



# SAS Viya

## Trustworthy AI & Open-Source

Chris Parrish, Sr. Data Scientist, Financial Services

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# Steps

- 1 Develop Models in Open-Source IDE with Libraries of Choice
- 2 Import SAS Viya Libraries SWAT, SASCTL & Connect to SAS Viya
- 3 Register Open-Source Models to SAS Viya
- 4 Retrieve & Review/Edit Score Code & Create Table with Score Code
- 5 Load SAS Viya Trustworthy AI APIs `explainModel`  
`fairAITools`
- 6 Use Score Code & Scored Tables to Run Trustworthy AI APIs
- 7 Save Trustworthy AI Metrics to SAS Viya
- 8 Create Dashboards/Workflows to Facilitate Decisions with Metrics

Distributed  
Computing!



# Trustworthy AI with SAS Viya & Open-Source

## Open-Source Editor



- 1 Import OS libraries  
Develop OS Models
- 2 Import SWAT  
Import SASCTL



## SAS Viya



- 8 Dashboards  
Workflows  
ModelOps

## 1 Develop Models in Open-Source IDE with Libraries of Choice

```
#####  
### Training Code ###  
#####
```

```
### estimate & fit model  
dm_model <- glm(as.formula(paste(dm_dec_target, " ~ .")), data=train, family=binomial(link=link))  
  
### score full data  
full <- subset(dm_inputdf, select=c(dm_dec_target, dm_input))  
fullX <- subset(dm_inputdf, select=dm_input)  
fully <- subset(dm_inputdf, select=dm_dec_target)  
dm_scoreddf_prob_event <- data.frame(predict(dm_model, newdata = full, type = 'response'))  
dm_scoreddf_prob_nonevent <- data.frame(1-predict(dm_model, newdata = full, type = 'response'))  
dm_scoreddf_class <- data.frame(ifelse(dm_scoreddf_prob_event[[1]] >= avg_prob, 1, 0))  
dm_scoreddf <- cbind(dm_scoreddf_prob_nonevent, dm_scoreddf_prob_event, dm_scoreddf_class)  
names(dm_scoreddf) <- c(dm_predictionvar[[1]], dm_predictionvar[[2]], dm_classtarget_intovar[[1]])  
  
### create tables with predicted values  
trainProba <- data.frame(predict(dm_model, newdata = X_train, type = 'response'))  
testProba <- data.frame(predict(dm_model, newdata = X_test, type = 'response'))  
validProba <- data.frame(predict(dm_model, newdata = X_valid, type = 'response'))  
trainData <- cbind(y_train, dm_classtarget_intovar=trainProba)  
testData <- cbind(y_test, dm_classtarget_intovar=testProba)  
validData <- cbind(y_valid, dm_classtarget_intovar=validProba)  
names(trainData) <- c(dm_dec_target, dm_predictionvar[[2]])  
names(testData) <- c(dm_dec_target, dm_predictionvar[[2]])  
names(validData) <- c(dm_dec_target, dm_predictionvar[[2]])  
  
### print model & results  
summary(dm_model)
```

## 2 Import SAS Viya Libraries SWAT, SASCTL & Connect to SAS Viya

```
library(swat)
```

```
conn <- swat::CAS(hostname=hostname_dev, port=port_dev, username, password, protocol=protocol_dev)
print(cas.builtins.serverStatus(conn))
```

```
#####
### Identify Table in CAS ###
#####
```

```
### caslib and table to use in modeling
caslib <- 'Public'
in_mem_tbl <- 'FINANCIAL_SERVICES_PREP'
```

```
### load table in-memory if not already exists in-memory
if (cas.table.tableExists(conn, caslib=caslib, name=in_mem_tbl)<=0) {
  cas.table.loadTable(conn, caslib=caslib, path=paste(in_mem_tbl,('.sashdat'), sep = ""),
    casout=list(name=in_mem_tbl, caslib=caslib, promote=TRUE))}
}
```

```
### show table to verify
cas.table.tableInfo(conn, caslib=caslib, wildIgnore=FALSE, name=in_mem_tbl)
```

```
#####
### Create Dataframe ###
#####
```

```
dm_inputdf <- to.casDataFrame(defCasTable(conn, in_mem_tbl, caslib=caslib))
sapply(dm_inputdf, class)
```

