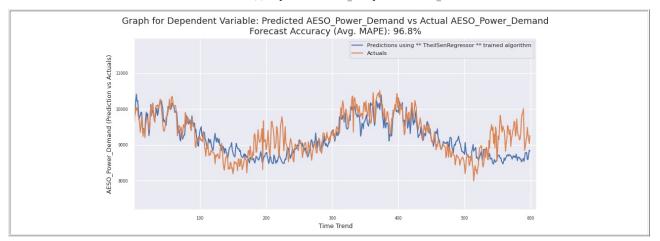
MAADSBML AutoML Report For ALBERTA-ELECTRIC-SYSTEM-OPERATOR_AESO Generated On: 2024-04-17 02:20:35 (UTC)

Best Model(s) Report For admin_aesopowerdemand_csv



MODEL DESCRIPTION

Model Trained On: 2024/04/17 Training Start Time: 0217 Training End Time: 0220 Was Data Normalized: Yes Was Data Shuffled: No Deep Analysis: No Total Training Data Set: 897 Training Data Percentage: 70% Total Test Data Set: 383 Total # of Variables: 4 Adjusted for Seasonality: Total Algorithms Run: 3600

Removed Outliers: N
Best Distribution FOR ACTUAL Y: VONMISES Dependent Variable: AESO POWER DEMAND

Independent Variables: ['Calgary_Weather', 'Edmonton_Weather', 'FtMac_Weather']

PREDICTION VARIABLE STATS

Mean: 9193.695 STD: 503.462 Kurtosis: -0.985 Skewness: 0.453 Coef. of Variation: 0.055 Shapiro Test for Normality: 0.936 Jarque-Bera Goodness of Fit: 44.819 Anderson: 12.205 KStat: 253896.817

KStatvar: 109187960.799 Wilcox: 0.000 Theil Slope: -1.021

ACTUAL VARIABLE STATS

Mean: 9281.250 STD: 545.222 Kurtosis: -0.891 Skewness: 0.098 Coef. of Variation: 0.059 Shapiro Test for Normality: 0.981 Jarque-Bera Goodness of Fit: 20.836 Anderson: 2.876

KStat: 297763.223 KStatvar: 164138770.163 Wilcox: 0.000 Theil Slope: -0.302

Statistics Showing Comparison Between Prediction and Actuals

Mood(actuals,predictions): 1.431 Pearson(actuals, predictions): 0.726 Kendall Tau(actuals,predictions): 0.473 Ansari(actuals,predictions): 178651.000 Jaccard_distance(actuals,predictions): 1.000 Minkowski_distance(actuals,predictions): 178919.938 Euclidean_distance(actuals,predictions): 9796.297

IMPORTANT FILE PATHS FOR RAW AND OUTPUT DATA

NOTE: These are DOCKER CONTAINER Paths. You can view these files inside the container by using the command: docker exec -it {container id} bash If you have re-run the container, The Docker RUN Volume Mappings are :: (For example here is the docker run command (use multiple -v for multiple mappings):

DOCKER RUN COMMAND: docker run -d -p 5595:5595 -p 5495:5495 -p 10000:10000 -v {HOST MACHINE FOLDER}:{CONTAINER FOLDER}:z --env TRAININGPORT=5595 --env PREDICTIONPORT=5495 --env ABORTPORT=10000 --env COMPANYNAME=MYCOMPANY --env MAXRUNTIME=20 --env MAINHOST=127.0.0.1 maadsdocker/maads-batchautoml-otics

Docker Volume Mappings:

1. (HOST MACHINE FOLDER)/csvuploads:/maads/agentfilesdocker/dist/maadsweb/csvuploads:z
2. (HOST MACHINE FOLDER)/pdfreports:/maads/agentfilesdocker/dist/maadsweb/pdfreports:z
3. (HOST MACHINE FOLDER)/autofeatures:/maads/agentfilesdocker/dist/maadsweb/autofeatures:z

4. {HOST MACHINE FOLDER}/outliers:/maads/agentfilesdocker/dist/maadsweb/outliers:z 5. {HOST MACHINE FOLDER}/sqlloads:/maads/agentfilesdocker/dist/maadsweb/sqlloads:z

6. (HOST MACHINE FOLDER)/networktemp:/maads/agentfilesdocker/dist/maadsweb/networktemp:z
7. {HOST MACHINE FOLDER}/networks:/maads/agentfilesdocker/networks:z
8. {HOST MACHINE FOLDER}/exception:/maads/agentfilesdocker/dist/maadsweb/exception:z

