APPENDIX A
SUPPLEMENTARY ALGORITHMS DETAILS

Algorithm S-I STRidge with Conditional Bound

Input: $(X, y) = \{(X_n, y_n)\}_{n=1}^{N}$: Dataset;
$\hat{\mathbf{f}}$: Vector of k candidate terms ($g(\mathcal{T}_i, X_n)$ is denoted as $\hat{f}_i(X_n)$ for agent i for simplicity);
lb, ub: Lower/upper bounds for coefficients ($0 \leq lb < ub$);
λ: Ridge regularization parameter;
ϵ_t: Tolerance threshold for convergence.
Output: $\boldsymbol{\xi}$: Sparse weight coefficient vector ($\xi_i = 0$ if pruned)

$\boldsymbol{\xi} \leftarrow \mathbf{0}_k$
$\mathcal{M} \leftarrow \mathbf{1}_k$ //Binary mask where $\mathcal{M}_i = 1$ indicates that the i^{th} term is retained
set a large value to initialize $error_{\text{prev}}$
repeat
  execute Ridge Regression:

$$\hat{\boldsymbol{\xi}} \leftarrow \arg\min_{\boldsymbol{\xi}} \sum_{n=1}^{N} \Big(y_n - \sum_{i=1}^{k} \mathcal{M}_i \xi_i \hat{f}_i(X_n)\Big)^2 + \lambda \sum_{i=1}^{k} \mathcal{M}_i \xi_i^2$$

  //Update weight coefficients and mask
  for $i = 1$ to k **do**
    if $|\hat{\xi}_i| < lb$ or $|\hat{\xi}_i| > ub$ **then**
      $\mathcal{M}_i \leftarrow 0$ //Prune term i if coefficient out of bounds
      $\xi_i \leftarrow 0$ //Set coefficient to zero
    else if $\mathcal{M}_i == 1$ **then**
      $\xi_i \leftarrow \hat{\xi}_i$ //Select the coefficient if the term is retained
    end if
  end for
  $error \leftarrow \sqrt{\sum_{n=1}^{N} \big(y_n - \sum_{i=1}^{k} \xi_i \hat{f}_i(X_n)\big)^2}$
  if $|error_{\text{prev}} - error| < \epsilon_t$ **or** $\mathcal{M}$ unchanged **then**
    break
  else
    $error_{\text{prev}} \leftarrow error$
  end if
until convergence or maximum iterations
return $\boldsymbol{\xi}$

APPENDIX B
SUPPLEMENTARY EXPERIMENTAL DETAILS

In this section, we provide a detailed description of the experimental procedures.

Table S-I outlines the hyperparameters used by MASR; in the experiments, DSR, NGGP, DGSR, and SPL employed the parameters provided in the original paper. For the Livermore-13 and Livermore-22 tasks, the maximum expression length constraint is set to 8.

Table S-II summarizes the value ranges of benchmark problem sets and the permitted symbol library for MASR.

Table S-III presents the detailed recovery rates of several algorithms in 20 independent training runs on the Nguyen, Synthetic, Livermore and BH benchmark problem sets. In particular, MASR employed 16 agents for Nguyen, Livermore and BH, and 32 agents for Synthetic.

Table S-IV shows the specific symbolic regression results for MASR on the Nguyen benchmark.

Table S-V shows the RMSE values of expressions recovered by different algorithms on the Jin benchmark problem sets, a collection characterized by function terms with floating-point coefficients instead of integers. The results demonstrate that MASR is suited for expressions with non-integer coefficients, benefiting from the robust fitting capability of STRidge.

Table S-VI presents the recovery results of MASR across various PDE study cases, along with the associated errors in the weight coefficients.

Table S-VII shows the results of the MASR overfit using 32 agents in Nguyen-4 and Nguyen-12, where it is evident that although the recovered expressions have an extremely low MSE value, their readability is significantly reduced, resembling more a numerical approximation than a clear mathematical expression.