## 3 Register Open-Source Models to SAS Viya

```
#####  
### Register to Model Manager ###  
#####  
  
library(isonlite)  
library(sasctl)  
library(pmm1)  
library(XML)  
library(zip)  
  
### define macro vars for model manager metadata script  
inputData <- dm_inputdf  
trainData <- train  
testData <- test  
targetVar <- dm_dec_target  
intervalVars <- dm_input  
analysisPrefix <- description  
threshPredProb <- avg_prob  
typeOfColumn <- as.data.frame(do.call(rbind, lapply(inputData, typeof)))  
fitted.prob <- predict(dm_model, newdata = X_train, type = 'response')  
trainData[[targetVar]] <- as.factor(trainData[[targetVar]])  
  
### create directories for metadata  
output_path <- file.path(output_dir, metadata_output_dir, model_name)  
if (file.exists(output_path)) {  
  unlink(output_path, recursive=TRUE) }  
  
### create output path  
dir.create(output_path)  
analysisFolder <- paste(output_path, '/', sep = '')  
jsonFolder <- paste(output_path, '/', sep = '')  
zip_folder <- paste(output_path, '/', sep = '')  
  
### create pmm1 (predictive model markdown language)  
pmm1_file <- saveXML(pmm1(dm_model, model.name = model_name, description = model_type),  
  paste0(zip_folder, '/', description, '.pmm1'))  
  
### move train code and score code to zip directory  
file.copy(file.path(output_dir, train_code_name), file.path(output_path, train_code_name))  
file.copy(file.path(output_dir, score_code_name), file.path(output_path, score_code_name))  
  
sess <- session(hostname_model, username=username, password=password)  
  
rm <- register_model(  
  session = sess,  
  file = paste0(zip_folder, '/', description, '.pmm1'),  
  name = model_name,  
  type = "pmm1",  
  project = project_name,  
  force = FALSE
```

4

## Retrieve Score Code from Model Manager...

Publish



2

Close



Home



Models



Projects



Deployments



Tasks

logit\_r\_finsvcs (1.0) | Project: Financial\_Services\_Version\_1 (1.0)

Files Variables Properties Versions



## SCORE CODE

score.sas



## VARIABLES

input.xml



output.xml



target.xml

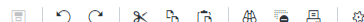


## OTHER

logit\_r\_finsvcs.xml



score.sas



```
1  /*****  
2  * PSCORE TIMESTAMP: 2023-14-4 20:15:41.47 ;  
3  * SAS VERSION: V.04.00M0P091922 ;  
4  * SAS HOSTNAME: sas-compute-server-b6236644-467d-4047-948f-d3ff2b9c55b7-3428 ;  
5  * SAS ENCODING: utf-8 ;  
6  * SAS USER: chparr ;  
7  * SAS LOCALE: EN_US ;  
8  * PMML Path: logit_r_finsvcs.xml ;  
9  * PMML SOURCE: SoftwareAG PMML Generator;  
10 * PMML SOURCE VERSION: 2.5.2;  
11 * PMML TIMESTAMP: 2023-04-24 15:55:09 ;  
12 * MODEL TYPE: GeneralRegressionModel ;  
13 * MODEL FUNCTION NAME: Regression ;  
14 *****/;  
15  
16  
17 PSCR_WARN = 0;  
18  
19 if missing("gender"n) then do;  
20     PSCR_WARN = 1;  
21 end;  
22 if missing("net_worth"n) then do;  
23     PSCR_WARN = 1;  
24 end;  
25 if missing("job_in_education"n) then do;  
26     PSCR_WARN = 1;  
27 end;  
28 if missing("job_in_hospitality"n) then do;  
29     PSCR_WARN = 1;  
30 end;  
31 if missing("at_current_job_1_year"n) then do;  
32     PSCR_WARN = 1;  
33 end;  
34 if missing("num_dependents"n) then do;  
35     PSCR_WARN = 1;  
36 end;  
37 if missing("age"n) then do;  
38     PSCR_WARN = 1;  
39 end;  
40 if missing("debt_to_income"n) then do;  
41     PSCR_WARN = 1;  
42 end;  
43 if missing("num_transactions"n) then do;  
44     PSCR_WARN = 1;  
45 end;  
46 if missing("credit_history_mos"n) then do;  
47     PSCR_WARN = 1;  
48 end;
```

## Model Summary

Created by: chparr

Modified by: chparr

Date modified: Apr 14, 2023 04:15 PM

Displayed version: 1.0

Latest published  
version: Not published

## Score Code Type

DATA step

## Algorithm

Generalized linear model

## Development Tool

PMML

## Function

regression

## Training Code Type

No property value is specified.