9. {HOST MACHINE FOLDER}/staging:/maads/agentfilesdocker/dist/staging:z

Path for Training Dataset File: /maads/agentfilesdocker/dist/maadsweb/csvuploads/aesopowerdemand.csv

Path for PDF Report (i.e. this file): /maads/agentfilesdocker/dist/maadsweb/pdfreports/admin_aesopowerdemand_csv_no_seasons.pdf
Path for AutoFeature File: /maads/agentfilesdocker/dist/maadsweb/autofeatures/admin_aesopowerdemand_csv_csv

Path for Outliers File: /maads/agentfilesdocker/dist/maadsweb/outliers/admin_aesopowerdemand_csv.csv

Path for Algo JSON File: /maads/agentifilesdocker/dist/maadsweb/exception/admin_aesopowerdemand_csv.csv
Path for Algo JSON File: /maads/agentfilesdocker/dist/maadsweb/exception/admin_aesopowerdemand_csv_trained_algo_no_seasons.json
Folder Path for MySQL Scripts: /maads/agentfilesdocker/dist/maadsweb/scuploads/
Path for Detailed Prediction File: /maads/agentfilesdocker/dist/maadsweb/csvuploads/admin_aesopowerdemand_csv_prediction_details.csv
Path for Algorithm Zip File (i.e pickle files): /maads/agentfilesdocker/dist/maadsweb/networktemp/admin_aesopowerdemand_csv.zip

Path for Algorithm Pickle Files:

1. /maads/agentfilesdocker/networks/Alberta-Electric-System-Operator_AESO)_ADMIN_AESOPOWERDEMAND_CSVALLSEASON_AG1_4_TheilSenRegressor_normal_897_ensemble_.pkl

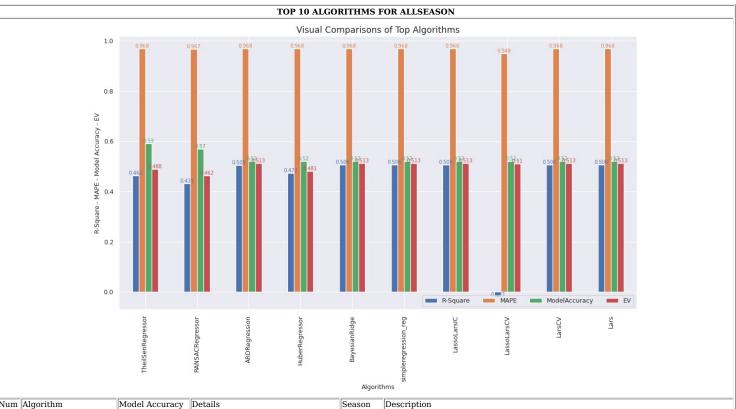
2. /maads/agentfilesdocker/networks/Alberta-Electric-System

Operator_AESO)_ADMIN_AESOPOWERDEMAND_CSVALLSEASON_AG1_4_TheilSenRegressor_normal_897_ensemble_scalerx_.pkl 3. /maads/agentfilesdocker/networks/Alberta-Electric-System

5. /madus/ngtentnessucker/networks/Antertackettr.Csystems Operator_AESO)_ADMIN_AESOPOWERDEMAND_CSVALLSEASON_AG1_4_TheilSenRegressor_normal_897_ensemble_scalery_.pkl