TABLE S-I: Hyperparameter Settings

Hyperparameter	**Value**
RNN Parameters	
Optimizer	Adam
RNN cell type	LSTM
RNN layers	2
RNN cell size	32
Learning rate	0.0001
Entropy weight	0.2
STRidge Regression	
Lower bound	0.0001
Upper bound	10000
Training Parameters	
Minimum expression length	3
Maximum expression length	6
Maximum expressions	1000000
Batch size	1000
Risk factor	0.01
Local reward weight (β)	0.001
Early stop threshold	1e-25

Hyperparameters were tuned via grid search on the Nguyen benchmark set. For each hyperparameter combination, the algorithm was independently run 10 times. The combination with the highest average recovery rate was selected; in cases of ties, the one with the lowest average MSE was chosen. The best hyperparameter configurations for each algorithm were used across all experiments and benchmark expressions. In MASR, the hyperparameter search space included the number of agents $\in \{4, 8, 16, 32\}$, batch size $\in \{250, 500, 1000\}$, learning rate $\in \{0.0003, 0.0005, 0.001\}$, entropy weight $\in \{0.01, 0.05, 0.1, 0.2, 0.3\}$, and risk factor $\in \{0.01, 0.1, 0.2\}$.

TABLE S-II: The benchmark symbolic regression problem is defined as follows: input variables $\mathcal{L}_{\text{Input}} = \{x_1, x_2, x_3, \ldots\}$ are determined by the number of variables in each benchmark expression. The notation $U(a, b, c)$ represents c random points uniformly sampled between a and b for each input variable (or time steps at 0.001 intervals for the PDE task), using distinct random seeds for training and test datasets. We define four standard token libraries: $\mathcal{L}_{\text{Koza}} = \{+, -, \times, \div, \sin, \cos, \exp, \log, ^2, ^3\} \cup \sum \mathcal{L}_{\text{Input}}$, $\mathcal{L}_{\text{Synth}} = \{+, -, \times, \div\} \cup \sum \mathcal{L}_{\text{Input}}$, and $\mathcal{L}_{\text{PolyPlus}} = \{+, -, \times, \div, \sin, \cos, \exp, \log\} \cup \sum \mathcal{L}_{\text{Input}}$.

Name	**Dataset**	**Library**
Nguyen-1 to Nguyen-6	$U(-1, 1, 20)$	L_{Koza}
Nguyen-7	$U(0, 2, 20)$	L_{Koza}
Nguyen-8	$U(0, 4, 20)$	L_{Koza}
Nguyen-9 to Nguyen-12	$U(0, 1, 20)$	L_{Koza}
Synthetic-1 to Synthetic-7	$U(-1, 1, 120)$	L_{Synth}
PolyPlus-1	$U(-1, 1, 20)$	L_{PolyPlus}
PolyPlus-2	$U(1, 10, 20)$	L_{PolyPlus}
PolyPlus-3 to PolyPlus-7	$U(-1, 1, 20)$	L_{PolyPlus}
PolyPlus-8	$U(1, 10, 20)$	L_{PolyPlus}
Jin-1 to Jin-5	$U(-3, 3, 100)$	L_{Koza}
Livermore-1	$U(-10, 10, 1000)$	L_{Koza}
Livermore-2	$U(-1, 1, 20)$	L_{Koza}
Livermore-3	$U(-1, 1, 20)$	L_{Koza}
Livermore-4	$U(0, 2, 20)$	L_{Koza}
Livermore-5	$U(0, 1, 20)$	L_{Koza}
Livermore-6	$U(-1, 1, 20)$	L_{Koza}
Livermore-7	$U(-1, 1, 20)$	L_{Koza}

TABLE S-III: Recovery rate (%) of several algorithms on the Nguyen, Livermore, Synthetic and PolyPlus benchmark problem sets across 20 independent runs, including 95% confidence intervals (task-level variation).

