AutoAIViz: Visualizations for AutoAI

User Tasks and Related Systems

An Overview

- Visualize pipelines
- User Interaction
- Edit pipelines
- Tune hyperparameters

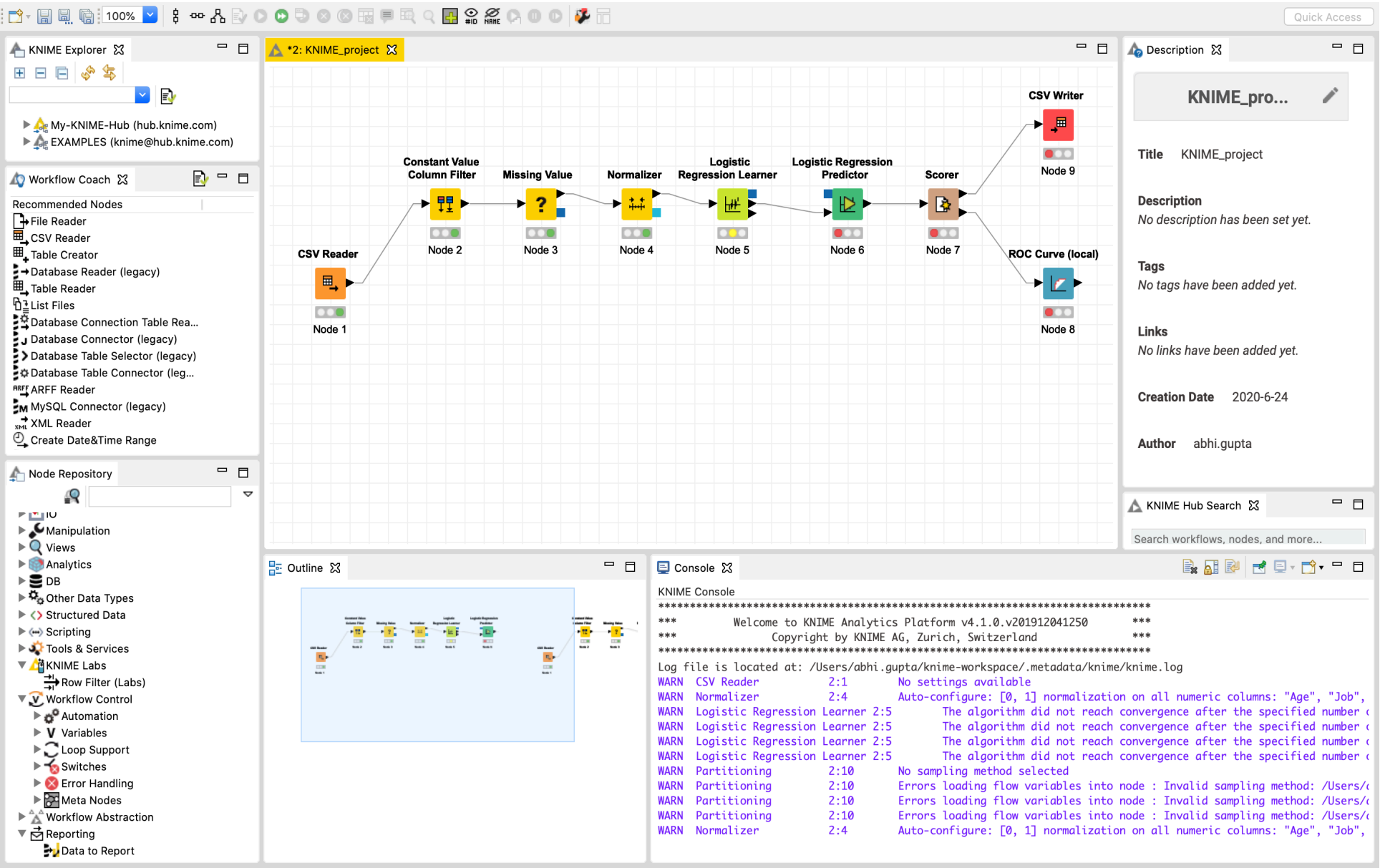
User Tasks

- T1: Visualize pipelines generated by AutoAI system
- T2: Compare and Edit these pipelines
- T3: Tune hyperparameters for different stages
- T4: Visualize pipelines on the basis of steps/hyperparameters
- T5: Create a good performing pipeline using knowledge derived from T4

Related Systems

- KNIME Analytics platform
- PipelineProfiler
- SPSS modeler
- Azure Machine Learning Designer

KNIME Analytics Platform



Pros:

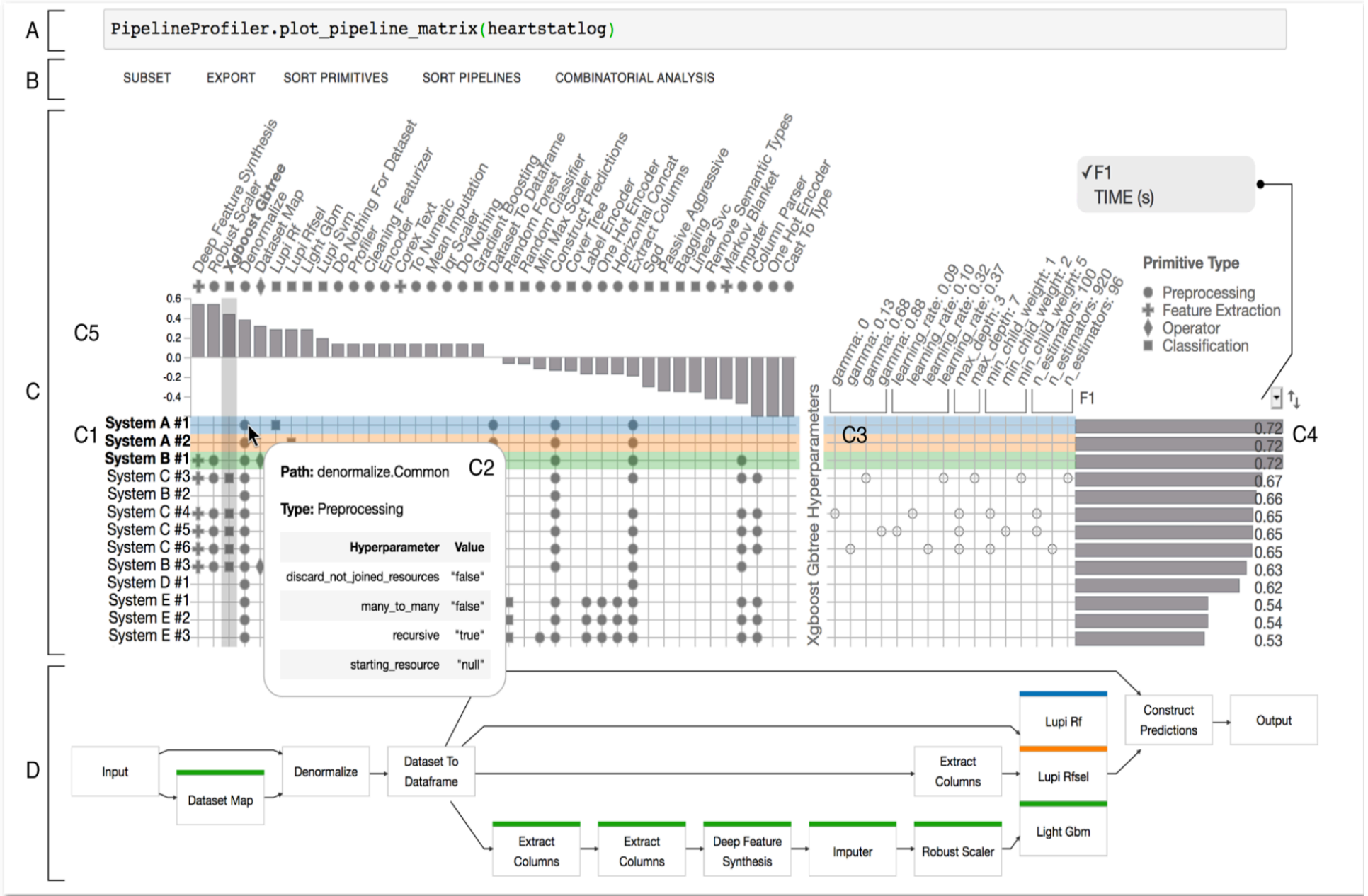
- Next node suggestions
- Easy to use drag and drop
- T3, T5 can be performed easily

Cons:

- Cannot look into multiple pipelines(T1, T2)
- Cannot look into pipelines generated by AutoML systems

PipelineProfiler: A Visual Analytics Tool for the Exploration of AutoML Pipelines

- Jorge Piazentin Ono, Sonia Castelo, Roque Lopez, Enrico Bertini, Juliana Freire, Claudio Silva



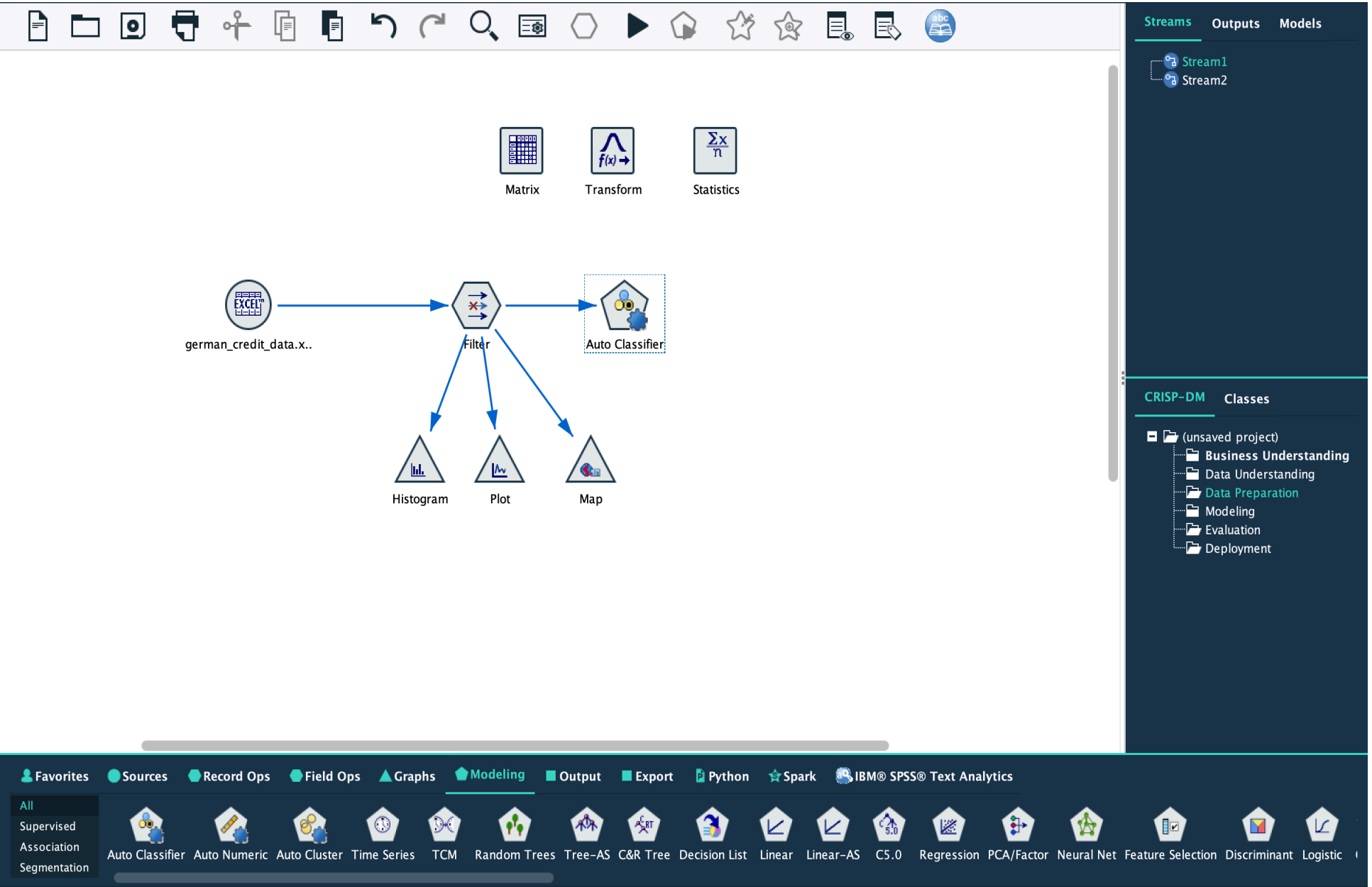
Pros:

- Supported with Jupyter Notebook
- Visualize multiple pipelines with the parameters
- T1, T2, T4 possible

Cons:

- Cannot make changes into the pipeline.
- T3, T5 not feasible

SPSS Modeler



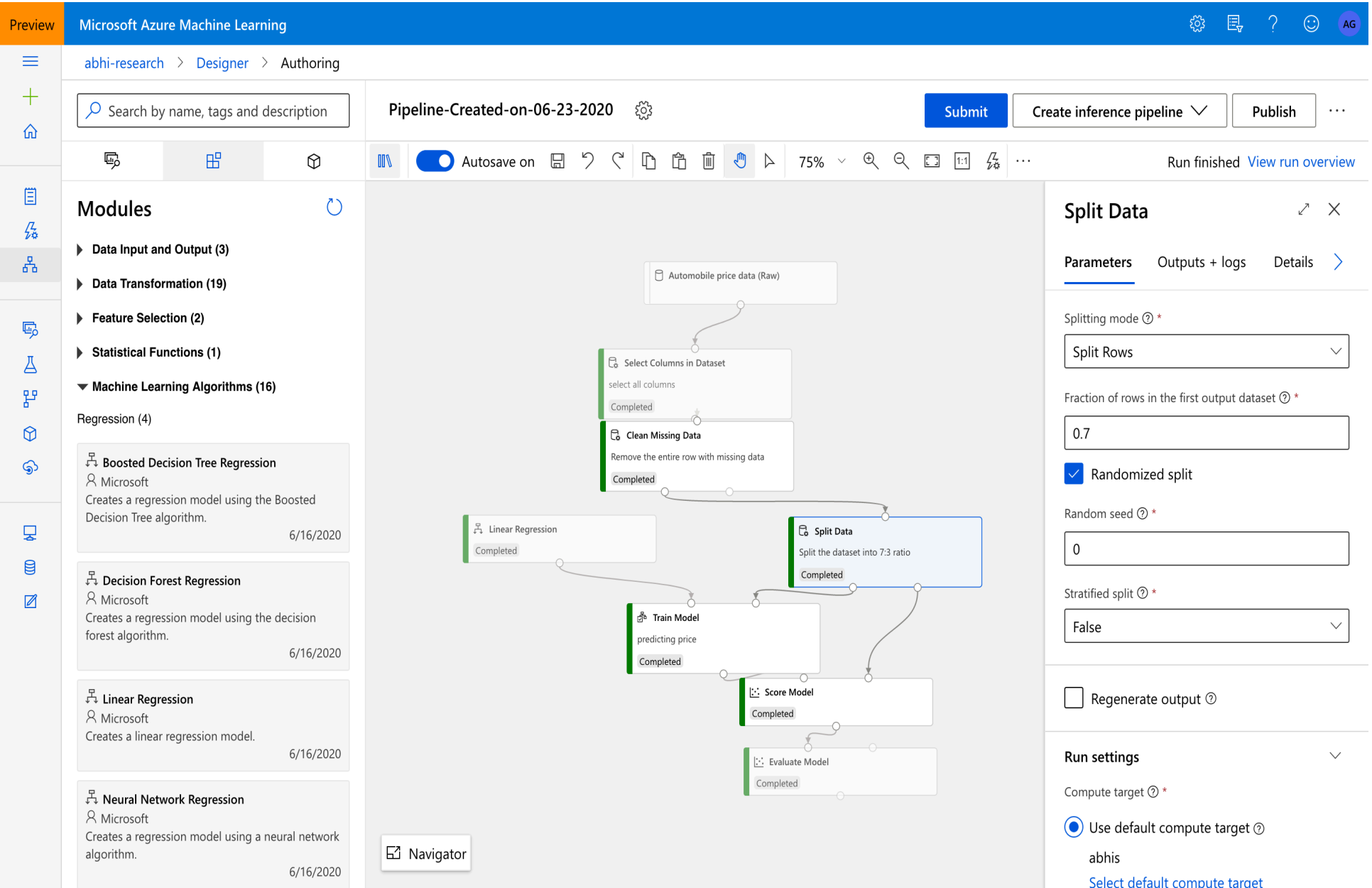
Pros:

- Easy to use drag and drop
- Automated Nodes
- T3, T5 can be performed easily

Cons:

- Cannot look into multiple pipelines at once (T1, T2)
- Cannot look into pipelines generated by AutoML systems

Azure Machine Learning Designer



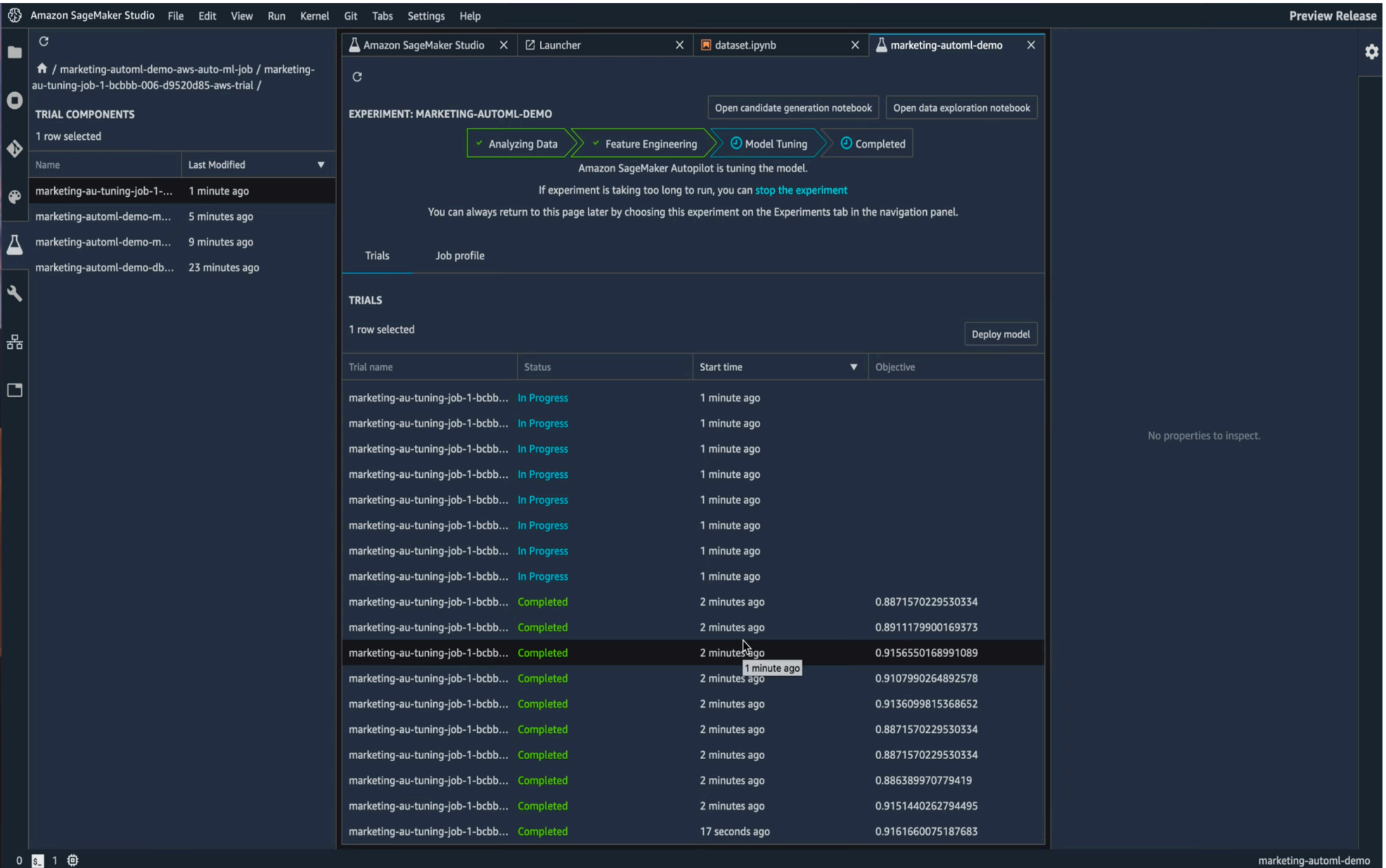
Pros:

- Easy to use drag and drop
- T3, T5 can be performed easily

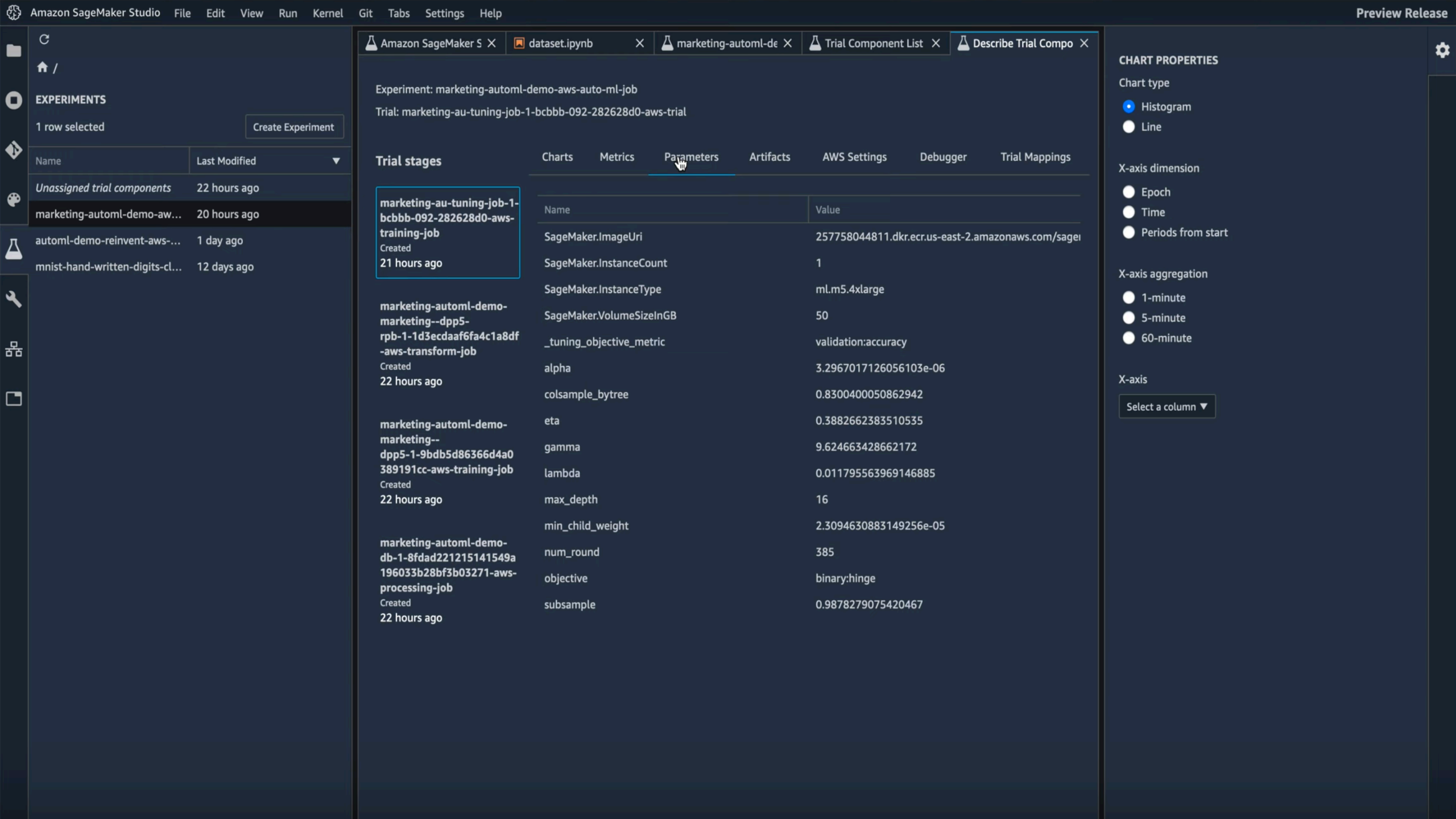
Cons:

- Cannot look into multiple pipelines at once (T1, T2)
- Cannot look into pipelines generated by AutoML systems