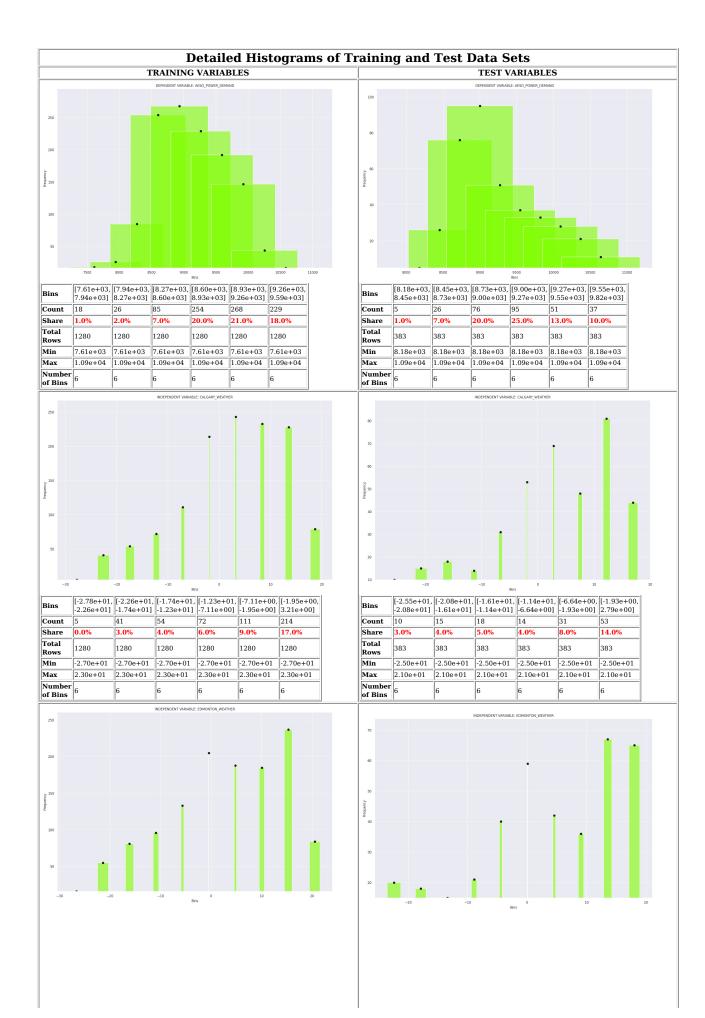
DESCRIPTIVE STATISTICS									
Variables	T-Statistic	Count	Mean	STD	MIN	25%	50%	75%	MAX
Calgary_Weather	-35.442	897.0	5.129	-27.75	10.061	-0.9	6.05	12.8	23.85
Edmonton_Weather	-38.8	897.0	4.998	-26.64	11.629	-3.0	6.25	14.65	25.75
FtMac_Weather	-40.088	897.0	1.239	-32.4	13.472	-8.95	2.9	12.9	23.85
AESO POWER DEMAND	NA	897.0	9245.152	7611.0	586.467	8792.0	9256.0	9687.0	10510.0

Algorithm	Description	Model Results	MAPE Accuracy	Forecast Months	Season
TheilSenRegressor	Theil-Sen Estimator: Theil-Sen Estimator: robust multivariate regression model.	COEFFICIENTS: [0.38676439 -0.5151319 -0.49644178] INTERCEPT: 0.911761131528117 R-square: 0.462 Mean Squared Error (MSE): 159945.736 Skewness: 1.162 Kurtosis: 3.953 Mean Square Model (MSM): 156683729.715 F-Statistic (F): 979.606 Jarque-Bera (JB): 157.711 Explained Variance (EV): 0.488 Multicolinearity Test (Avg. VIF): 19.321 Heteroscedasticity Test (Avg P-Value): -1.000 (Based on White Test, there seems to be heteroscedasticity in the model) Autocorrelation (Durbin-Watson) Test: 0.370 (Based on DW Test - there seems to be autocorrelation in your model)	0.968	1 - 12	allseason