RStudio

logit\_finsvcs\_r\_trustworthy\_ai.R ×

score\_code ×

4

...Review/Edit Score Code & Create Table with Score Code

←→

Filter

DataStepSrc

1PSCR\_WARN = 0;

```
PSCR_WARN = 0;

    if missing(gender) then do;
        PSCR_WARN = 1;
    end;

    if missing(net_worth) then do;
        PSCR_WARN = 1;
    end;

    if missing(job_in_education) then do;
        PSCR_WARN = 1;
    end;
    if missing(job_in_hospitality) then do;
        PSCR_WARN = 1;
    end;
    if missing(at_current_job_1_year) then do;
        PSCR_WARN = 1;
    end;
    if missing(num_dependents) then do;
        PSCR_WARN = 1;
    end;
    if missing(age) then do;
        PSCR_WARN = 1;...
```





```
#####  
### Trustworthy AI - Partial Dependence, SHAP values, Assess Bias, Bias Mitigation ###  
#####
```

```
loadActionSet(conn, 'explainModel')  
loadActionSet(conn, 'fairAITools')
```

5

Load SAS Viya Trustworthy AI APIs

## 6 Use Score Code & Scored Tables to Run Trustworthy AI APIs

### Partial Dependency

```
cas.explainModel.partialDependence(conn,
  table=list(caslib=caslib, name=in_mem_tbl),
  seed=12345,
  modelTable=list(name=score_code_tbl),
  modelTableType="DATASTEP",
  predictedTarget=dm_predictionvar[[2]],
  analysisVariable=list(name=pd_var[[i]], nBins=20),
  inputs=dm_input,
  outputTables=list(names=list(PartialDependence=list(name='partialdependence',
    replace=TRUE)))
)
```

### SHAPley Values

```
cas.explainModel.shapleyExplainer(conn,
  table=list(caslib=caslib, name=in_mem_tbl),
  query=list(caslib=caslib, name=in_mem_tbl, where=query_part),
  modelTable=list(name=score_code_tbl),
  modelTableType="DATASTEP",
  predictedTarget=dm_predictionvar[[2]],
  inputs=dm_input,
  depth=1,
  outputTables=list(names=list(Shapleyvalues=list(name='shapleyvalues',
    caslib=caslib, replace=TRUE)))
)
```

### Bias Metrics

```
cas.fairAITools.assessBias(conn,
  table = 'scored_tbl',
  modelTableType = "NONE",
  response = dm_dec_target,
  predictedVariables = list(dm_predictionvar[[1]], dm_predictionvar[[2]]),
  responseLevels = dm_classtarget_level,
  sensitiveVariable = bias_var[[i]]
)
```

```

biasMetric='DEMOGRAPHICPARITY',
event='1',
learningRate='0.01',
maxIters='10',
predictedVariables=c('P_event_indicator0', 'P_event_indicator1'),
response='event_indicator',
responseLevels=c('0', '1'),
sensitiveVariable='gender',
table='financial_services_prep',
tolerance='0.005',
tuneBound='True',
trainProgram='
  decisionTree.gbtreeTrain result=train_res /
    table=table,
    weight=weight,
    target="event_indicator",
    inputs= {
      "at_current_job_1_year", "num_dependents",
      "age", "amount", "credit_history_mos", "credit_score",
      "debt_to_income", "net_worth", "num_transactions"
    },
    nominals={"event_indicator"},
    nBins=50,
    quantileBin=True,
    maxLevel=5,
    maxBranch=2,
    leafSize=5,
    missing="USEINSEARCH",
    minUseInSearch=1,
    binorder=True,
    varImp=True,
    mergeBin=True,
    encodeName=True,
    nTree=15,
    seed=12345,
    ridge=1,
    savestate={
      name="finsvcs_gb_astore",
      replace=True
    }
  ;
  astore.score result=score_res /
    table=table,
    casout=casout,
    copyVars=copyVars,
    rstore="finsvcs_gb_astore"
  ;

