.

The original PySensors code provided an implementation of Sparse Sensor Placement for Reconstruction (SSPOR) using the QR optimizer for optimal sensor selection in unconstrained placement settings in which the number of sensors  $p$  is equivalent to the number of modes  $r$ . The previous version offered only limited support for constraints and for specifying the number of sensors, which restricts its applicability to many real-world problems. The Cost-Constrained QR (CCQR) framework incorporated heterogeneous cost functions into the optimization process to accommodate practical deployment constraints. The Sparse Sensor Placement Optimization for Classification (SSPOC) framework identified minimal sensor configurations that can classify high dimensional signals  $\mathbf{x} \in \mathbb{R}^n$  as belonging to one of  $c$  classes. Data is projected into a reduced spectral or data-driven basis  $r \ll n$  to enable efficient optimization. Different basis functions such as Identity, SVD and RandomProjection implemented in PySensors can significantly impact sensor selection effectiveness and reconstruction quality (Manohar, Brunton, et al., 2018).

This new version of PySensors focuses specifically on practical engineering applications where measurement data is inherently noisy and spatial deployment constraints are unavoidable. Key improvements include constraint-aware optimization methods that handle spatial restrictions and sensor density limitations. This version of PySensors implements methodologies introduced in (Klishin et al., 2023) and (Karnik et al., 2024) to make them accessible to scientists and engineers in all domains. These enhancements transform PySensors from a purely academic tool into a practical platform for solving real-world sensing challenges while maintaining

70 mathematical rigor. Our code is thoroughly documented and contains extensive examples.  
71 PySensors is completely open-source and adheres to PEP8 stylistic standards.

## 72 New Features

73 PySensors 1.0 implemented two sensor placement methods for reconstruction: (1) QR, a greedy  
74 optimization technique that places sensors throughout an unconstrained domain, and (2) CCQR,  
75 a cost-constrained optimization technique that accepts a user-defined vector of sensor costs  
76 throughout the domain, penalizing larger-cost locations for sensor placement.

77 Traditional QR factorization presents challenges for under-sampling ( $p < r$ ) and over-sampling  
78 ( $p > r$ ) regimes in which the number of sensors is strictly greater or less than the model rank,  
79 respectively, and cannot enforce complex spatial constraints. PySensors 2.0 addresses these  
80 limitations through two new optimization algorithms: Generalized QR (GQR) and Two Point  
81 Greedy (TPGR).

82 Implementing spatially constrained sensor placement requires a deeper intervention in the  
83 underlying QR optimization framework. To address this requirement, we add the generalized  
84 QR GQR optimization functionality based on recent work (Karnik et al., 2024), which provides  
85 the architectural flexibility needed to handle complex spatial constraints. We enhance the  
86 algorithm's capabilities by implementing diverse spatial constraints options: maxn, exactn,  
87 predetermined, and distance. Pre-defined constraint regions include 'Circle', 'Ellipse', 'Poly-  
88 gon', 'Parabola', 'Line', and 'Cylinder'. Additionally, users can define a custom constraint using  
89 a .py python file or an equation string.

90 The objective that the QR optimizer is based on suffers from two limitations, it is not defined for  
91 the under-sampling regime, in which the number of sensors is less than the model rank ( $p < r$ ),  
92 and the underlying optimization is difficult to interpret and visualize directly. Ref.(Klishin et al.,  
93 2023) resolves these limitations by adding a prior regularization and decomposing the resulting  
94 objective into sums over the placed sensors

$$\mathcal{H} \equiv -\log \det(\mathbf{S}^{-2} + (\mathbf{S}\Psi_r)^T(\mathbf{S}\Psi_r)/\eta^2) \approx E_b + \sum_{i \in \gamma} h_i + \sum_{i \neq j \in \gamma} J_{ij}$$

95 The Two Point Greedy (TPGR) optimizer uses the above approximate objective, which allows  
96 the user to specify any number of sensors  $p$  for a given mode number  $r$ . In contrast, the QR  
97 pivoting algorithm always returns exactly  $p = r$  sensors, ordered by decreasing importance,  
98 with any additional sensors selected randomly. Beyond this flexibility, TPGR can also generate  
99 sensor placement energy landscapes, providing insight into the relative quality of different  
100 sensor configurations.