Amazon SageMaker



- Amazon SageMaker Studio, a machine learning Integrated Development Environment (IDE) to build, train and debug models, track experiments and deploy models in production.
- Also provided as a service in AWS.
- It has an Autopilot mode for automatically carrying out machine learning jobs.
- Autopilot mode takes in S3 path to data and target Variable
- Notebooks corresponding to Data exploration and model Generation steps are created
- Compare different pipelines


Amazon SageMaker Studio
File
Edit
View
Run
Kernel
Git
Tabs
Settings
Help
Preview Release
EXPERIMENTS
1 row selected
Create Experiment
Name
Last Modified
Unassigned trial components
22 hours ago
marketing-automl-demo-aw...
20 hours ago
automl-demo-reinvent-aws-...
1 day ago
mnist-hand-written-digits-cl...
12 days ago
Amazon SageMaker S
dataset.ipynb
marketing-automl-de
Trial Component List
Describe Trial Compo
Experiment: marketing-automl-demo-aws-auto-ml-job
Trial: marketing-au-tuning-job-1-bcbbb-092-282628d0-aws-trial
Trial stages
marketing-au-tuning-job-1-bcbbb-092-282628d0-aws-training-job
Created
21 hours ago
marketing-automl-demo-marketing--dpp5-rpb-1-1d3ecdaaf6fa4c1a8df-aws-transform-job
Created
22 hours ago
marketing-automl-demo-marketing--dpp5-1-9bdb5d86366d4a0389191cc-aws-training-job
Created
22 hours ago
marketing-automl-demo-db-1-8fdad221215141549a196033b28bf3b03271-aws-processing-job
Created
22 hours ago
Charts
Metrics
Parameters
Artifacts
AWS Settings
Debugger
Trial Mappings
Name
Value
SageMaker.ImageUri
257758044811.dkr.ecr.us-east-2.amazonaws.com/sagei
SageMaker.InstanceCount
1
SageMaker.InstanceType
ml.m5.4xlarge
SageMaker.VolumeSizeInGB
50
_tuning_objective_metric
validation:accuracy
alpha
3.2967017126056103e-06
colsample_bytree
0.8300400050862942
eta
0.3882662383510535
gamma
9.624663428662172
lambda
0.011795563969146885
max_depth
16
min_child_weight
2.3094630883149256e-05
num_round
385
objective
binary:hinge
subsample
0.9878279075420467
CHART PROPERTIES
Chart type
Histogram
Line
X-axis dimension
Epoch
Time
Periods from start
X-axis aggregation
1-minute
5-minute
60-minute
X-axis
Select a column

Amazon SageMaker Studio File Edit View Run Kernel Git Tabs Settings Help Preview Release

/

EXPERIMENTS

1 row selected Create Experiment

Name	Last Modified
Unassigned trial components	22 hours ago
marketing-automl-demo-aw...	20 hours ago
automl-demo-reinvent-aws-...	1 day ago
mnist-hand-written-digits-cl...	12 days ago

Amazon SageMaker S | dataset.ipynb | marketing-automl-de | Trial Component List | Trial Component Cha

TRIAL COMPONENTS 6 rows selected. Select rows to toggle chart visibility.

Experiment	Trial	Trial Component	Type
marketing-automl-de...	marketing-au-tuning-...	marketing-au-tuning-job-1-bcbbb-092-282628d0-aws-training-job	Training job
marketing-automl-de...	marketing-au-tuning-...	marketing-au-tuning-job-1-bcbbb-211-0f05152d-aws-training-job	Training job
marketing-automl-de...	marketing-au-tuning-...	marketing-au-tuning-job-1-bcbbb-061-bc744fbc-aws-training-job	Training job
marketing-automl-de...	marketing-au-tuning-...	marketing-au-tuning-job-1-bcbbb-050-67f2f3b1-aws-training-job	Training job
marketing-automl-de...	marketing-au-tuning-...	marketing-au-tuning-job-1-bcbbb-183-eadf2928-aws-training-job	Training job
marketing-automl-de...	marketing-au-tuning-...	marketing-au-tuning-job-1-bcbbb-031-770ad4d5-aws-training-job	Training job

1 CHART

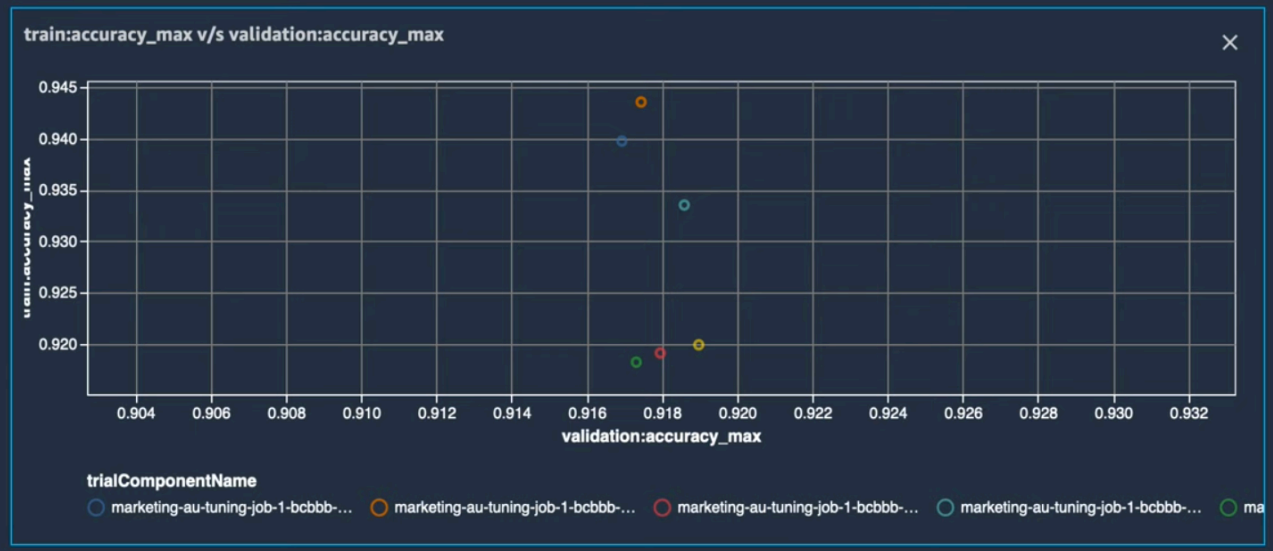


CHART PROPERTIES

Data type
- Time series
- Summary statistics

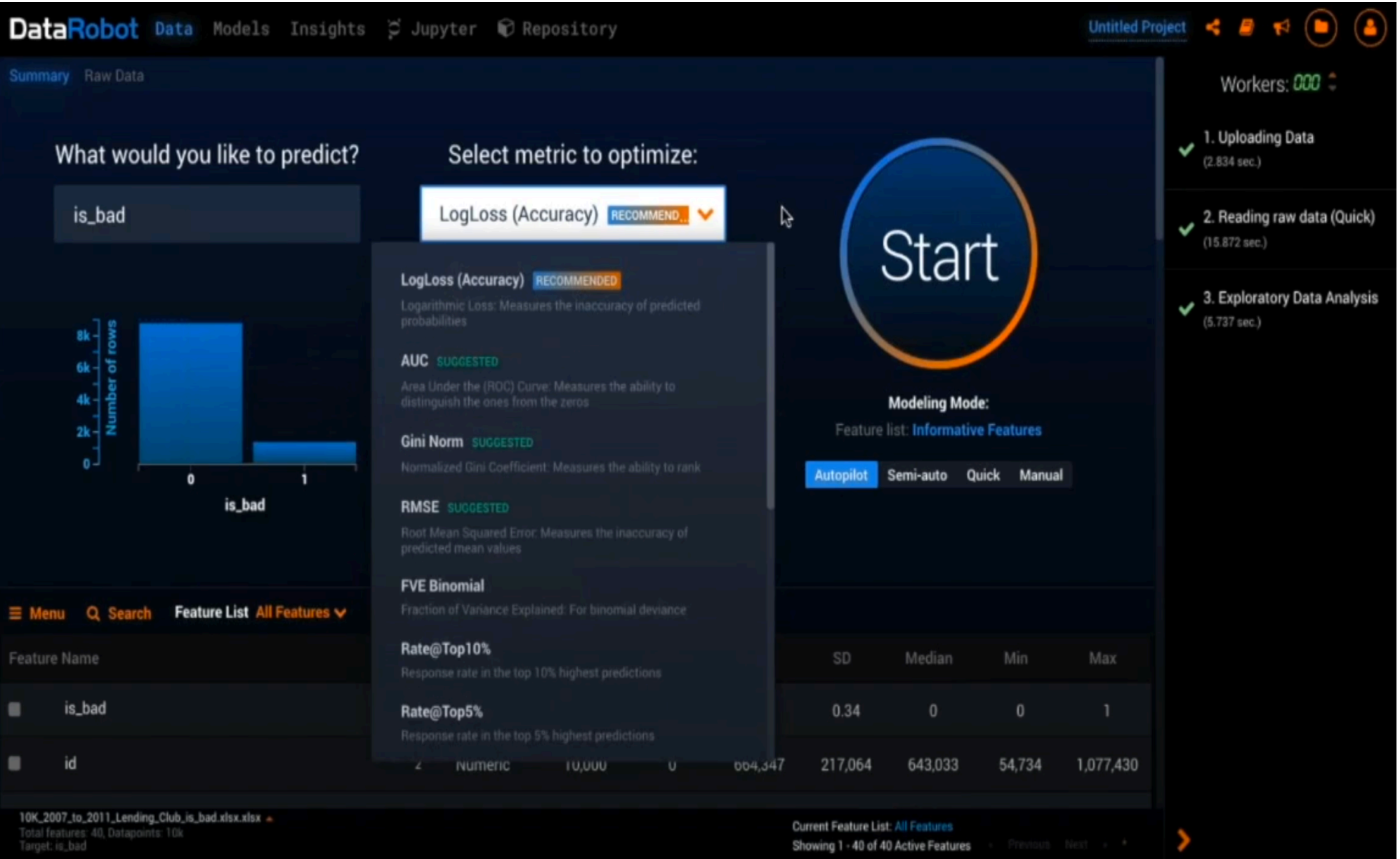
Chart type
- Bar
- Histogram
- Line
- Scatter plot

X-axis

validation:accuracy_max

- ObjectiveMetric_min
- ObjectiveMetric_max
- ObjectiveMetric_avg
- ObjectiveMetric_count
- ObjectiveMetric_std
- ObjectiveMetric_last
- validation:error_min
- validation:error_max
- validation:error_avg
- validation:error_count
- validation:error_std
- validation:error_last

DataRobot



- Autopilot, semi-auto and other modes.
- Configure hyperparameters.
- Look into the generated Pipelines (DAGs)
- Multiple pipelines can be visualized at once
- Cannot edit these generated pipelines

DataRobot Data Models Insights Jupyter Repository Untitled Project

Leaderboard Learning Curves Speed vs Accuracy Model Comparison

Menu Search + Add New Model Metric LogLoss

Workers: 020

Processing (13)