```

6

Use Score Code & Scored Tables  
to Run Trustworthy AI APIs

AvailableData SourcesImport

Filter

LOGIT\_R\_FINSVCS\_BIAS\_METRICS  
05/15/23 10:30 AM • chparr

LOGIT\_R\_FINSVCS\_GROUP\_METRICS  
05/15/23 10:30 AM • chparr

LOGIT\_R\_FINSVCS\_MAX\_DIFFERENCES  
05/15/23 10:30 AM • chparr

LOGIT\_R\_FINSVCS\_PARTIAL\_DEPENDENCE  
05/12/23 04:23 PM • chparr

LOGIT\_R\_FINSVCS\_SHAPLEY\_COLS  
05/11/23 04:25 PM • chparr

LOGIT\_R\_FINSVCS\_SHAPLEY\_ROWS  
05/11/23 04:25 PM • chparr

7

Save Trustworthy AI Metrics to SAS Viya

LOGIT\_R\_FINSVCS\_BIAS\_METRICS

DetailsSample Data

Sample rows: 100

BiasMetrics.Metric	BiasMetrics.Metric...	BiasMetrics.Value	BiasMetrics.Base	BiasMetrics.Comp...	BiasMetrics.Note	bias_var
DemographicParity	Demographic Parity (...)	0.2700138592	1	0		gender
PredictiveParity	Predictive Parity	0.2608617321	1	0		gender
EqualAccuracy	Equal Accuracy	0.0104854922	1	0		gender
EqualizedOdds	Equalized Odds	0.1143410853	1	0	Max FPR difference is ...	gender
EqualOpportunity	Equal Opportunity	0.0221152282	1	0		gender
DemographicParity	Demographic Parity (...)	0.5095753114	1	0		at_current_job_1_year
PredictiveParity	Predictive Parity	0.4885545495	1	0		at_current_job_1_year
EqualAccuracy	Equal Accuracy	0.033361479	1	0		at_current_job_1_year
EqualizedOdds	Equalized Odds	0.3402771202	1	0	Max FPR difference is ...	at_current_job_1_year
EqualOpportunity	Equal Opportunity	0.0683770024	1	0		at_current_job_1_year
DemographicParity	Demographic Parity (...)	0.5532470789	0	1		job_in_education
PredictiveParity	Predictive Parity	0.5405194138	0	1		job_in_education
EqualAccuracy	Equal Accuracy	0.0132791736	1	0		job_in_education
EqualizedOdds	Equalized Odds	0.0921896075	0	1	Max FPR difference is ...	job_in_education
EqualOpportunity	Equal Opportunity	0.058453901	0	1		job_in_education
DemographicParity	Demographic Parity (...)	0.2836018916	1	0		job_in_hospitality
PredictiveParity	Predictive Parity	0.2775080545	1	0		job_in_hospitality
EqualAccuracy	Equal Accuracy	0.0204527173	1	0		job_in_hospitality
EqualizedOdds	Equalized Odds	0.1980191087	1	0	Max FPR difference is ...	job_in_hospitality
EqualOpportunity	Equal Opportunity	0.0255460822	1	0		job_in_hospitality
DemographicParity	Demographic Parity (...)	0.6381466046	7	0		num_dependents
PredictiveParity	Predictive Parity	0.6307643342	7	0		num_dependents
EqualAccuracy	Equal Accuracy	0.0719900703	7	2		num_dependents
EqualizedOdds	Equalized Odds	0.25467202	3	0	Max FPR difference is ...	num_dependents
EqualOpportunity	Equal Opportunity	0.0985639687	7	0		num_dependents

## Input Variable

credit\_score

The partial dependency plot shows how the change in the average prediction changes as the input variable changes.

Thus, PD plots show how changes to the values of a model input affect the model's predictions.