101 PySensors 2.0 adds the Regularized Least Squares solution derived in Ref.(Klishin et al.,  
102 2023):

$$\mathbf{A}_{RLS} = (\mathbf{S}^{-2} + (\mathbf{S}\Psi_r)^T(\mathbf{S}\Psi_r)/\eta^2)^{-1} (\mathbf{S}\Psi_r)^T/\eta^2,$$

103 This Regularized Least Squares solution is the new default reconstruction solver for PySensors  
104 2.0, replacing the Least Squares solution via the Moore-Penrose pseudoinverse. We implement  
105 uncertainty quantification metrics from (Klishin et al., 2023) to assess the propagation of  
106 measurement noise through reconstruction algorithms and provide robust pointwise error  
107 estimates in reconstruction outputs. In addition, this version adds support for custom bases,  
108 so that researchers can transform their data into an alternative basis such as dynamic mode  
109 decomposition (DMD) modes before passing it to PySensors.

110 Finally, we demonstrate these new functionalities using new notebook examples for nuclear  
111 energy component systems, and update and streamline existing notebooks for sea surface  
112 temperature and image reconstruction.

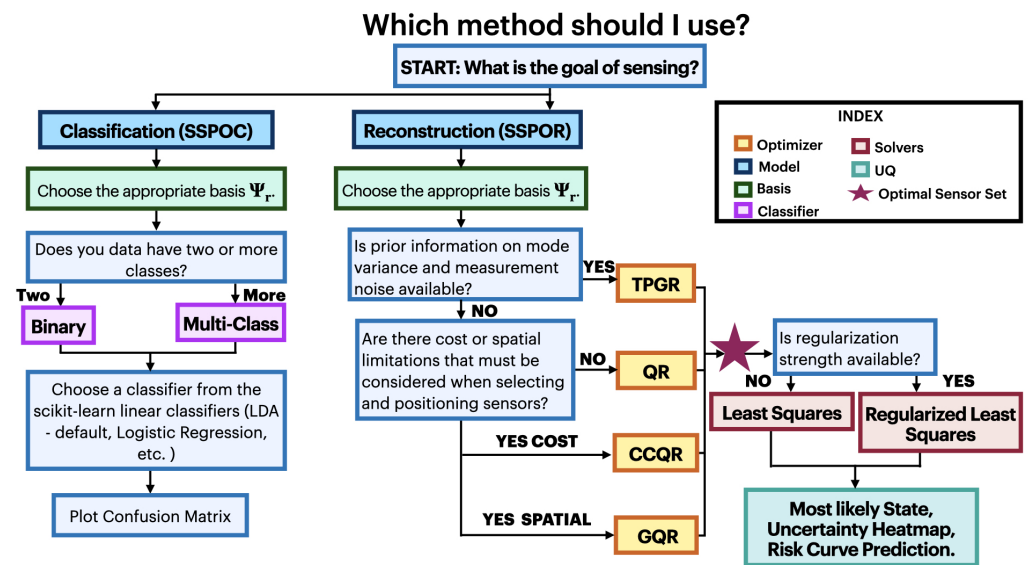


Figure 2: A flowchart to suggest which method to use

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## References

- Alonso, M. T., López-Dekker, P., & Mallorquí, J. J. (2010). A novel strategy for radar imaging based on compressive sensing. *IEEE Transactions on Geoscience and Remote Sensing*, 48(12), 4285–4295. <https://doi.org/10.1109/TGRS.2010.2051231>
- Brunton, B. W., Brunton, S. L., Proctor, J. L., & Kutz, J. N. (2016). Sparse sensor placement optimization for classification. *SIAM Journal on Applied Mathematics*, 76(5), 2099–2122. <https://doi.org/10.1137/15M1036713>
- Clark, E., Brunton, S. L., & Kutz, J. N. (2020). Multi-fidelity sensor selection: Greedy algorithms to place cheap and expensive sensors with cost constraints. *IEEE Sensors Journal*, 21(1), 600–611. <https://doi.org/10.1109/JSEN.2020.3013094>
- Donoho, D. L. (2006). Compressed sensing. *IEEE Transactions on Information Theory*, 52(4), 1289–1306. <https://doi.org/10.1109/TIT.2006.871582>
- Erichson, N. B., Mathelin, L., Yao, Z., Brunton, S. L., Mahoney, M. W., & Kutz, J. N. (2020). Shallow neural networks for fluid flow reconstruction with limited sensors. *Proceedings of the Royal Society A*, 476(2238), 20200097. <https://doi.org/10.1098/rspa.2020.0097>