Benchmark	Expression	MASR	SPL	DGSR	NGGP	DSR
Nguyen-1	$x_1^3 + x_1^2 + x_1$	100	100	100	100	100
Nguyen-2	$x_1^4 + x_1^3 + x_1^2 + x_1$	100	100	100	100	100
Nguyen-3	$x_1^5 + x_1^4 + x_1^3 + x_1^2 + x_1$	100	100	100	100	100
Nguyen-4	$x_1^6 + x_1^5 + x_1^4 + x_1^3 + x_1^2 + x_1$	100	100	100	100	100
Nguyen-5	$\sin(x_1^2)\cos(x_1) - 1$	100	100	100	100	70
Nguyen-6	$\sin(x_1) + \sin(x_1 + x_1^2)$	100	100	100	100	100
Nguyen-7	$\log(x_1 + 1) + \log(x_1^2 + 1)$	90	100	60	95	30
Nguyen-8	$\sqrt{x_1}$	100	100	90	100	90
Nguyen-9	$\sin(x_1) + \sin(x_2^2)$	100	100	100	100	100
Nguyen-10	$2\sin(x_1)\cos(x_2)$	100	100	100	100	100
Nguyen-11	$x_1^{x_2}$	100	100	100	100	100
Nguyen-12	$x_1^4 - x_1^3 + \frac{1}{2}{x_2}^2 - x_2$	100	35	0	0	0
Average recovery rate (%)		**99.17 ± 1.83**	**94.58 ± 11.92**	**87.50 ± 18.99**	**91.25 ± 18.28**	**82.50 ± 21.18**
Livermore-1	$\frac{1}{3} + x_1 + \sin(x_1^2)$	100	100	60	100	5
Livermore-2	$\sin(x_1^2)\cos(x_1) - 2$	100	30	100	100	90
Livermore-3	$\sin(x_1^3)\cos(x_1^2) - 1$	100	50	100	100	60
Livermore-4	$\log(x_1 + 1) + \log(x_1^2 + 1) + \log(x_1)$	100	70	100	100	75
Livermore-5	$x_1^4 - x_1^3 + x_1^2 - x_2$	100	100	50	20	0
Livermore-6	$4x_1^4 + 3x_1^3 + 2x_1^2 + x_1$	100	15	90	90	100
Livermore-7	$\sinh(x_1)$	100	20	0	0	0
Livermore-8	$\cosh(x_1)$	100	0	0	0	0
Livermore-9	$x_1^9 + x_1^8 + x_1^7 + x_1^6 + x_1^5 + x_1^4 + x_1^3 + x_1^2 + x_1$	0	30	30	10	0
Livermore-10	$6\sin(x_1)\cos(x_2)$	100	80	40	0	0
Livermore-11	$\frac{x_1^4}{x_2 + x_1}$	100	0	100	100	15
Livermore-12	$\frac{x_1^5}{x_2^3}$	100	100	100	100	60
Livermore-13	$x_1^{1/3}$	100	100	100	100	50
Livermore-14	$x_1^3 + x_1^2 + x_1 + \sin(x_1) + \sin(x_1^2)$	100	25	100	100	0
Livermore-15	$x_1^{1/5}$	0	0	100	100	0
Livermore-16	$x_1^{2/5}$	0	0	60	90	5
Livermore-17	$4\sin(x_1)\cos(x_2)$	100	90	30	60	0
Livermore-18	$\sin(x_1^2)\cos(x_1) - 5$	100	20	100	60	0
Livermore-19	$x_1^5 + x_1^4 + x_1^2 + x_1$	100	90	100	100	100