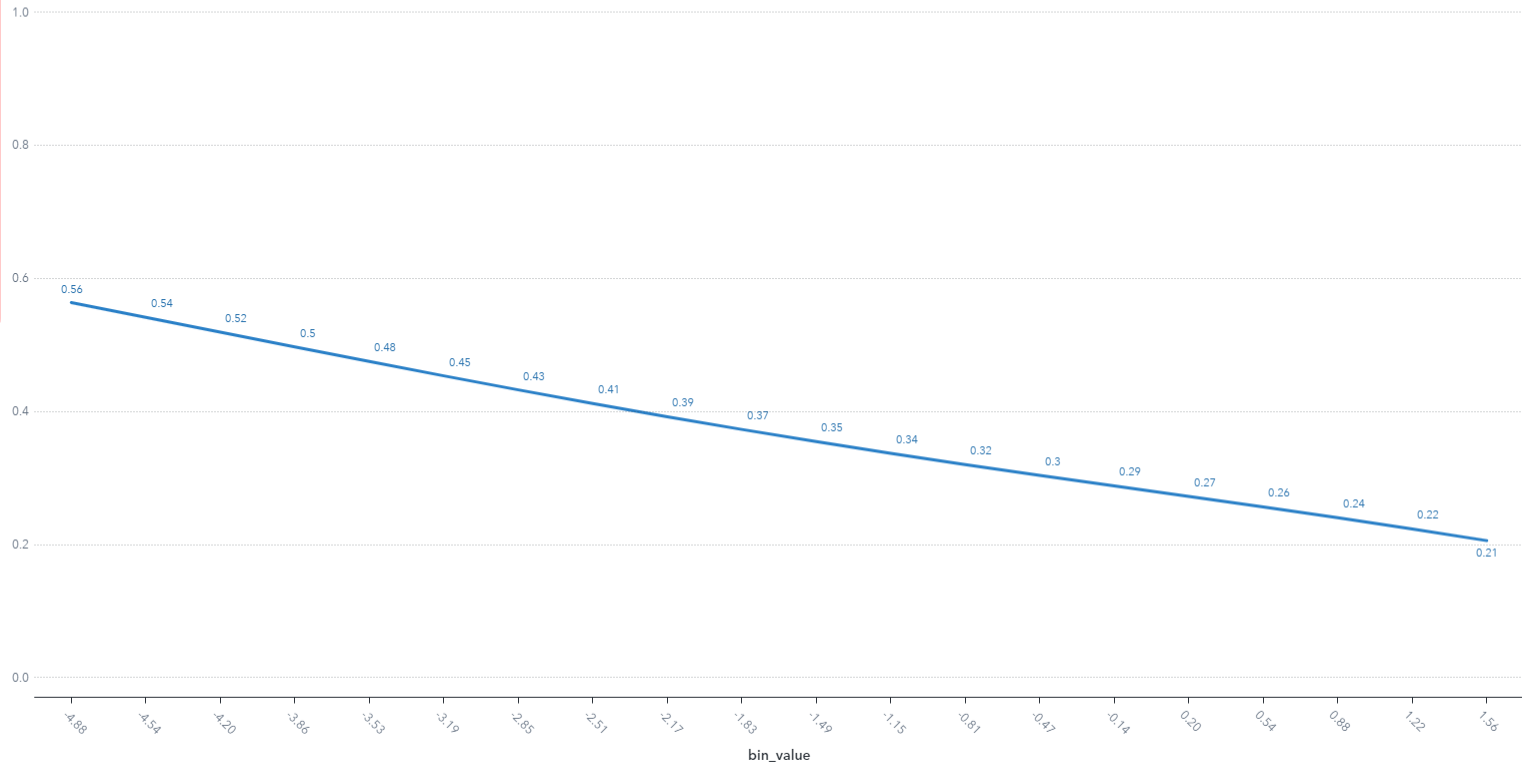
PD plots can also visualize how a potentially sensitive variable can impact the average target event value.

For example, if the plot includes a protected characteristic (or its proxy), and the average prediction decreases as the input value increases, it could imply that the higher the value of the protected characteristic then the lower the probability of the event. This could be problematic if the event includes a desired outcome for the customer and the input variable measures the increasing extent of the customer's protected characteristic (or its proxy).

8

## Create Dashboards/Workflows to Facilitate Decisions with Metrics

mean\_prediction by bin\_value



## trustworthy\_ai\_open\_source

partial\_dependence\_r\_logit

shapley\_local\_r\_logit

shapley\_dist\_r\_logit

assess\_bias\_r\_logit

Account ID

432

SHAPley values are a measure of variable importance for a single observation.

They are an additive measure of importance, the sum of which equals the predicted output from the model that is being explaining.