- Karnik, N., Abdo, M. G., Estrada-Perez, C. E., Yoo, J. S., Cogliati, J. J., Skifton, R. S., Calderoni, P., Brunton, S. L., & Manohar, K. (2024). Constrained optimization of sensor placement for nuclear digital twins. *IEEE Sensors Journal*. <https://doi.org/10.1109/JSEN.2024.3368875>

- 139 Klise, K. A., Nicholson, B., & Laird, C. D. (2017). Sensor placement optimization using  
140 chama. *Number SAND2017-11472*. Albuquerque, NM: Sandia National Laboratories.  
141 <https://doi.org/10.2172/1405271>
- 142 Klishin, A. A., Kutz, J. N., & Manohar, K. (2023). Data-induced interactions of sparse sensors.  
143 *arXiv Preprint arXiv:2307.11838*. <https://doi.org/10.48550/arXiv.2307.11838>
- 144 Krause, A., Singh, A., & Guestrin, C. (2008). Near-optimal sensor placements in gaussian  
145 processes: Theory, efficient algorithms and empirical studies. *Journal of Machine Learning*  
146 *Research*, 9(2). <https://dl.acm.org/doi/10.5555/1390681.1390689>
- 147 Manohar, K., Brunton, B. W., Kutz, J. N., & Brunton, S. L. (2018). Data-driven sparse  
148 sensor placement for reconstruction: Demonstrating the benefits of exploiting known  
149 patterns. *IEEE Control Systems Magazine*, 38(3), 63–86. <https://doi.org/10.1109/MCS.2018.2810460>
- 151 Manohar, K., Hogan, T., Buttrick, J., Banerjee, A. G., Kutz, J. N., & Brunton, S. L. (2018).  
152 Predicting shim gaps in aircraft assembly with machine learning and sparse sensing. *Journal*  
153 *of Manufacturing Systems*, 48, 87–95. <https://doi.org/10.1016/j.jmsy.2018.01.011>
- 154 Narayanan, S. D., Patel, Z. B., Agnihotri, A., & Batra, N. (2020). A toolkit for spatial  
155 interpolation and sensor placement. *Proceedings of the 18th Conference on Embedded*  
156 *Networked Sensor Systems*, 653–654. <https://doi.org/10.1145/3384419.3430407>
- 157 Silva, B. M. de, Manohar, K., Clark, E., Brunton, B. W., Kutz, J. N., & Brunton, S. L.  
158 (2021). PySensors: A python package for sparse sensor placement. *Journal of Open Source*  
159 *Software*, 6(58), 2828. <https://doi.org/10.21105/joss.02828>
- 160 Yi, T.-H., Li, H.-N., & Gu, M. (2011). Optimal sensor placement for structural health  
161 monitoring based on multiple optimization strategies. *The Structural Design of Tall and*  
162 *Special Buildings*, 20(7), 881–900. <https://doi.org/10.1002/tal.712>