Model Name & Description | Feature List & Sample Size | Validation | Cross Validation | Holdout

eXtreme Gradient Boosted Trees Classifier with Early Stopping BP31

M31

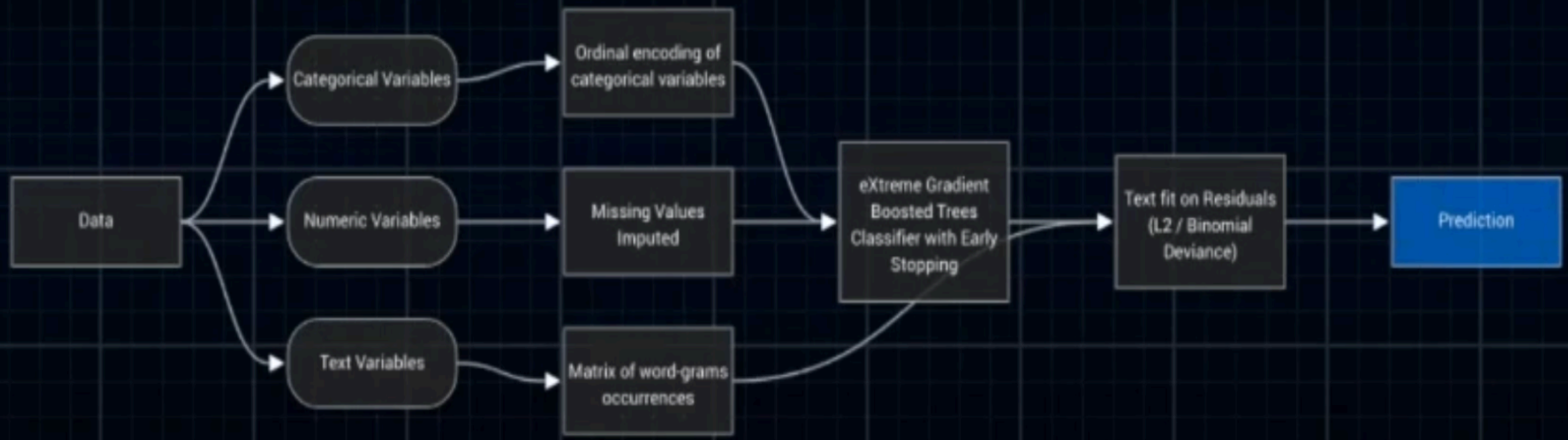
Ordinal encoding of categorical variables | Missing values imputed | Matrix of word-grams occurrences | eXtreme Gradient Boosted Trees Classifier with Early Stopping | Text fit on Residuals (L2 / Binomial Deviance)

Informative Features 16.0 % | 0.3070 | Run

Blueprint Lift Chart Model X-Ray Feature Impact Model Info Model Log ROC Curve Advanced Tuning DataRobot Prime Deploy Model Predict Reason Codes

Download

1.0x



Gradient Boosted Greedy Tre... 16.00% sample , CV #1 4% 2.4 GB RAM 0.0 CPUs

eXtreme Gradient Boosted Tr... 32.00% sample , CV #1 2% 1.3 GB RAM 0.9 CPUs

Auto-Tuned Word N-Gram Text... 32.00% sample , CV #1 4% 2.4 GB RAM 0.5 CPUs

Auto-Tuned Word N-Gram Text... 32.00% sample , CV #1 2% 1.3 GB RAM 0.9 CPUs

Auto-Tuned Word N-Gram Text... 32.00% sample , CV #1 4% 2.5 GB RAM

Queue (8)

eXtreme Gradient Boosted Tr... 32.00% sample , CV #1

ExtraTrees Classifier (Gini... 32.00% sample , CV #1

DataRobot Data Models Insights Jupyter Repository Untitled Project

Leaderboard Learning Curves Speed vs Accuracy Model Comparison

Menu Search + Add New Model Metric LogLoss

Workers: 020

Processing (12)

Model Name & Description | Feature List & Sample Size | Validation | Cross Validation | Holdout

eXtreme Gradient Boosted Trees Classifier with Early Stopping

base_margin_initialize: False

colsample_bylevel: 1.0

colsample_bytree: 0.3

interval: 10

learning_rate: 0.05

max_delta_step: 0.0

max_depth: 3,5,7

min_child_weight: 1.0

max_depth 5 4 3

eXtreme Gradient Boosted Tr... 64.00% sample , CV #1 4% 2.4 GB RAM 2.0 CPUs

Auto-Tuned Word N-Gram Text... 64.00% sample , CV #1 4% 2.4 GB RAM 0.0 CPUs

Auto-Tuned Word N-Gram Text... 64.00% sample , CV #1 4% 2.6 GB RAM 0.0 CPUs

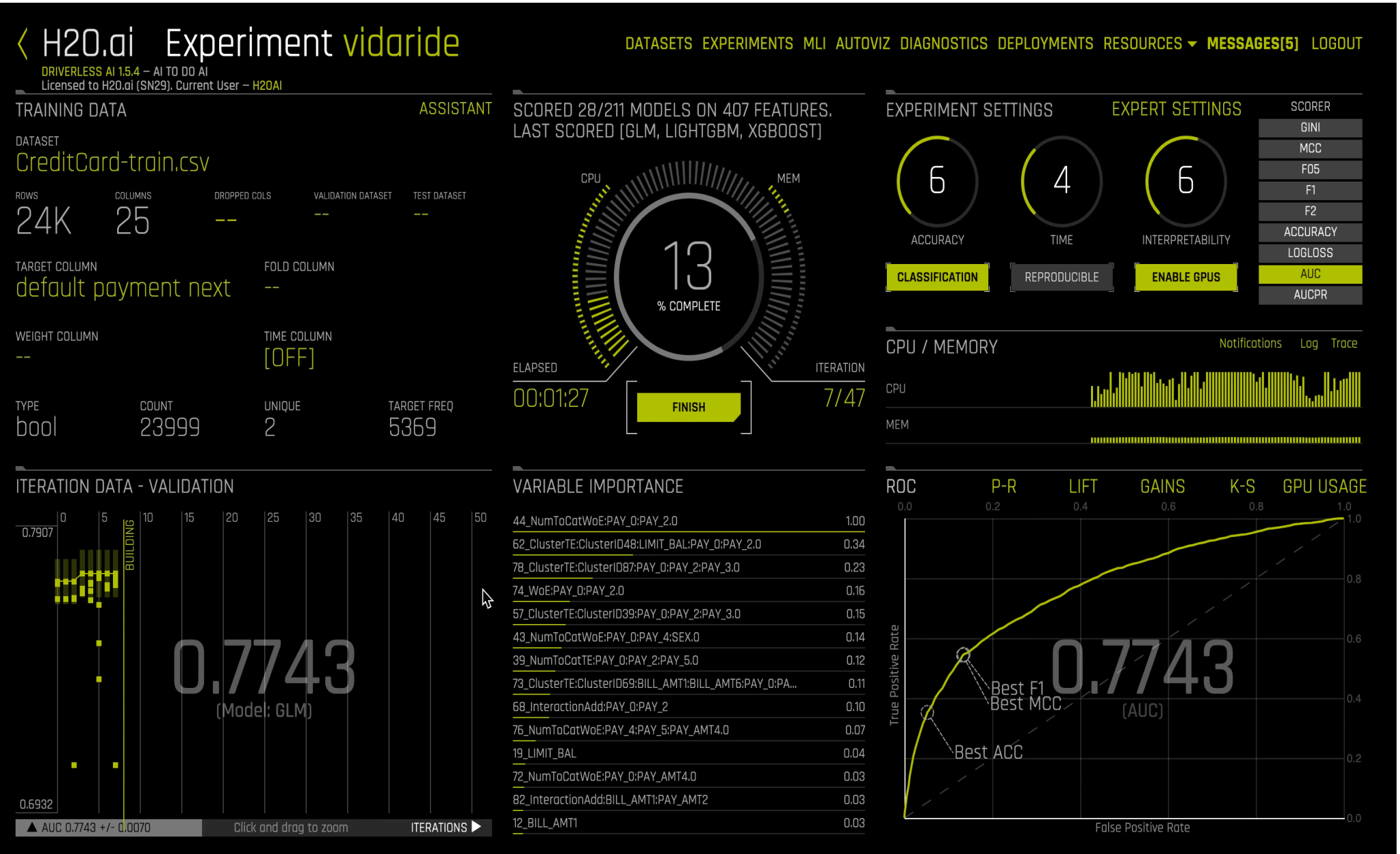
Auto-Tuned Word N-Gram Text... 64.00% sample , CV #1 4% 2.6 GB RAM 0.5 CPUs

Auto-Tuned Word N-Gram Text... 64.00% sample , CV #1 2% 1.4 GB RAM 0.7 CPUs

eXtreme Gradient Boosted Tr... 64.00% sample , CV #1 4% 2.6 GB RAM 0.8 CPUs

eXtreme Gradient Boosted Tr... 64.00% sample , CV #1 2% 1.3 GB

H2O



- Experiment summary option generates a document with details of all the steps in the experiment
- Feature importance and various visualizations showing model performance are present
- Cannot reconfigure hyperparameters
- Cannot make changes to the generated pipelines

H2O.ai Experiment duvidemi

DRIVERLESS AI 1.5.4 – AI TO DO AI
Licensed to H2O.ai (SN29). Current User – H2OAI

TRAINING DATA

ASSISTANT

DATASET
CreditCard-train.csv

ROWS	COLUMNS	DROPPED COLS	VALIDATION DATASET	TEST DATASET
24K	25	0	--	--

TARGET COLUMN
default payment next

FOLD COLUMN
--

WEIGHT COLUMN
--

TIME COLUMN
[OFF]

TYPE	COUNT	UNIQUE	TARGET FREQ
bool	23999	2	5369

STATUS: COMPLETE

- DEPLOY
- INTERPRET THIS MODEL
- DIAGNOSE MODEL ON NEW DATASET...
- SCORE ON ANOTHER DATASET
- TRANSFORM ANOTHER DATASET...
- DOWNLOAD PREDICTIONS
- DOWNLOAD PYTHON SCORING PIPELINE
- DOWNLOAD MOJO SCORING PIPELINE
- DOWNLOAD EXPERIMENT SUMMARY
- DOWNLOAD LOGS

EXPERIMENT SETTINGS

EXPERT SETTINGS

ACCURACY	TIME	INTERPRETABILITY
6	2	8

CLASSIFICATION | REPRODUCIBLE | ENABLE GPUS

SCORER: GINI, MCC, F05, F1, F2, ACCURACY, LOGLOSS, AUC, AUCPR

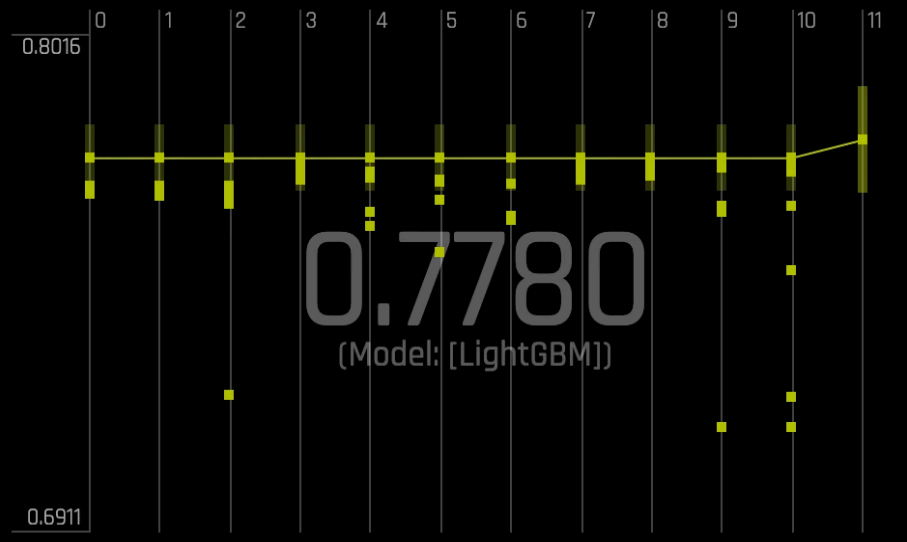
CPU / MEMORY

Notifications Log Trace

CPU

MEM

ITERATION DATA - VALIDATION



VARIABLE IMPORTANCE

10_PAY_0	1.00
11_PAY_2	0.57
13_PAY_4	0.36
17_PAY_AMT2	0.19
8_LIMIT_BAL	0.19
14_PAY_5	0.18
16_PAY_AMT1	0.18
18_PAY_AMT3	0.14
1_BILL_AMT1	0.12
3_BILL_AMT3	0.12
2_BILL_AMT2	0.09
15_PAY_6	0.08
0_AGE	0.08