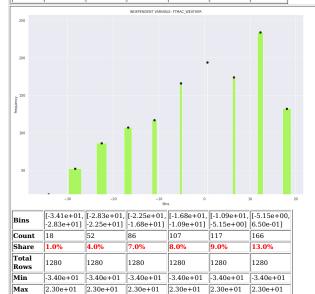
N.T	A1	M - 1 - 1 A	D-t-2-	Algoria	
Num	Algorithm	Model Accuracy	Details	Season	Description
1	TheilSenRegressor	0.5895	R-square: 0.462 MAPE: 0.968 Explained Variance (EV): 0.488 MSE: 159945.736 MSM: 156683729.715 Skewness: 1.162 Kurtosis: 3.953 F: 979.606 DW: 0.37 JB: 157.711	allseason	THEIL-SEN ESTIMATOR: Theil-Sen Estimator: robust multivariate regression model.
2	RANSACRegressor	0.5698	R-square: 0.431 MAPE: 0.967 Explained Variance (EV): 0.462 MSE: 169115.428 MSM: 176298117.746 Skewness: 1.192 Kurtosis: 3.988 F: 1042.472 DW: 0.411 JB: 166.438	allseason	RANSAC (RANDOM SAMPLE CONSENSUS) ALGORITHM.: RANSAC is an iterative algorithm for the robust estimation of parameters from a subset of inliers from the complete data set. More information can be found in the general documentation of linear models.
3	ARDRegression	0.5244	R-square: 0.505 MAPE: 0.968 Explained Variance (EV): 0.513 MSE: 147107.923 MSM: 127358849.42 Skewness: 0.776 Kurtosis: 3.535 F: 865.751 DW: 0.381 JB: 67.32	allseason	BAYESIAN ARD: Fit the weights of a regression model, using an ARD prior. The weights of the regression model are assumed to be in Gaussian distributions. Also estimate the parameters lambda (precisions of the distributions of the weights) and alpha (precision of the distribution of the noise). The estimation is done by an iterative procedures (Evidence Maximization)
4	HuberRegressor	0.5235	R-square: 0.472 MAPE: 0.968 Explained Variance (EV): 0.481 MSE: 157089.942 MSM: 154347018.354 Skewness: 0.977 Kurtosis: 3.941 F: 982.539 DW: 0.379 JB: 117.577	allseason	HUBER REGRESSOR: Linear regression model that is robust to outliers.
5	<u>BayesianRidge</u>	0.5225	R-square: 0.506 MAPE: 0.968 Explained Variance (EV): 0.513 MSE: 146958.733 MSM: 128147002.277 Skewness: 0.773 Kurtosis: 3.531 F: 871.993 DW: 0.386 JB: 66.766	allseason	BAYESIAN RIDGE REGRESSION: Fit a Bayesian ridge model and optimize the regularization parameters lambda (precision of the weights) and alpha (precision of the noise).
			R-square: 0.506 MAPE: 0.968 Explained Variance (EV): 0.513 MSE: 146918.712		

6	simpleregression_reg	0.5210	MSM: 128961343.199 Skewness: 0.77 Kurtosis: 3.526 F: 877.773 DW: 0.391 JB: 66.216	allseason	LINEAR REGRESSION: Simple multivariate linear regression
7	LassoLarsIC	0.5207	R-square: 0.506 MAPE: 0.968 Explained Variance (EV): 0.513 MSE: 146918.712 MSM: 128961343.199 Skewness: 0.77 Kurtosis: 3.526 F: 877.773 DW: 0.391 JB: 66.216	allseason	LASSO MODEL FIT WITH LARS USING BIC OR AIC FOR MODEL SELECTION: Lasso model fit with Lars using BIC or AIC for model selection
8	LassoLarsCV	0.5207	R-square: -0.021 MAPE: 0.948 Explained Variance (EV): 0.51 MSE: 303482.203 MSM: 225553876.692 Skewness: -1.268 Kurtosis: 2.128 F: 743.219 DW: 0.191 JB: 179.747	allseason	CROSS-VALIDATED LASSO, USING THE LARS ALGORITHM: The optimization objective for Lasso is:
9	LarsCV	0.5207	R-square: 0.506 MAPE: 0.968 Explained Variance (EV): 0.513 MSE: 146918.712 MSM: 128961343.199 Skewness: 0.77 Kurtosis: 3.526 F: 877.773 DW: 0.391 JB: 66.216	allseason	LEAST ANGLE REGRESSION WITH CROSS-VALIDATION: Cross-validated Least Angle Regression model
10	Lars	0.5207	R-square: 0.506 MAPE: 0.968 Explained Variance (EV): 0.513 MSE: 146918.712 MSM: 128961343.199 Skewness: 0.77 Kurtosis: 3.526 F: 877.773 DW: 0.391 JB: 66.216	allseason	LEAST ANGLE REGRESSION MODEL A.K.A. LAR: Least-angle regression (LARS) is a regression algorithm for high-dimensional data, developed by Bradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani. LARS is similar to forward stepwise regression. At each step, it finds the predictor most correlated with the response. When there are multiple predictors having equal correlation, instead of continuing along the same predictor, it proceeds in a direction equiangular between the predictors.