Livermore-20	$\exp(-x_1^2)$	100	100	100	100	100
Livermore-21	$x_1^8 + x_1^7 + x_1^6 + x_1^5 + x_1^4 + x_1^3 + x_1^2 + x_1$	0	65	100	100	0
Livermore-22	$\exp(-0.5x_1^2)$	100	100	10	90	5
Average recovery rate (%)		**81.82 ± 17.50**	**53.86 ± 17.80**	**71.36 ± 16.55**	**73.64 ± 17.50**	**30.23 ± 17.74**
Synthetic-1	$x_{12} + x_9(x_{10} + x_{11}) + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7x_8$	100	35	20	0	0
Synthetic-2	$x_{10} + x_{11} + x_{12} + x_3(x_1 + x_2) + x_4x_5 + x_6 + x_7 + x_8 + x_9$	100	0	100	100	80
Synthetic-3	$x_{10} + x_9(x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8) + x_{11} + x_{12}$	0	0	0	0	0
Synthetic-4	$x_8(x_6 + x_7) - (x_{10} + x_{11}x_{12} + x_9)x_1 + x_2 + x_3 + x_4 + x_5$	0	0	0	0	0
Synthetic-5	$x_{10} + x_{11} + x_{12} + x_9(x_1 + x_2) - x_3 + x_4 + x_5 + x_6 + x_7 + x_8$	100	30	45	0	0
Synthetic-6	$x_1(x_{10} - x_{11}) + x_{12} + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9$	100	60	100	100	60
Synthetic-7	$x_1x_2 - x_{11}(x_{10} + x_6 + x_7) + x_8 - x_9 + x_{12} + x_3 + x_4 + x_5$	100	0	0	0	0
Average recovery rate (%)		**71.43 ± 45.13**	**17.86 ± 22.31**	**37.86 ± 42.03**	**28.57 ± 45.13**	**20.00 ± 32.04**
PolyPlus-1	$x_1^2 + x_1 + \exp(x_1) + \log(x_1 + 1) + \sin(x_1) + \cos(x_1)$	85	0	0	0	0
PolyPlus-2	$x_2^2 + x_1 + \exp(x_1) + \log(x_2) + \sin(x_1) + \cos(x_2)$	100	0	50	0	0
PolyPlus-3	$\exp(x_1)/2 + \exp(x_2)/2$	100	90	100	100	75
PolyPlus-4	$\exp(x_1) + \exp(x_2) + \exp(-x_1)$	100	25	10	0	0
PolyPlus-5	$x_1^2 + x_2^2 + x_1x_2 + \sin(x_1)\cos(x_2)$	100	0	95	0	0
PolyPlus-6	$x_1^2 + x_1 + x_1\log(x_1) + \log(x_1^2)$	100	20	0	15	0
PolyPlus-7	$x_1^2 + x_1 + x_1\exp(x_1)$	100	100	100	100	100
PolyPlus-8	$\sin(x_1) + \cos(x_2) - \exp(x_3) + \log(x_4) + x_5x_6$	80	0	0	0	0
Average recovery rate (%)		**95.62 ± 6.86**	**29.38 ± 34.93**	**44.38 ± 39.81**	**26.88 ± 37.98**	**21.88 ± 34.32**