Charting HyperSHAP values can help visualize how a potentially sensitive variable can impact the predicted probability of an individual customer.

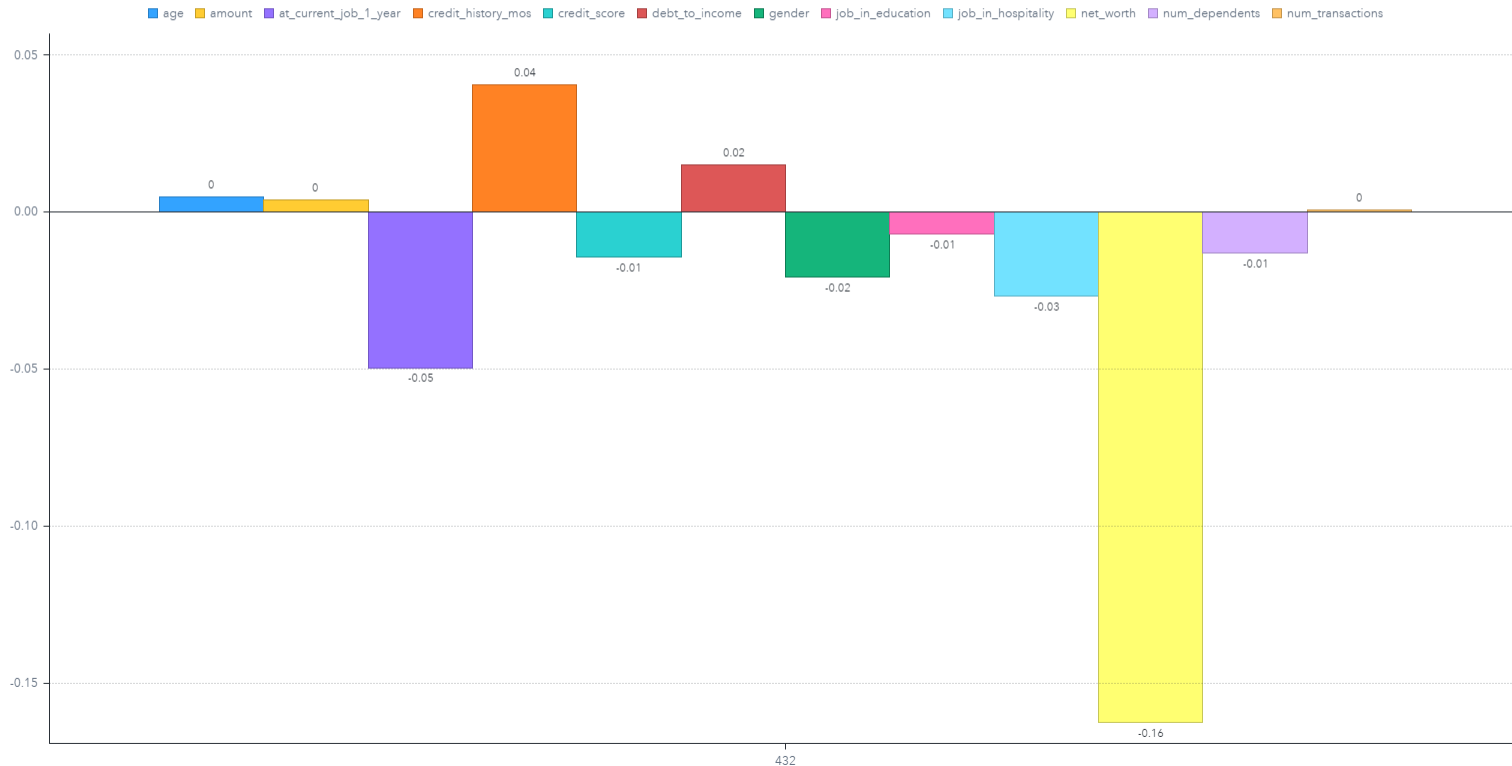
For example, if the largest (absolute) value in the SHAP Values chart is -0.32, then it decreases the predicted probability of the event by 0.32.

And if this variable was a sensitive variable (e.g., a protected characteristic or its proxy), then it could imply discriminatory behavior if the customer was declined a product based on this sensitive variable.