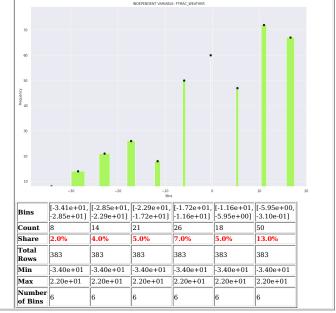


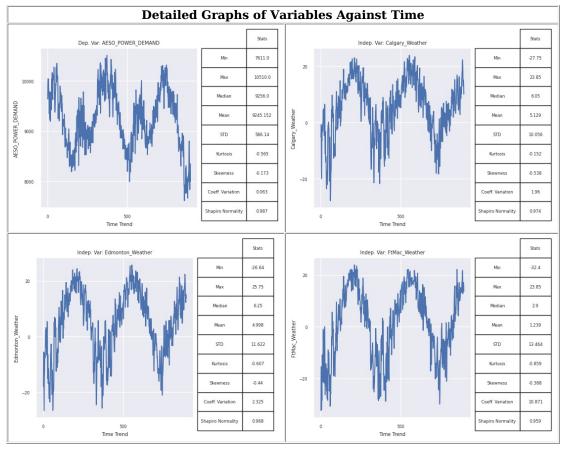
Bins	[-2.66e+01, -2.14e+01]	[-2.14e+01, -1.62e+01]	[-1.62e+01, -1.09e+01]	[-1.09e+01, -5.68e+00]	[-5.68e+00,	[-4.45e- 01, 4.79e+00]
Count	16	55	81	96	133	205
Share	1.0%	4.0%	6.0%	8.0%	10.0%	16.0%
Total Rows	1280	1280	1280	1280	1280	1280
Min	-2.60e+01	-2.60e+01	-2.60e+01	-2.60e+01	-2.60e+01	-2.60e+01
Max	2.50e+01	2.50e+01	2.50e+01	2.50e+01	2.50e+01	2.50e+01
Number of Bins	6	6	6	6	6	6

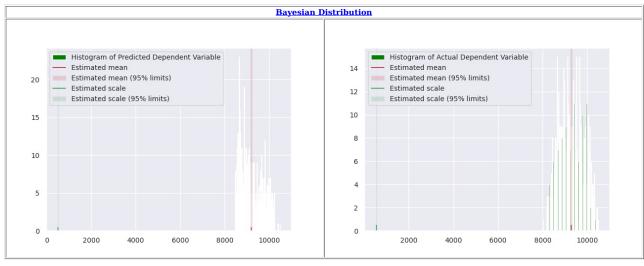
				[-8.91e+00,		
Dilis	-1.79e+01]	-1.34e+01]	-8.91e+00]	-4.42e+00]	7.50e-02]	4.57e+00]
Count	20	18	15	21	40	59
Share	5.0%	5.0%	4.0%	5.0%	10.0%	15.0%
Total Rows	383	383	383	383	383	383
Min	-2.20e+01	-2.20e+01	-2.20e+01	-2.20e+01	-2.20e+01	-2.20e+01
Max	2.20e+01	2.20e+01	2.20e+01	2.20e+01	2.20e+01	2.20e+01
Number of Bins	6	6	6	6	6	6

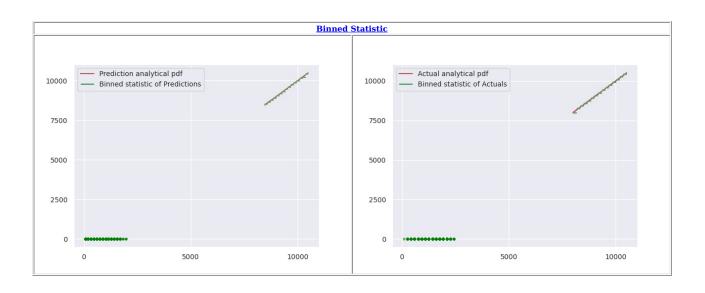


Number of Bins

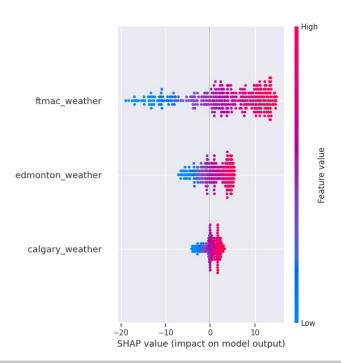








MODEL EXPLANATION



- The x-axis represents the model's output values of AESO_POWER_DEMAND

 The plot is centered on the x-axis at explainer.expected value.

 All values are relative to the model's expected value like a linear model's effects are relative to the intercept.

 The y-axis lists the model's features. By default, the features are ordered by descending importance.

 The importance is calculated over the observations plotted. This is usually different than the importance ordering for the entire dataset.