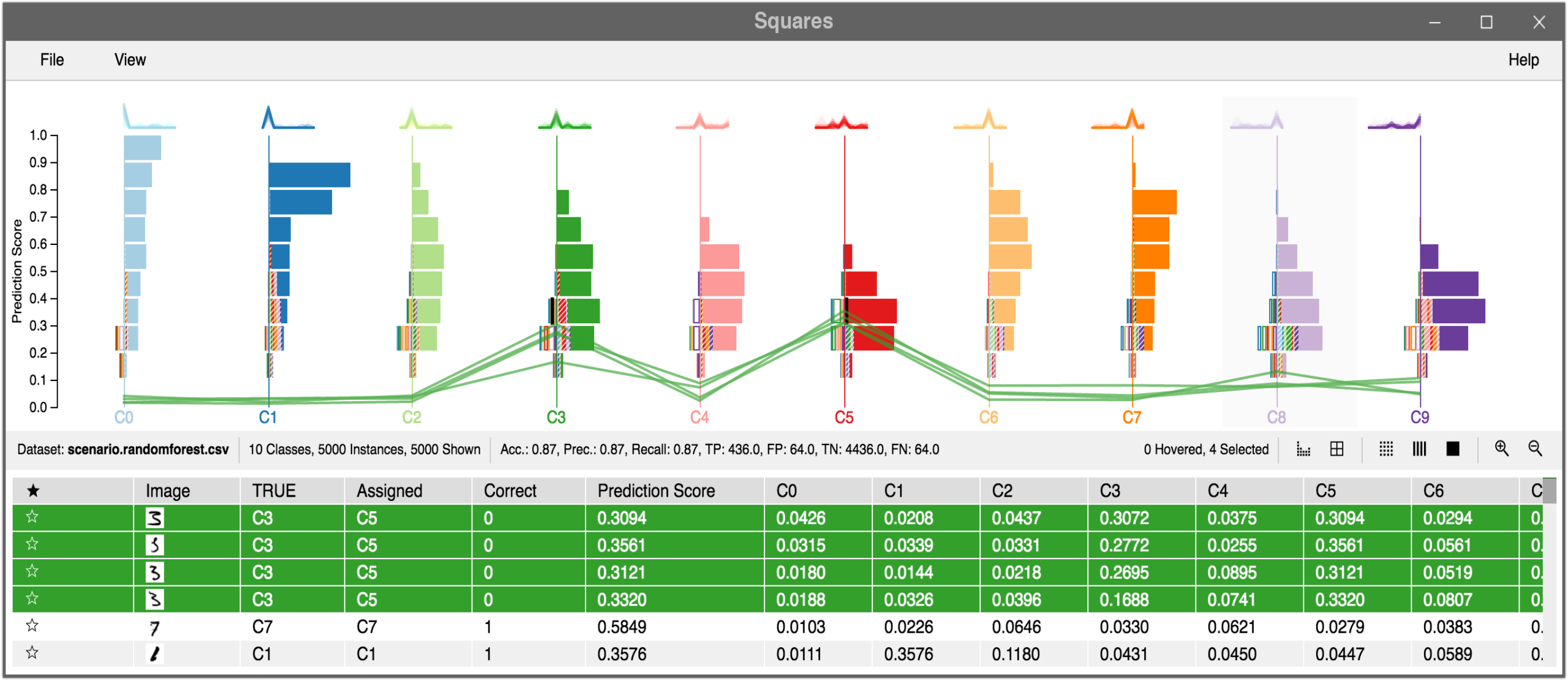
ROC P-R LIFT GAINS K-S SUMMARY

Experiment: duvidemi, 2019-03-20 20:02, 1.5.4
Settings: 6/2/8, seed=600116061, GPUs enabled
Train data: CreditCard-train.csv (23999, 25)
Validation data: N/A
Test data: N/A
Target column: default payment next month (binary, 22.372% target class)
System specs: Docker/Linux, 240 GB, 32 CPU cores, 4/4 GPUs
Max memory usage: 3.44 GB, 0.836 GB GPU
Recipe: AutoDL (10 iterations, 8 individuals)
Validation scheme: stratified, 1 internal holdout
Feature engineering: 284 features scored (13 selected)
Timing:
Data preparation: 6.31 secs
Model and feature tuning: 64.61 secs (28 of 32 models trained)
Feature evolution: 24.98 secs (12 of 48 models trained)
Final pipeline training: 15.19 secs (4 models trained)
Python / MOJO scorer building: 16.07 secs / 0.00 secs
Validation score: AUC = 0.77402 +/- 0.0070665 (baseline)
Validation score: AUC = 0.77799 +/- 0.01048 (final pipeline)
Test score: AUC = N/A

Some other Related Systems

Squares: Supporting Interactive Performance Analysis for Multiclass Classifiers - Donghao Ren, Saleema Amershi, Bongshin Lee, Jina Suh, and Jason D. Williams

- Datatype: MNIST digits dataset
- Focus: Multiclass Classification
- Feature Extraction: No
- Statistics(accuracy, precision, recall, or logarithmic loss) and confusion matrices efficiently summarize performance, aggregated values can obscure important information about a model’s behavior



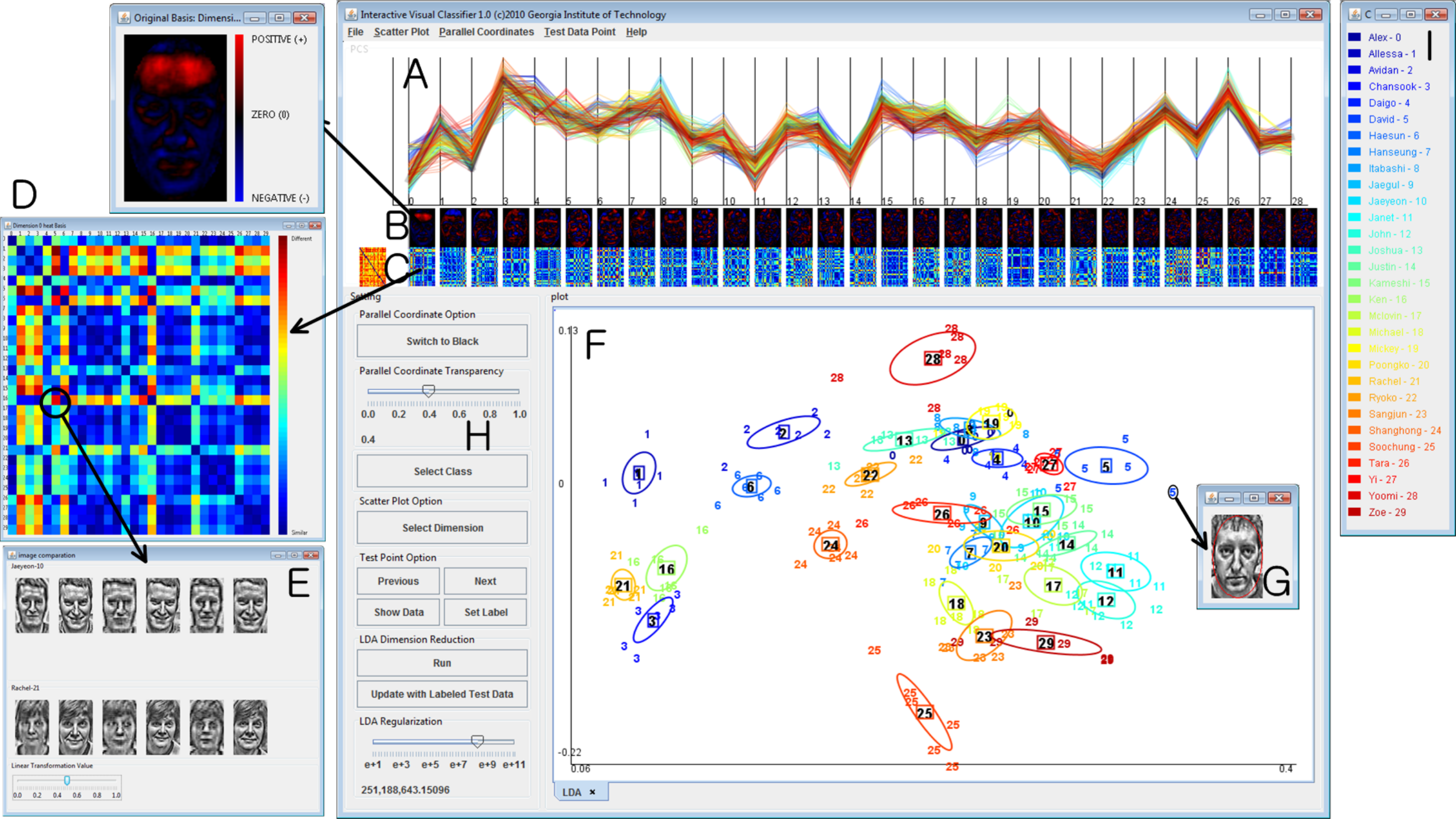
★	Image	TRUE	Assigned	Correct	Prediction Score	C0	C1	C2	C3	C4	C5	C6	C
☆		C3	C5	0	0.3094	0.0426	0.0208	0.0437	0.3072	0.0375	0.3094	0.0294	0.
☆		C3	C5	0	0.3561	0.0315	0.0339	0.0331	0.2772	0.0255	0.3561	0.0561	0.
☆		C3	C5	0	0.3121	0.0180	0.0144	0.0218	0.2695	0.0895	0.3121	0.0519	0.
☆		C3	C5	0	0.3320	0.0188	0.0326	0.0396	0.1688	0.0741	0.3320	0.0807	0.
☆		C7	C7	1	0.5849	0.0103	0.0226	0.0646	0.0330	0.0621	0.0279	0.0383	0.
☆		C1	C1	1	0.3576	0.0111	0.3576	0.1180	0.0431	0.0450	0.0447	0.0589	0.

Squares reveals scores for an instance across all classes on demand when a user hovers or clicks on a box in the display (G1). Scores are displayed using parallel coordinates, with a polyline intersecting each axis at the corresponding score level for that class

iVisClassifier: An Interactive Visual Analytics System for Classification Based on Supervised Dimension Reduction

- Jaegul Choo, Hanseung Lee, Jaeyeon Kihm, Haesun Park

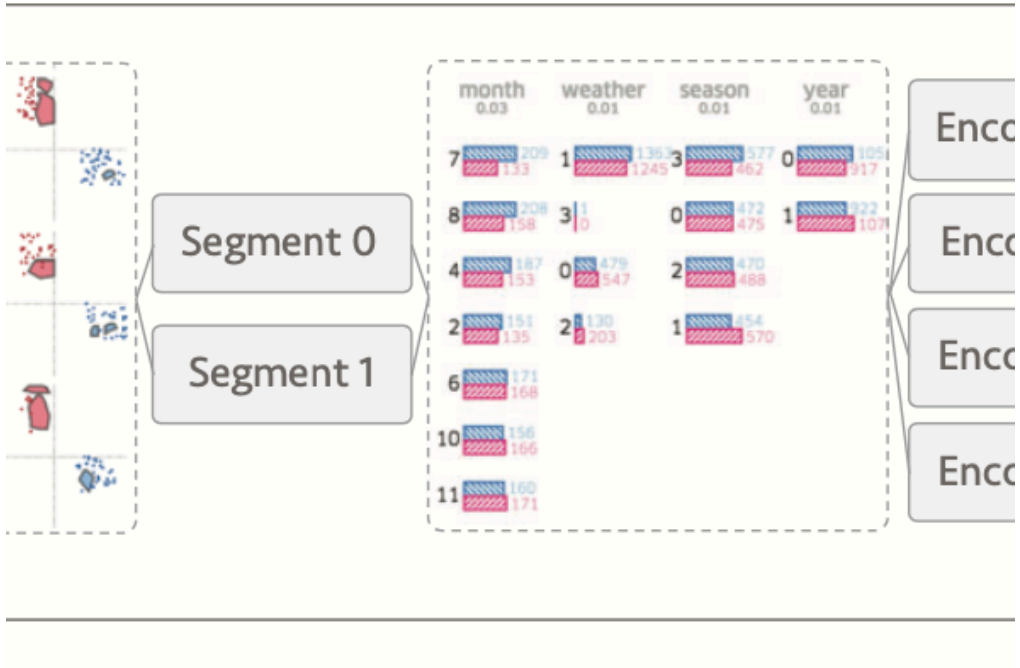
- Datatype: Image
- Focus: Classification
- Dimensionality Reduction
- Classification for high dimensional data using LDA