8

## Create Dashboards/Workflows to Facilitate Decisions with Metrics

SHAP Values



trustworthy\_ai\_open\_source

partial\_dependence\_r\_logit

shapley\_local\_r\_logit

shapley\_dist\_r\_logit

assess\_bias\_r\_logit

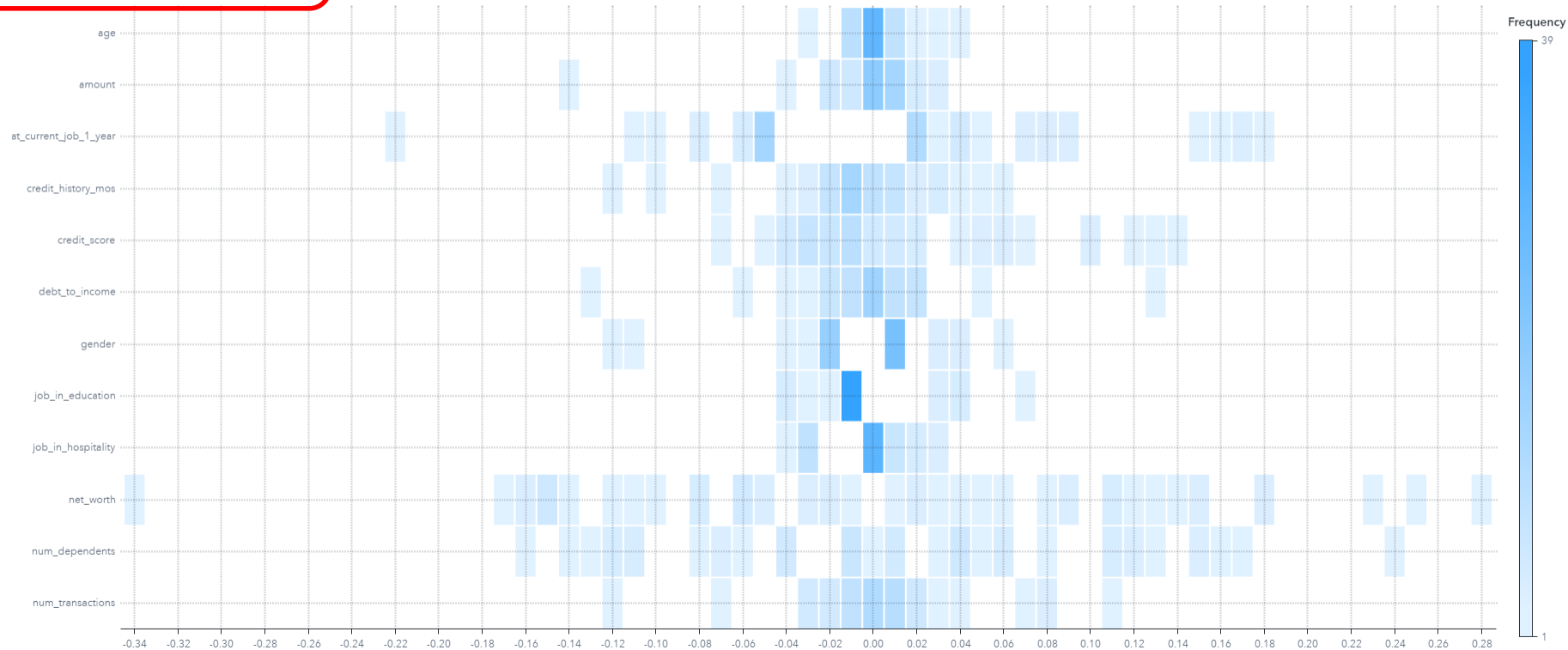
Input Variable

Variable

Distribution of SHAP Value by Selected Input

8

## Create Dashboards/Workflows to Facilitate Decisions with Metrics



partial\_dependence\_r\_logit shapley\_local\_r\_logit shapley\_dist\_r\_logit assess\_bias\_r\_logit ⋮

Average Prediction for Event ▾

8

## Create Dashboards/Workflows to Facilitate Decisions with Metrics

The maximum differences plot shows the differences in the selected metric in the drop-down box, which may indicate the extent of bias between the base and comparison values of each variable. The base and comparison values can be viewed by hovering over each variable.

Max. Difference in Metric by Variable Assessed for Bias