TABLE S-IV: MASR's recovered expressions and mean RMSE on Nguyen Benchmark Problem Sets

Name	Recovered Expression	MSE
Nguyen-1	$1.00000 \cdot (x_1 + x_1^2 + x_1^3)$	1.87720×10^{-31}
Nguyen-2	$-0.99999 \cdot (-x_1 + x_1^3) + 0.99999 \cdot ((x_1 + x_1^2)^2)$	1.18092×10^{-31}
Nguyen-3	$1.00000 \cdot x_1 + 1.00000 \cdot x_1^2 + 1.00000 \cdot x_1^3 + 1.00000 \cdot x_1^2 \cdot (x_1^2 + x_1^3)$	1.02468×10^{-31}
Nguyen-4	$0.50000 \cdot (x_1^2) + 1.00000 \cdot (x_1 + (x_1^2 + x_1) \cdot x_1^3) + 0.50000 \cdot (x_1^2) + 1.00000 \cdot ((x_1^3)^2) + 1.00000 \cdot (x_1^3)$	9.39333×10^{-31}
Nguyen-5	$-1.00000 \cdot (1)^3 + 1.00000 \cdot (\sin(x_1^2) \cdot \cos(x_1))$	5.78792×10^{-30}
Nguyen-6	$1.00000 \cdot (\sin(x_1 + x_1^2) + 1.00000 \cdot \sin(x_1))$	1.33051×10^{-32}
Nguyen-7	$0.50000 \cdot (\log((x_1 + 1)^2)) + 1.00000 \cdot (\log(x_1^2 + 1))$	5.60084×10^{-31}
Nguyen-8	$1.00000 \cdot \sqrt{x_1}$	1.59393×10^{-32}
Nguyen-9	$1.00000 \cdot (\sin(x_2^2) + 1.00000 \cdot \sin(x_1)$	9.69367×10^{-32}
Nguyen-10	$2.00000 \cdot (\sin(x_1) \cdot \cos(x_2))$	2.27455×10^{-32}
Nguyen-11	$1.00000 \cdot (\exp(x_2 \cdot \log(x_1)))$	1.89399×10^{-32}
Nguyen-12	$1.00000 \cdot ((x_1^2)^2) - 1.00000 \cdot (x_1 + x_2) - 0.50000 \cdot x_2^2 + 1.00000 \cdot (x_1 + x_2^2) - 1.00000 \cdot (x_1^3)$	6.69458×10^{-31}

TABLE S-V: Comparison of the root-mean-square error(RMSE) for MASR,DSR, NGGP and SPL in the Jin benchmark problem set which includes floating-point constant values. In the table, the value of 0 indicates that the RMSE at this location is less than 1×10^{-10}.