Original Basis: Dimensi...
POSITIVE (+)
ZERO (0)
NEGATIVE (-)
D
Interactive Visual Classifier 1.0 (c)2010 Georgia Institute of Technology
File
Scatter Plot
Parallel Coordinates
Test Data Point
Help
PCS
A
B
C
Setting
Parallel Coordinate Option
Switch to Black
Parallel Coordinate Transparency
0.0 0.2 0.4 0.6 0.8 1.0
0.4
H
Select Class
Scatter Plot Option
Select Dimension
Test Point Option
Previous
Next
Show Data
Set Label
LDA Dimension Reduction
Run
Update with Labeled Test Data
LDA Regularization
e+1 e+3 e+5 e+7 e+9 e+11
251,188,643.15096
plot
F
0.13
0
-0.22
0.06
0.4
LDA
Dimension 0 heat Basis
Different
Similar
image comparation
Jaeyeon-10
Rachel-21
Linear Transformation Value
0.0 0.2 0.4 0.6 0.8 1.0
E
G
Alex - 0
Allessa - 1
Avidan - 2
Chansook - 3
Daigo - 4
David - 5
Haesun - 6
Hanseung - 7
Itabashi - 8
Jaegul - 9
Jaeyeon - 10
Janet - 11
John - 12
Joshua - 13
Justin - 14
Kameshi - 15
Ken - 16
Mclovin - 17
Michael - 18
Mickey - 19
Poongko - 20
Rachel - 21
Ryoko - 22
Sangjun - 23
Shanghong - 24
Soochung - 25
Tara - 26
Yi - 27
Yoomi - 28
Zoe - 29

Manifold: A Model-Agnostic Framework for Interpretation and Diagnosis of Machine Learning Models

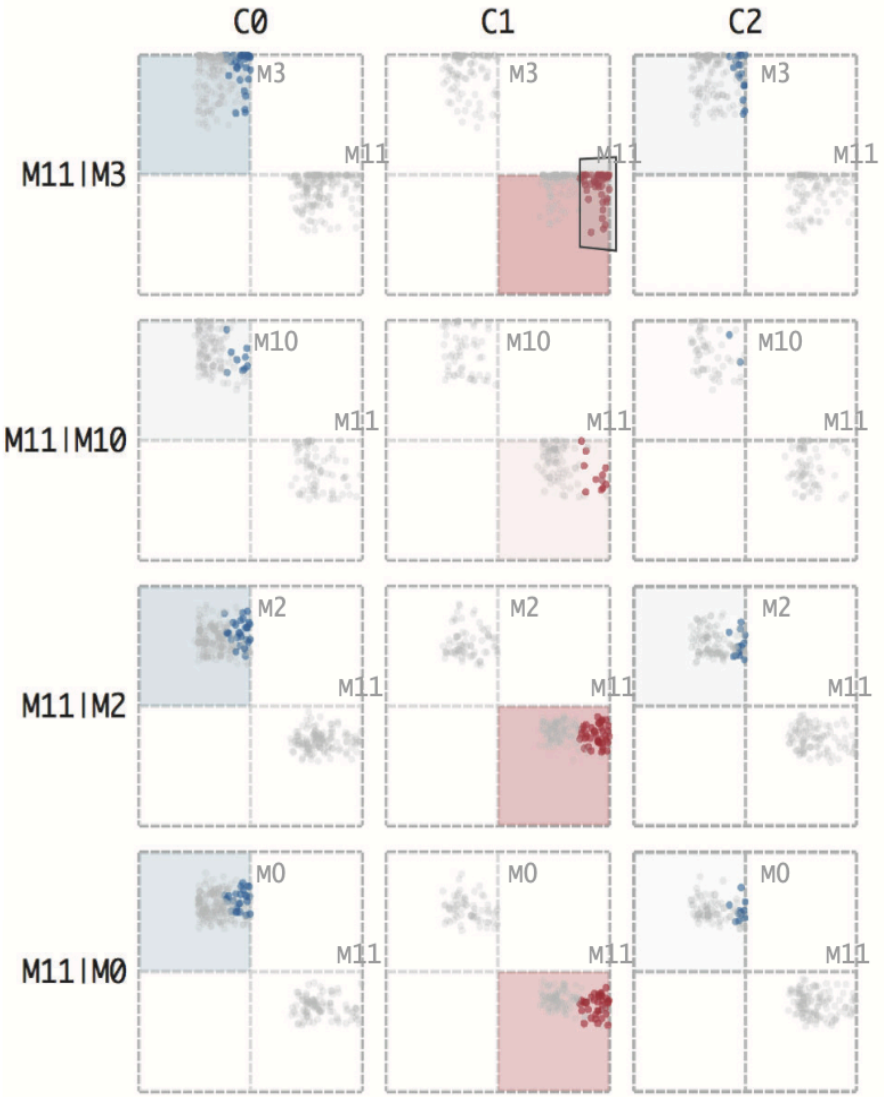
- Jiawei Zhang, Yang Wang, Piero Molino, Lezhi Li and David S. Ebert, Fellow, IEEE

- A generic environment for comparing and debugging a broad range of machine learning models
- Feature Engineering: Yes
- Focus: Regression/ Classification
- Tabular view for the users to visually discriminate features
- After model pairs and it allows the users to effectively inspect *symptom* data(specific data slices) instances and make hypotheses accordingly



Between Model Comparison

An overview of model performance over classes.

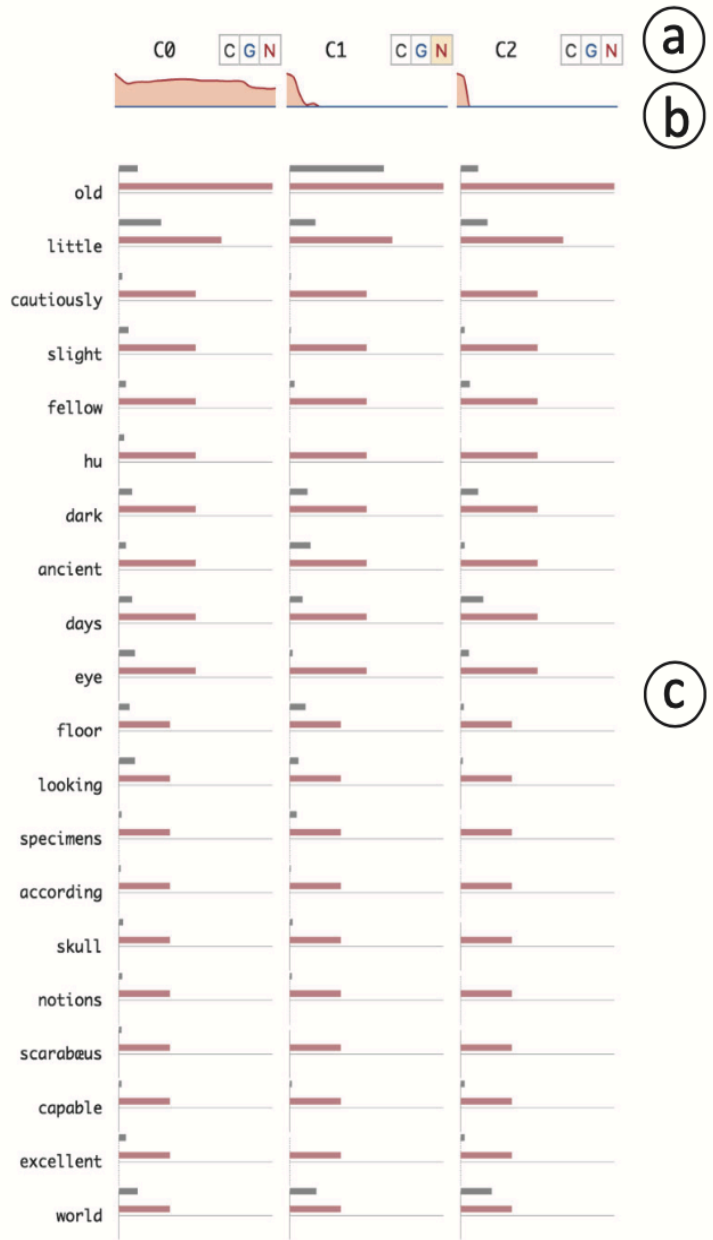


** A larger coordinate indicates higher prediction confidence*

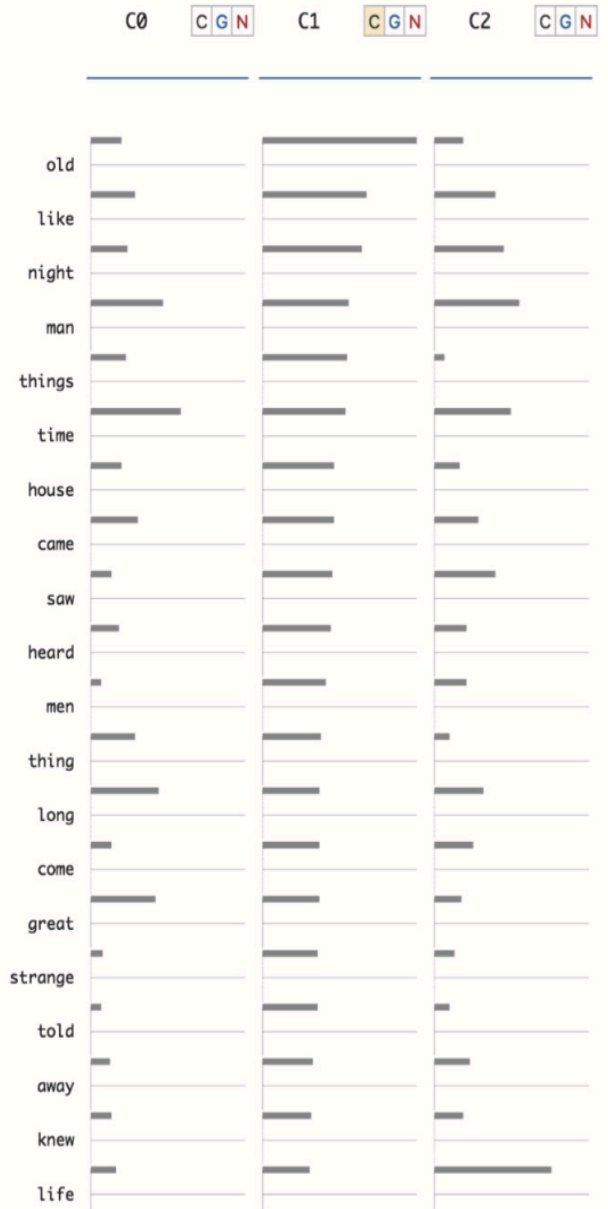
(1)

Feature Attribution

Contributing features that lead to the discrepancy between data segments.



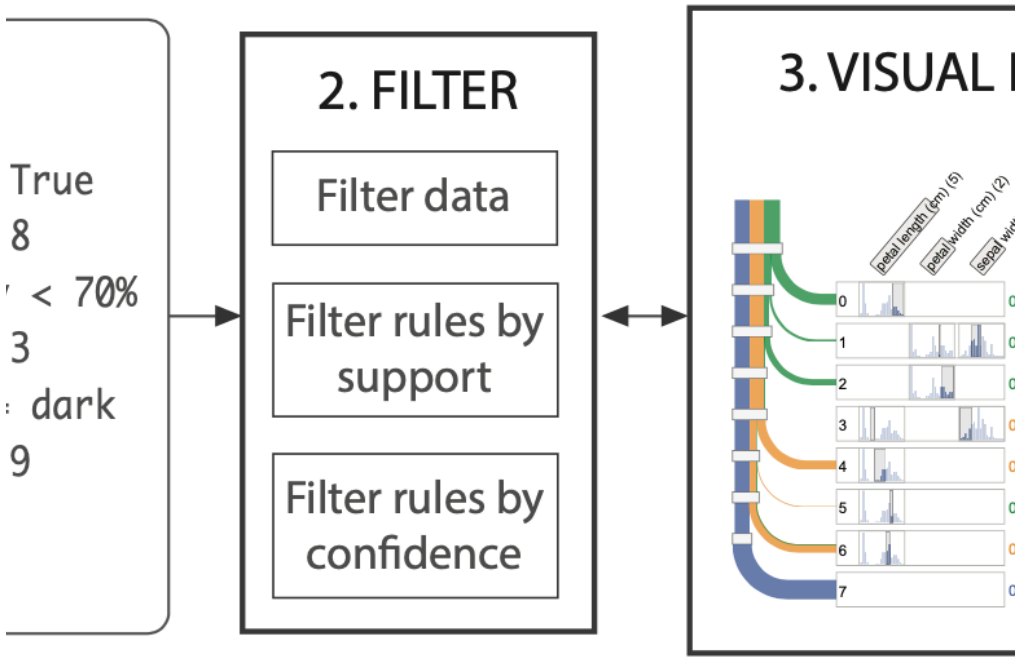
(2)