 In addition to feature importance ordering, the decision plot also supports hierarchical cluster feature ordering and user-defined feature ordering.

 Each elementaries are districtly in progressed by the colored lists.
- Each observation's prediction is represented by a colored line.
 At the top of the plot, each line strikes the x-axis at its corresponding observation's predicted value. This value determines the color of the line on a
- Moving from the bottom of the plot to the top, SHAP values for each feature are added to the model's base value.
 This shows how each feature contributes to the overall prediction.
 At the bottom of the plot, the observations converge at explainer.expected_value.
 The points in the graph are the values of the feature in the training dataset.

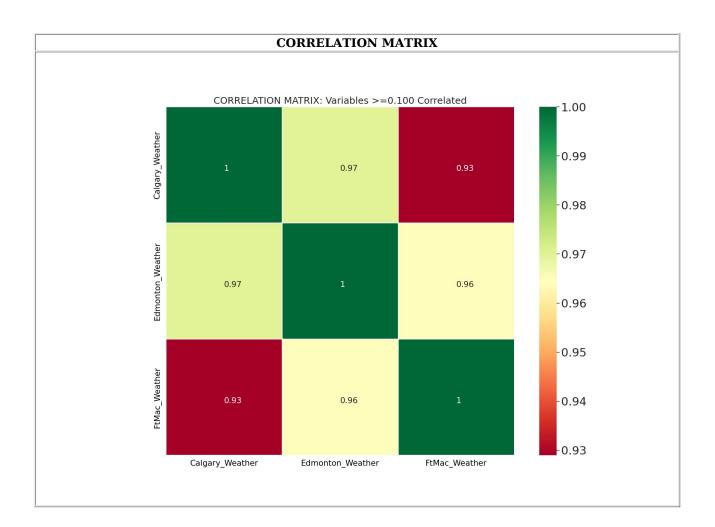
FEATURE SELECTION						
RFE Variable (Most important to Least Important)						
AESO_Power_Demand	0.304					
Calgary_Weather	0.235					
Edmonton_Weather	0.232					
FtMac_Weather	0.229					
Best Variable(s) From Genetic Algorithm						
AESO_Power_Demand						
FtMac_Weather						
FtMac_Weather						
Excluded Variable(s)						
Calgary_Weather						
Edmonton_Weather						
PCA for Best Variable(s)	Value					
AESO_Power_Demand_pca_1	0.707					
AESO_Power_Demand_pca_2	0.707					
AESO_Power_Demand_pca_3	-0.081					
Calgary_Weather_pca_1	-0.590					
Calgary_Weather_pca_2	0.448					
Calgary_Weather_pca_3	0.672					
FtMac_Weather_pca_1	-0.707					
FtMac_Weather_pca_2	0.707					
FtMac_Weather_pca_3	-0.736					
PCA Explained Variance	Value					
PCA1	0.873					
PCA2	0.127					
PCA3	0.023					

- Feature selection shows which variables were more influential than other variables

 It uses two core algorithms: Recursive Feature Elimination (RFE) and Genetic Algorithm to determine influence

 It also performs PCA (principal component analysis) analysis to determine the influence of the best variables in the model

 These results should be used in conjunction with other information as well as theory to establish relevance and confidence in the chosen model formulation



CORRELATED FEATURES					
Feature(s)	Feature(s)	Correlation >= 0.100			
O Calgary_Weather	FtMac_Weather	0.929			
1 Edmonton_Weather	FtMac_Weather	0.964			
2 Calgary_Weather	Edmonton_Weather	0.970			
3 Calgary_Weather	Calgary_Weather	NaN			

SUGGESTED CORRELATED FEATURES TO DELETE						
	2 Feature(s) to Delete	e Correlation				
	Calgary_Weather	0.929				
	1 Edmonton_Weather	0.964				

END OF REPORT

MAADSBML Python Library: https://pypi.org/project/maadsbml/
MAADSBML Docker Container For Windows: https://hub.docker.com/r/maadsdocker/maads-batch-automl-otics
MAADSBML Docker Container For MAC: https://hub.docker.com/r/maadsdocker/maads-batch-automl-otics-arm64
MAADSBML Sample Code and Setup: https://github.com/smaurice101/raspberrypi/tree/main/maadsbml

MAADSBML
Developed and Maintained by: Otics Advanced Analytics, Inc.
Toronto, Ontario, Canada
https://www.otics.ca
Email: support@otics.ca