Benchmark	Expression	DSR	NGGP	SPL	MASR
Jin-1	$2.5x_1^4 - 1.3x_1^3 + 0.5x_2^2 - 1.7x_2$	0.46	0	0	0
Jin-2	$8.0x_1^2 + 8.0x_2^3 - 15.0$	0	0	0	0
Jin-3	$0.2x_1^3 + 0.5x_2^3 - 1.2x_2 - 0.5x_1$	0.00052	0	0	0
Jin-4	$1.5\exp(x_1) + 5.0\cos(x_2)$	0.00014	0	0	0
Jin-5	$6.0\sin(x_1)\cos(x_2)$	0	0	0	0
RMSE		**0.092**	**0**	**0**	**0**

TABLE S-VI: Recovered PDEs and the corresponding weight coefficient error

Name	Expression	Weight Coefficient Error
Kdv(1D)	$u_t = -1.0004uu_x - 0.0025u_{xxx}$	$0.02\% \pm 0.02\%$
Burgers(1D)	$u_t = -1.0004uu_x + 0.0984u_{xx}$	$0.82\% \pm 0.78\%$
Chafee-Infante(1D)	$u_t = 1.0002u_{xx} + 1.0004u - 1.0008u^3$	$0.05\% \pm 0.03\%$
Diffusion(2D)	$u_t = 0.1991u_{xx} + 0.1991u_{yy}$	$0.45\% \pm 0.0\%$
CDE(2D)	$u_t = -0.1976u_x - 0.4941u_y + 0.9918u_{xx} + 0.9918u_{yy}$	$1.01\% \pm 0.19\%$

TABLE S-VII: Expressions Overfitted by MASR on Nguyen-4 and Nguyen-12 Benchmarks with 32 Agents

Name	**Label**	**Recovered Expression**	**MSE**
Nguyen-4	$x_1^6+x_1^5+x_1^4+x_1^3+x_1^2+x_1$	$0.03623\cdot(\log((\sin(\exp(x_1)))^2))$ $-\,0.00073\cdot(\sin(\log(x_1^3)))$ $-\,0.27180\cdot E$ $+\,0.02666\cdot(\log(\sin(x_1))\cdot\cos(x_1^2))$ $-\,0.09812\cdot(x_1\cdot\exp(-x_1)\cdot\exp(x_1^2))$ $-\,0.00903\cdot(x_1\cdot(\cos(\exp(x_1^2+x_1)))^2)$ $+\,0.01447\cdot(x_1\cdot(x_1^3)^2)^3$ $-\,0.11587\cdot(x_1^3)^3$ $+\,0.00197\cdot(-x_1+(\cos((\log(x_1^2))^3))^2)$ $+\,0.01952\cdot(\log(x_1))$ $+\,0.25326\cdot(x_1\cdot x_1^2+x_1)$ $-\,0.03175\cdot(x_1+\cos(x_1))$ $+\,0.00870\cdot(x_1+(\exp(x_1+\sin(x_1)))^3)$ $-\,0.00096\cdot(\cos(\log(-x_1+(\log(x_1))^2)))$ $+\,0.00020\cdot(\cos((\log(\log((x_1^3)^3)))^3))$ $-\,0.05217\cdot(-\log(\exp(x_1)/x_1))$ $-\,0.02899\cdot((\sin(\exp(x_1))^3)^3)$ $+\,0.00241\cdot((\cos(\log(x_1)))^2)$ $+\,0.00071\cdot((\sin(x_1+x_1/x_1^2))^2)$ $+\,0.00017\cdot((x_1+(\exp(x_1^3))^3)^2)$ $-\,0.01217\cdot(\log(\log(x_1)))$ $+\,0.00036\cdot(-x_1+\log(\sin((x_1^2)^2)))$ $+\,0.01065\cdot(\exp((\cos(x_1))^3))$ $-\,0.01217\cdot(\log(\log(x_1)))$ $+\,0.27840\cdot(\exp(\exp(x_1)))$	9.39333×10^{-31}
Nguyen-12	$x_1^4-x_1^3+\frac{1}{2}x_2^2-x_2$	$0.04336\cdot\log(x_2)$ $-\,0.00557\cdot((-x_1+(x_2^2)^2)^2)^3$ $-\,0.00679\cdot(x_2\cdot(x_1-\cos(\exp(x_1))))$ $-\,0.06199\cdot(x_1\cdot\sin(\exp((0^2)^3)))$ $+\,0.05196\cdot(x_1+\sin(2\cdot x_1+\exp(x_1)))$ $-\,0.67030\cdot\sin(x_2)$ $-\,0.25751\cdot(x_1-x_1^2)$ $+\,0.04301\cdot(\cos(x_1+(x_1\cdot x_2)^3))^2$ $-\,0.03952\cdot(x_1\cdot\log(-x_1^2+\log(x_1)))$ $-\,0.00130\cdot(x_1\cdot\cos(x_1/x_1^2))$ $+\,0.00268\cdot((x_2^2/x_2)^3)/x_1$ $+\,0.00200\cdot\exp(\exp((\sin(x_2^3))^2))$ $-\,0.07700\cdot(x_1+\log(\log((\exp(\cos(x_1)))^2)))$ $+\,0.04336\cdot\log(x_2)$ $-\,0.00130\cdot(x_1\cdot\cos(x_1/x_1^2))$ $-\,0.30271\cdot\exp(\sin(x_2))$ $+\,0.27640\cdot\exp(x_1)$ $-\,0.16368\cdot(-x_1+\sin(\log((\exp(x_1^2))^2)))$ $-\,0.00140\cdot(-x_1+x_2/(x_1\cdot(\cos(x_1))^2))$ $+\,0.18888\cdot(-x_1+\cos(x_1))$ $+\,0.02525\cdot\exp(x_2^2+\sin(x_1))$ $-\,0.25574\cdot((\cos(x_2))^2)^2$ $-\,0.00255\cdot\cos((x_2-\exp(x_1^2))/x_1)$ $-\,0.07703\cdot(\log(x_2)-\cos(\exp(x_1)))$ $-\,0.01004\cdot(\log(x_2)-\cos(\log(x_1)))$ $+\,0.19445\cdot\sin(x_2^3)$	2.54795×10^{-30}