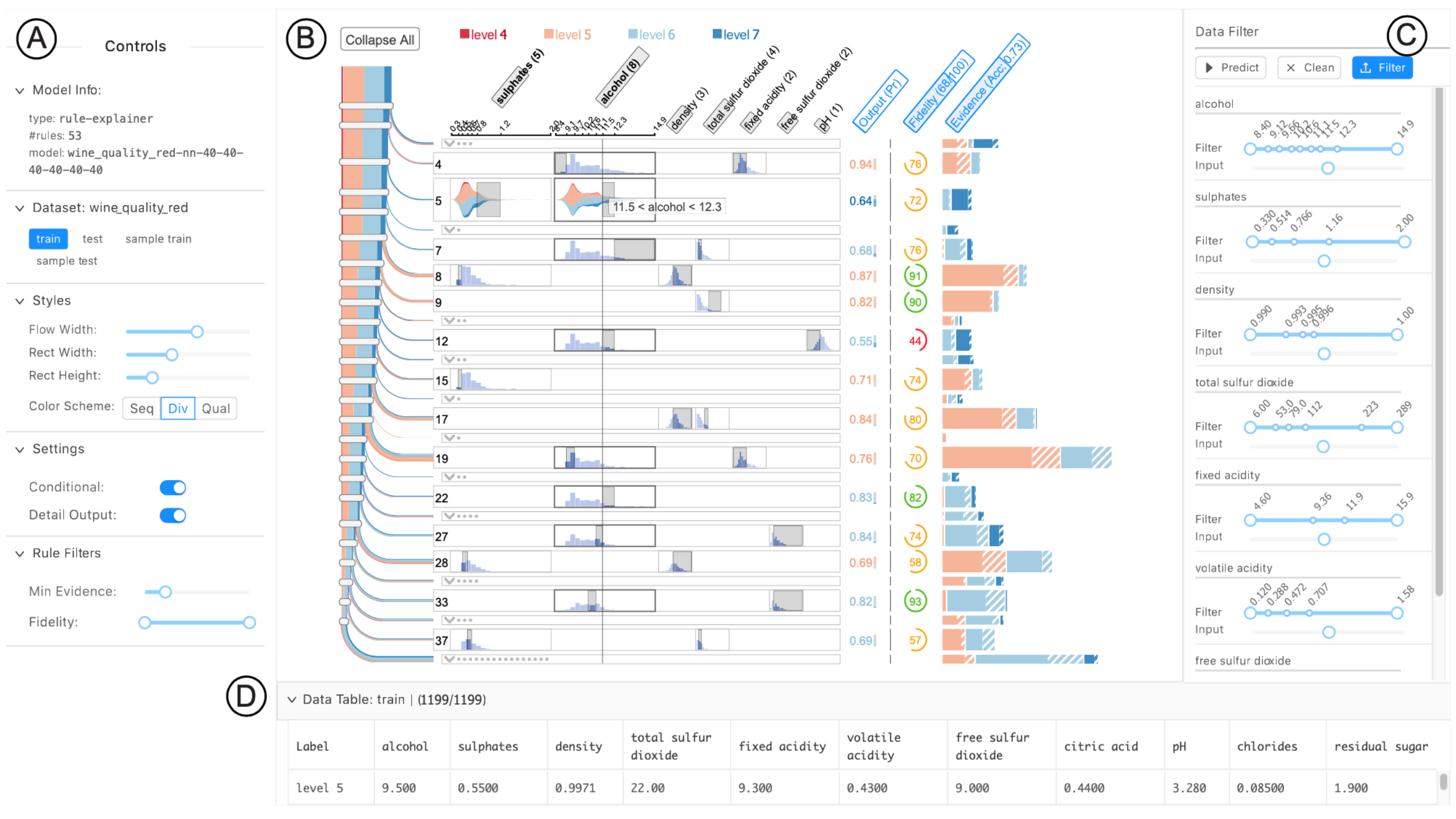


(3)

RuleMatrix: Visualizing and Understanding Classifiers with Rules - Yao Ming, Huamin Qu, Member, IEEE, and Enrico Bertini, Member, IEEE

- Datatype: Classification
- Rule-based knowledge representation from its input-output behavior
- User Interactions: filtering data, filtering rules, details on demand
- Allows visual inspection of the reasoning logic of the model, as well as systematic exploration of the data used to train the model.




A
Controls
Model Info:
type: rule-explainer
#rules: 53
model: wine_quality_red-nn-40-40-40-40-40-40
Dataset: wine_quality_red
train
test
sample train
sample test
Styles
Flow Width:
Rect Width:
Rect Height:
Color Scheme:
Seq
Div
Qual
Settings
Conditional:
Detail Output:
Rule Filters
Min Evidence:
Fidelity:
B
Collapse All
level 4
level 5
level 6
level 7
sulphates (5)
alcohol (8)
density (3)
total sulfur dioxide (4)
fixed acidity (2)
free sulfur dioxide (2)
pH (1)
Output (Pr)
Fidelity (68/100)
Evidence (Acc: 0.73)
11.5 < alcohol < 12.3
C
Data Filter
Predict
Clean
Filter
alcohol
sulphates
density
total sulfur dioxide
fixed acidity
volatile acidity
free sulfur dioxide
Filter
Input
D
Data Table: train | (1199/1199)
Label
alcohol
sulphates
density
total sulfur dioxide
fixed acidity
volatile acidity
free sulfur dioxide
citric acid
pH
chlorides
residual sugar
level 5
9.500
0.5500
0.9971
22.00
9.300
0.4300
9.000
0.4400
3.280
0.08500
1.900

EnsembleMatrix: Interactive Visualization to Support Machine Learning with Multiple Classifiers - Justin Talbot, Bongshin Lee, Ashish Kapoor, Desney S. Tan

- An interactive visualization system that presents a graphical view of confusion matrices to help users under- stand relative merits of various classifiers
- Focus**:** multiclass classification
- Datatype: CalTech 101 dataset(Image data)

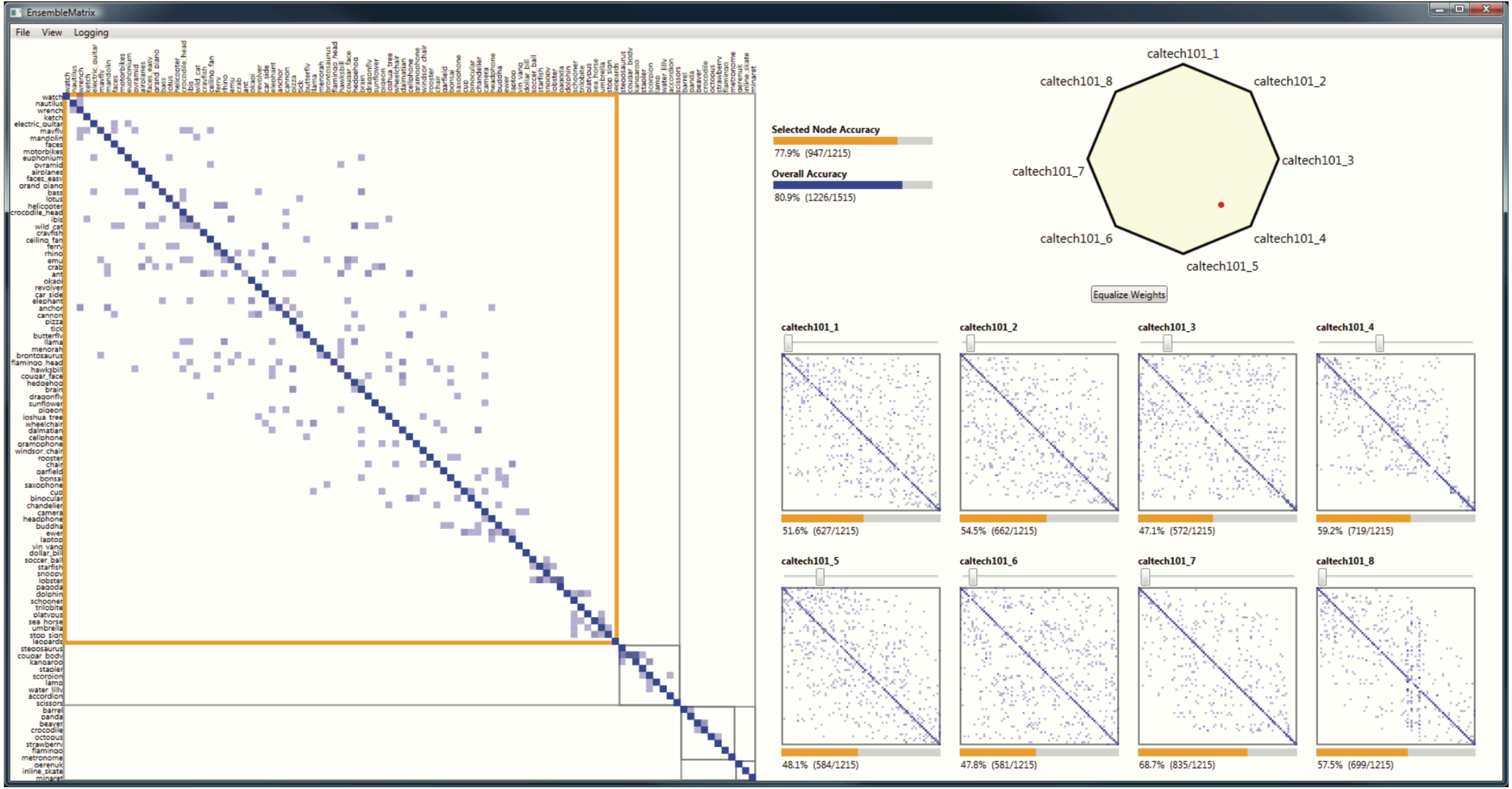


Figure 1. Primary view in EnsembleMatrix. Confusion matrices of component classifiers are shown in thumbnails on the right. The matrix on the left shows the confusion matrix of the current ensemble classifier built by the user.

PipelineProfiler: A Visual Analytics Tool for the Exploration of AutoML Pipelines
- Jorge Piazentin Ono, Sonia Castelo, Roque Lopez, Enrico Bertini, Juliana Freire, Claudio Silva

- Datatype: Statlog heart dataset
- Focus: Classification
- an interactive visualization tool that allows the exploration and comparison of the solution space of machine learning (ML) pipelines produced by AutoML systems.
- Feedback, case studies, think-aloud to test efficiency of their system.