Appendix C
Real World Experiment

This section provides a detailed exploration of the physical laws governing the free fall of balls with air resistance. The experimental ball-drop dataset [1] includes records of 11 different types of balls, as shown in Figure S-I. These balls were dropped from a bridge and recorded at a sampling rate of 30 Hz. Since air resistance affects each ball differently, leading to distinct physical laws, we explored the physical laws for each type of ball individually. The dataset for each ball was divided into a training set, consisting of the first 2 seconds of recordings, and a test set, comprising the remaining drop time. We explored the physical laws using the training data for each ball and then calculated the error on the test set. Table S-VIII present the physical laws discovered by MASR and three other baseline physical models.

Fig. S-I: The experimental balls dropped from the bridge [1].From left to right:golf ball,tennis ball,whiffle ball1, whiffle ball2,base ball,yellow whiffle ball,orange whiffle ball,green basketball,and blue basketball.Volleyball is not shown here.

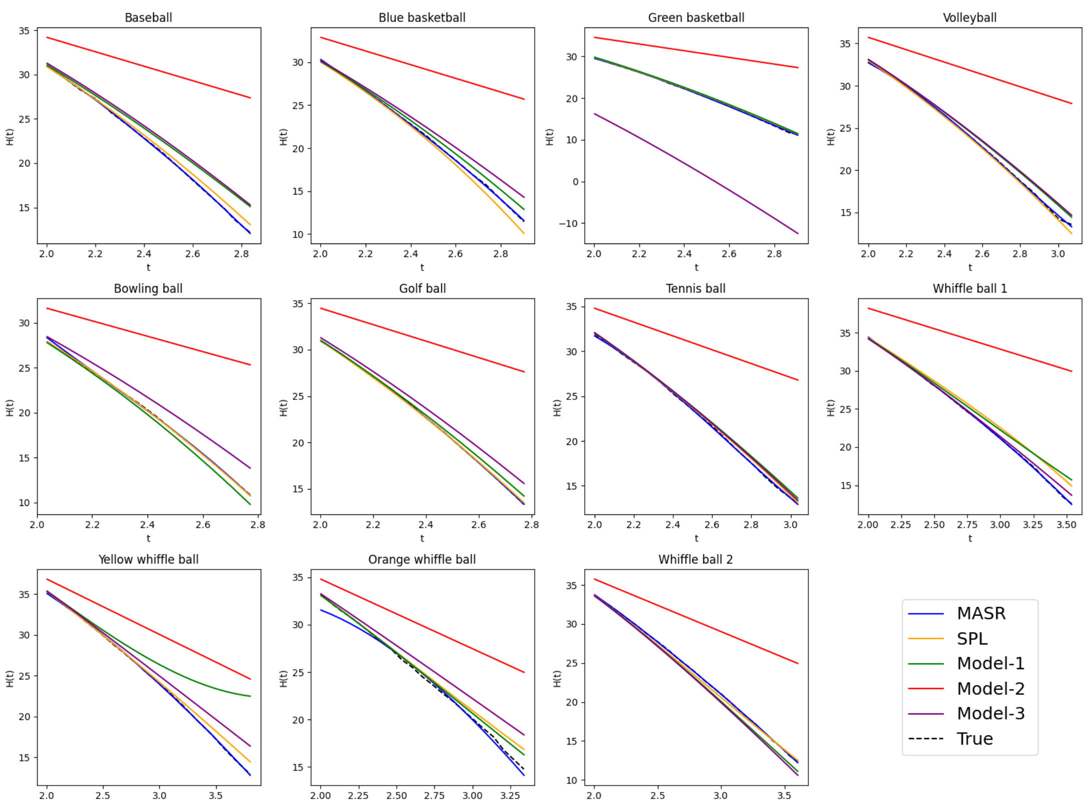

Fig. S-II: Trajectories after 2 seconds predicted by uncovered physical laws

TABLE S-VIII: Model Expressions for Different Types of Balls

Type	**Model**	**Expression**
baseball	MASR	$H(t) = -1.1832(2t)^2 - 24.7983(-2) - 0.1362(\sin(t^2))^3 - 0.2531(t\cos(t))$
	SPL	$H(t) = 47.8042 + 0.6253t - 4.5383t^2$
	Model-1	$H(t) = 47.682 + 1.456t - 5.629t^2 + 0.376t^3$
	Model-2	$H(t) = 45.059 - 8.156t + 5.448\exp(0t)$
	Model-3	$H(t) = 48.051 - 183.467\log(\cosh(0.217t))$
blue basketball	MASR	$H(t) = -1.2345\exp(t) + 9.702\left(\exp\left(\frac{1}{2}\right)^3 + \cos(t)\right) + 0.0068\left(t - \sin\left(\exp(t) - 1\right)\right)$
	SPL	$H(t) = 46.4726 - 5.105t^2 + t^3 - 0.251t^4$
	Model-1	$H(t) = 46.513 - 0.493t - 3.919t^2 + 0.034t^3$
	Model-2	$H(t) = 43.522 - 7.963t + 5.306\exp(0t)$
	Model-3	$H(t) = 46.402 - 84.791\log(\cosh(0.319t))$
green basketball	MASR	$H(t) = -0.7611t^3 + 36.954 - 7.6656\cos^2(t)$
	SPL	$H(t) = 45.9087 - 4.1465t^2 + \log(\cosh(1))$
	Model-1	$H(t) = 46.438 - 0.314t - 3.882t^2 - 0.055t^3$
	Model-2	$H(t) = 45.312 - 8.043t + 5.346\exp(0t)$
	Model-3	$H(t) = 46.391 - 124.424\log(\cosh(0.362t))$
volleyball	MASR	$H(t) = 0.7251\cos\left(t\left(t - \frac{1}{t}\right) - 2t\right) - 10.4255\cos^2(t) +$ $80.5748\left(t + \frac{t}{2t} + \exp(t)\right) - 81.2299\left(t + \exp(t)\right)$
	SPL	$H(t) = 48.0744 - 3.772t^2$
	Model-1	$H(t) = 48.046 + 0.362t - 4.352t^2 + 0.218t^3$
	Model-2	$H(t) = 45.32 - 7.317t + 5.037\exp(0t)$
	Model-3	$H(t) = 48.124 - 107.816\log(\cosh(0.27t))$
bowling ball	MASR	$H(t) = -3.0183\exp\left(-t + \frac{t}{-t + \sin(\sin(t)^3)} + \sin(\sin(t)^3)\right) + 12.9625\cos^2(t) +$ $9.5648\left(t - t^2 - \sin(t) + \cos(t)\right) + 58.9133$
	SPL	$H(t) = 46.1329 - 3.8173t^2 - 0.2846t^3 + 4.14 \times 10^{-5}\exp(20.7385t^2)\exp(-12.4538t^4)$
	Model-1	$H(t) = 46.139 - 0.091t - 3.504t^2 - 0.431t^3$
	Model-2	$H(t) = 43.336 - 8.552t + 5.676\exp(0t)$
	Model-3	$H(t) = 46.342 - 247.571\log(\cosh(0.189t))$
golf ball	MASR	$H(t) = 0.0051\cos\left(t^3 - \exp(t)\right)t^2 + 27.8905\exp(\cos(1)) - 44.9419\left(\frac{t - \sin(t)}{t + \sin(t)}\right)$
	SPL	$H(t) = 49.5087 - 4.9633t^2 + \log(\cosh(t))$
	Model-1	$H(t) = 49.413 + 0.532t - 5.061t^2 + 0.102t^3$
	Model-2	$H(t) = 46.356 - 8.918t + 5.964\exp(0t)$
	Model-3	$H(t) = 49.585 - 178.47\log(\cosh(0.23t))$
tennis ball	MASR	$H(t) = -2.5207t^2 + 5.3867\cos^3(t) + 42.2359 - 0.0012\left(t - t^3\right)^2$
	SPL	$H(t) = 47.8577 - 4.0574t^2 + \log(\cosh(0.121t^3))$
	Model-1	$H(t) = 47.738 + 0.658t - 4.901t^2 + 0.325t^3$
	Model-2	$H(t) = 45.016 - 7.717t + 5.212\exp(0t)$
	Model-3	$H(t) = 47.874 - 114.19\log(\cosh(0.269t))$
whiffle ball 1	MASR	$H(t) = 11.0641\sin\left(t^6\exp(-t^3)\right) - 0.5197t^3 + 5.6093\cos(t) + 48.3661\sin(1)$
	SPL	$H(t) = 4.1634t^2 - t^3 + 47.0133\exp(-0.1511t^2)$
	Model-1	$H(t) = 46.969 + 0.574t - 4.506t^2 + 0.522t^3$
	Model-2	$H(t) = 44.259 - 5.373t + 4.689\exp(0t)$
	Model-3	$H(t) = 47.062 - 34.083\log(\cosh(0.462t))$
yellow whiffle ball	MASR	$H(t) = -2.0859\left(t^2 + e\right) - 0.0315\cos\left(t - \exp(\exp(t))\right) + 0.9019e^4 - 0.8940\cos^2(t)$
	SPL	$H(t) = \frac{148.9911}{\log(\cosh(t)) + 3.065} - \frac{14.5828t^2}{\log(\cosh(t)) + 3.065} + 48.6092\frac{\log(\cosh(t))}{\log(\cosh(t)) + 3.065}$
	Model-1	$H(t) = 48.613 - 0.047t - 4.936t^2 + 0.826t^3$
	Model-2	$H(t) = 45.443 - 6.789t + 4.973\exp(0t)$
	Model-3	$H(t) = 48.594 - 12.49\log(\cosh(0.86t))$
orange whiffle ball	MASR	$H(t) = 0.6568\sin\left(\frac{t^2}{2t^2} - t\right) + 12.2733\sin(t) -$ $0.0598t\exp(t)\cos\left(t^2\exp(-t)\right) + 40.1675\cos(\exp(0))$
	SPL	$H(t) = -1.6626t + 47.8622\exp(-0.06815t^2)$
	Model-1	$H(t) = 47.836 - 1.397t - 3.822t^2 + 0.422t^3$
	Model-2	$H(t) = 44.389 - 7.358t + 5.152\exp(0t)$
	Model-3	$H(t) = 47.577 - 12.711\log(\cosh(0.895t))$

References

[1] B. M. de Silva, D. M. Higdon, S. L. Brunton, and J. N. Kutz, “Discovery of physics from data: Universal laws and discrepancies,” *Frontiers in Artificial Intelligence*, vol. 3, p. 25, 2020.