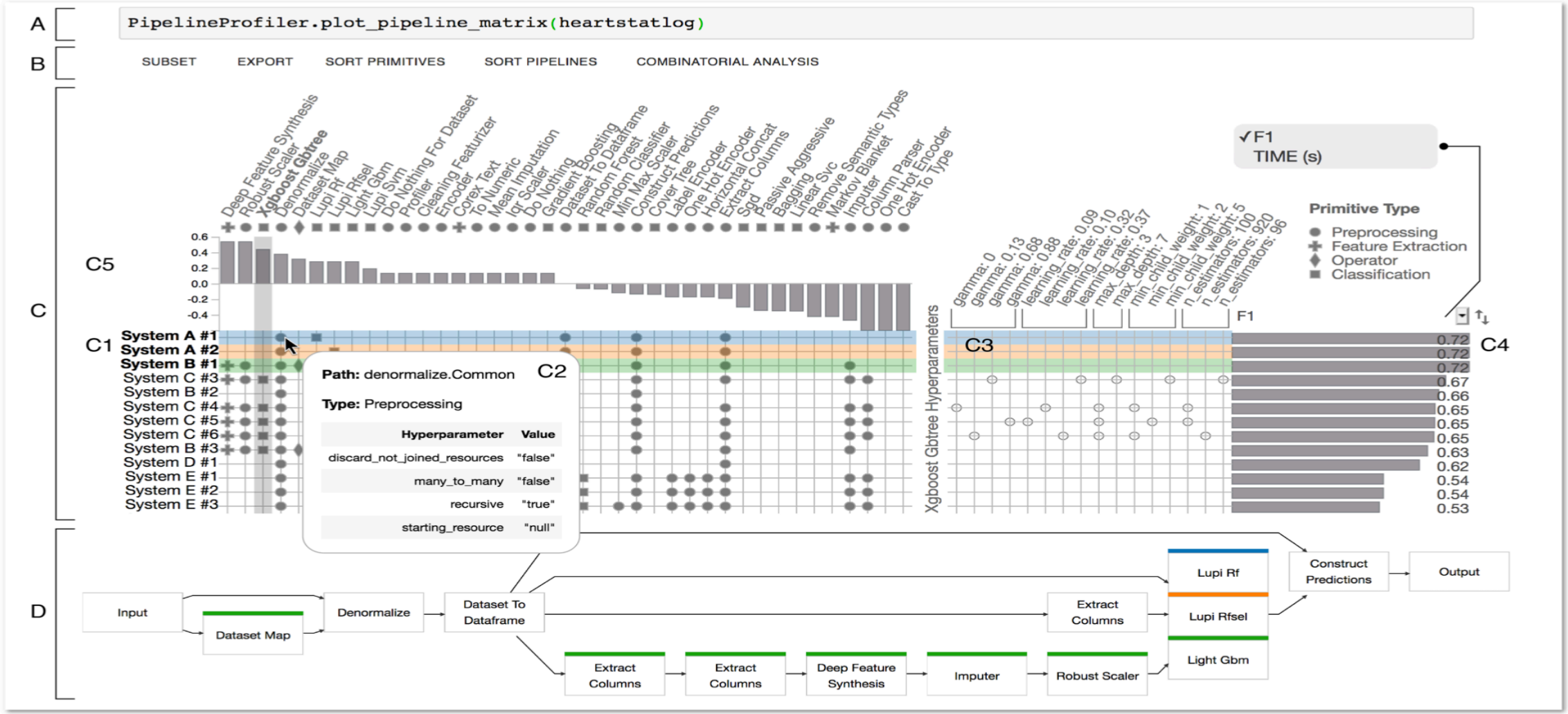


Fig. 1. *PipelineProfiler* applied to the analysis of binary classification pipelines generated by five AutoML systems for the *Statlog (Heart) Data Set*. A) The system is integrated with Jupyter Notebook and can be used with one line of code. B) *PipelineProfiler* menu, with options to subset, export, sort and perform automated analysis on pipelines. C) Pipeline Matrix: C1) Primitives (columns) used by the pipelines (rows). C2) Tooltip showing the metadata and hyperparameters for a primitive. C3) One-hot-encoded hyperparameters (columns) for the primitive *Xgboost Gbtree* across pipelines (rows). C4) Pipeline scores: users can select different metrics to rank pipelines. C5) Primitive Contribution View, showing the correlations between primitive usage and pipeline scores – here, we see that *Deep Feature Synthesis* has the highest correlation score with F1 scores. D) Pipeline Comparison View: visual comparison of the top-3 scoring pipelines (blue, orange and green).

ATMSeer: Increasing Transparency and Controllability in Automated Machine Learning - Qianwen Wang, Yao Ming, Zhihua Jin, Qiaomu Shen, Dongyu Liu, Micah J. Smith, Kalyan Veeramachaneni, Huamin Qu

- Datatype: arsenic-female-bladder dataset (text data)
- Focus: Regression/ Classification
- An interactive visualization tool that helps users analyze the searched models and refine the search space
- ATMSeer offers a visual summary of the searched models to increase the transparency of AutoML.

Figure 2: The Interface of ATMSeer. The user creates/resume AutoML process using the control panel (a), observe the high-level statistics of an AutoML process in the overview panel (b), and analyze the process in different granularities with the AutoML profiler (c).

PEAX: INTERACTIVE VISUAL ANALYSIS AND EXPLORATION OF COMPLEX CLINICAL PHENOTYPE AND GENE EXPRESSION ASSOCIATION

MICHAEL A. HINTERBERG, DAVID P. KAO, MICHAEL R. BRISTOW, LAWRENCE E. HUNTER, J. DAVID PORT, and CARSTEN GORG

- Datatype: BORG data (“Effect of β-blockers on Structural Remodeling and Gene Expression in the Failing Human Heart”)
- Focus: Classification, Decision Trees
- Rather than defining mere presence or absence of disease, certain types of cancer can be more precisely graded or staged when specific gene sequences and expression characteristics are known
- Patients with different genotypes may exhibit differential response to drug treatment

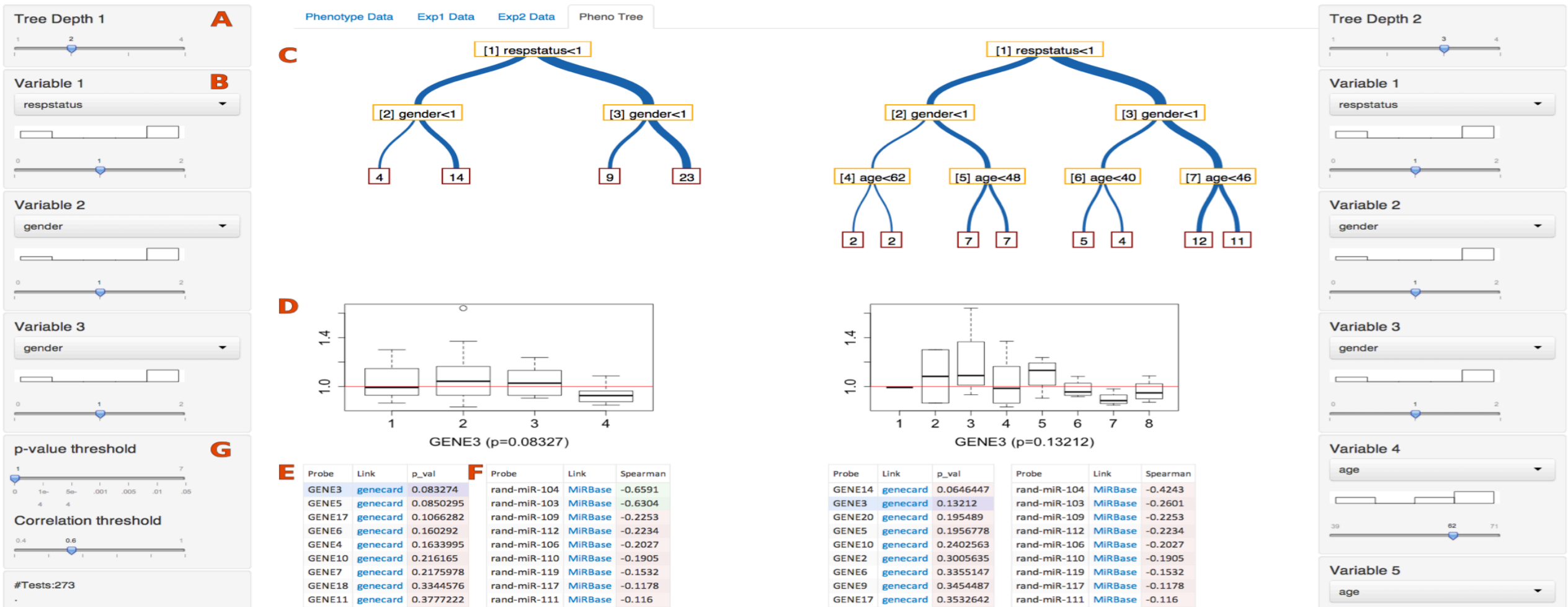


Fig. 1. Sample Screenshot of PEAX. On the left are various controls for defining sub-phenotype, including the depth of the decision tree (A), the decision variable for each node (B), and the decision variable threshold. A histogram of the sub-population of patients is shown below each decision node drop-down box. Together, these controls define the decision tree (C). A boxplot (D) shows distribution of a selected gene from a candidate list of genes (E), while a separate adjacent table (F) shows the top correlating miRNA expression levels with the selected gene. Selectable thresholds (G) allow for highlighting of significant associations in either table. Displayed data are random for illustrative purposes, due to confidentiality of clinical research work described in this paper. The entire set of controls, and resulting tree, boxplot, and associative tables, are replicated on the right side to allow for definition, viewing, and comparing of juxtaposed models.

ModelTracker: Redesigning Performance Analysis Tools for Machine Learning
- Saleema Amershi, Max Chickering, Steven M. Drucker, Bongshin Lee, Patrice Simard, Jina Suh

- An interactive visualization that subsumes information contained in numerous traditional summary statistics and graphs while displaying example-level performance and enabling direct error examination and debugging.
- Focus: Supervised Machine Learning

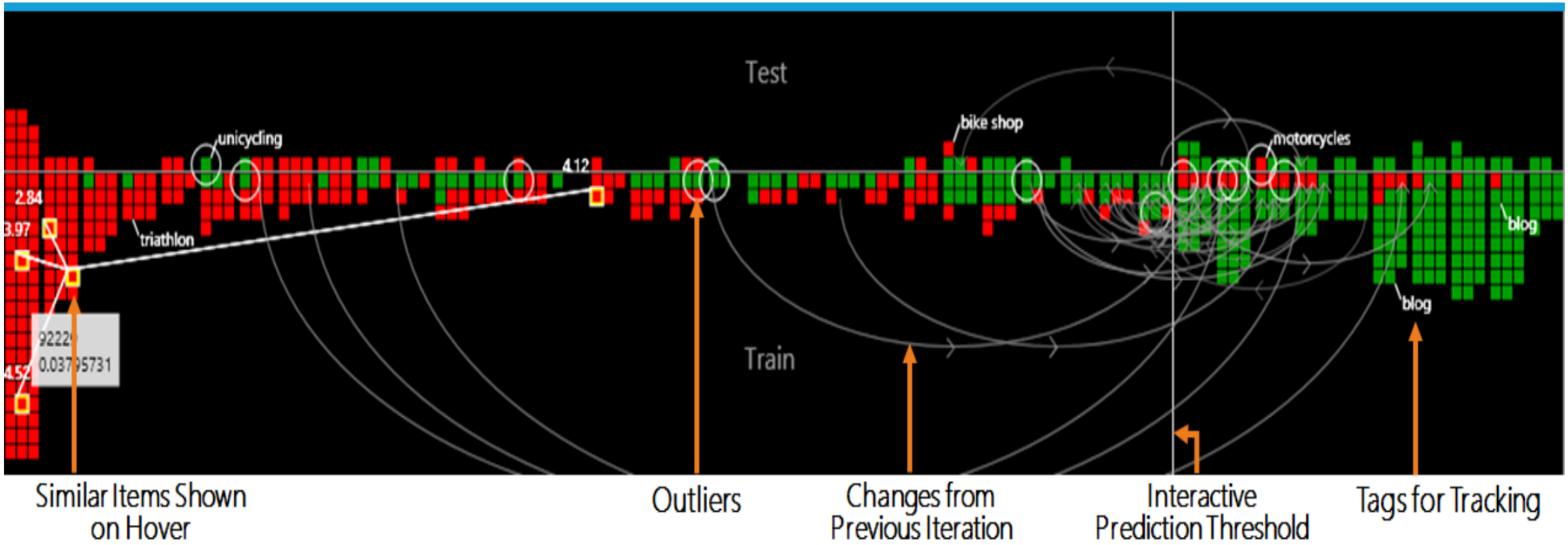


Figure 1. ModelTracker conveys overall model performance while enabling direct data inspection. Boxes represent user labeled examples and color indicates the label given (green for *positive* and red for *negative*). *Test* examples are placed at the top and *train* examples at the bottom. Examples are laid out horizontally according to the model's prediction scores, with low scoring examples to the left and high scoring examples to the right. A high performing model will have most green boxes to the right and most red boxes to the left of the display. Users can interact directly with ModelTracker to reveal additional information (e.g., hovering over an example reveals its nearest neighbors in the current feature space), inspect examples (by clicking on boxes to pull up the corresponding raw data in the display), and annotate examples for better performance tracking.

Some Other Systems

- Prospector: how a specific feature contributes to the prediction by adjusting the feature value and examine the corresponding change of the predicted result.
- *FeatureInsight:* for improving the feature engineering through interactive visual summaries.

Conclusion

We are trying to achieve a system that can:

- Visualize multiple pipelines at once(like in PipelineProfiler)
- Create new pipelines from scratch(like in SPSS, KNIME, and AzureML)
- Edit/tune the pipelines generated by AutoML systems

References

- https://dl.acm.org/doi/abs/10.1145/2939502.2939503
- https://arxiv.org/abs/2005.00160
- https://ieeexplore.ieee.org/abstract/document/8440085
- https://dl.acm.org/doi/abs/10.1145/3290605.3300911
- https://ieeexplore.ieee.org/abstract/document/5652443
- https://ieeexplore.ieee.org/abstract/document/7539404
- https://ieeexplore.ieee.org/abstract/document/8440091
- https://dl.acm.org/doi/abs/10.1145/3097983.3098043
- https://dl.acm.org/doi/abs/10.1145/1518701.1518895

Thank you!