



CDW Documentation

Responsible AI Test

Responsible AI Test

Purpose

Evaluate the Responsible AI dashboard and see what it does.

Test Process

Here's a structured list of **Responsible AI Dashboard Deployment Steps** using the corrected scripts. Each step includes:

- **Step Number & Action**
- **Purpose**
- **Expected Result**

Step 1: Install Required Packages

```
pip install --upgrade raiutils raiwidgets responsibleai ipywidgets
```

Purpose:

Install the Python packages required to run Responsible AI analysis and render the dashboard.

Expected Result:

Packages are installed without errors; dashboard widgets can render in the notebook (after kernel restart).

Step 2: Load and Preprocess the Dataset

```
from sklearn.datasets import fetch_openml
import pandas as pd

data = fetch_openml(name='adult', version=2, as_frame=True)
df = data.frame.dropna()
```

Purpose:

Load a well-known classification dataset (Adult Census Income) and remove any missing values to avoid downstream errors.

Expected Result:

A clean DataFrame with no null values is loaded.

□ Step 3: Split Dataset into Train and Test Sets

```
from sklearn.model_selection import train_test_split

target_column = 'class'
X = df.drop(columns=[target_column])
y = df[target_column]

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,
random_state=42)
```

□ Purpose:

Separate features and target, then split into training/testing sets for model training and evaluation.

□ Expected Result:

X_train, X_test, y_train, y_test variables created and stratified properly.

□ Step 4: Define Preprocessing and Train a Model

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier

categorical_cols = X_train.select_dtypes(include=['object',
'category']).columns.tolist()
numerical_cols = X_train.select_dtypes(include=['int64',
'float64']).columns.tolist()

preprocessor = ColumnTransformer([
    ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols),
    ('num', StandardScaler(), numerical_cols)
])

clf = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(n_estimators=10, random_state=42))
])

clf.fit(X_train, y_train)
```

□ Purpose:

Build a model pipeline that encodes categorical features, scales numeric ones, and trains a classifier.

□ Expected Result:

Pipeline is trained successfully on the training data without conversion errors.

□ Step 5: Prepare Data for RAIInsights

```
# Ensure target column is a supported type
y_train_clean = y_train.astype(str)
y_test_clean = y_test.astype(str)

train_data = X_train.copy()
train_data[target_column] = y_train_clean

test_data = X_test.copy()
test_data[target_column] = y_test_clean
```

□ Purpose:

Re-attach the target column (as string) to the feature DataFrames — required for RAIInsights.

□ Expected Result:

train_data and test_data DataFrames contain all required columns including the target.

□ Step 6: Initialize the Responsible AI Insights Object

```
from responsibleai import RAIInsights, FeatureMetadata

feature_metadata = FeatureMetadata(categorical_features=categorical_cols)

rai_insights = RAIInsights(
    model=clf,
    train=train_data,
    test=test_data,
    target_column=target_column,
    task_type="classification",
    feature_metadata=feature_metadata
)
```

□ Purpose:

Create a RAIInsights object that acts as the core engine for the Responsible AI dashboard.

□ Expected Result:

RAIInsights object is initialized successfully and ready for configuration.

□ Step 7: Add Responsible AI Analysis Tools

```
rai_insights.explainer.add()
rai_insights.error_analysis.add()
```

```
rai_insights.counterfactual.add(total_CFs=5, desired_class='opposite')
rai_insights.causal.add(treatment_features=categorical_cols)
```

□ **Purpose:**

Attach various tools (explanation, error analysis, counterfactuals, causal inference) to the insights engine.

□ **Expected Result:**

No errors thrown; tools are queued for computation.

□ **Step 8: Compute Insights**

```
rai_insights.compute()
```

□ **Purpose:**

Run analysis for all selected tools. This step may take a minute or more.

□ **Expected Result:**

Tool outputs are generated for the first 5,000 rows of the test set.

□ **Step 9: Launch the Responsible AI Dashboard**

```
from raiwidgets import ResponsibleAIDashboard

ResponsibleAIDashboard(rai_insights)
```

□ **Purpose:**

Open an interactive dashboard to explore insights such as feature importance, what-if analysis, and error breakdowns.

□ **Expected Result:**

A dashboard is displayed inside the notebook. Interactive plots and controls are available for analysis.

Download

```
NOTE: Due to the way that these URLs are deployed, this step will fail because the notebook sends the wrong headers and this is expected. You have to either pull the notebook local and use it from the terminal or register the dashboard/dataset and review it through the portal.
```

Output



Data analysis

Table view [Chart view](#)

View the dataset in a table format for all features and rows.

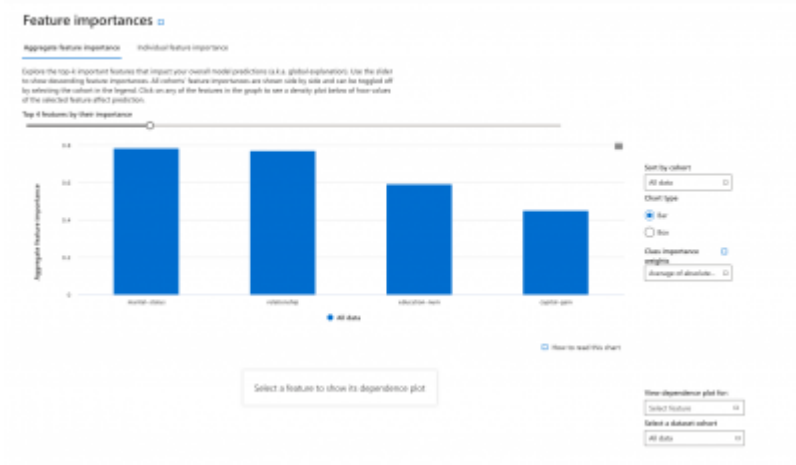
| Index | TrueY | PredictedY | age | workclass | salary | education | education-num | sex |
|-------|-------|------------|-----|-----------|--------|--------------|---------------|------|
| 5 | ++00 | ++00 | 41 | Private | 20704 | Bachelors | 13 | Male |
| 10 | ++00 | ++00 | 34 | Private | 20004 | Some college | 16 | Male |
| 11 | ++00 | ++00 | 47 | Private | 40004 | HS grad | 9 | Male |
| 13 | ++00 | ++00 | 42 | Private | 17504 | Prof school | 10 | Male |
| 22 | ++00 | ++00 | 47 | Local gov | 17000 | Assoc voc | 10 | Male |
| 36 | ++00 | ++00 | 31 | Private | 16011 | HS grad | 9 | Male |
| 44 | ++00 | ++00 | 38 | Private | 20014 | Assoc voc | 11 | Male |
| 52 | ++00 | ++00 | 42 | Private | 12004 | Tech sch | 8 | Male |

Data analysis

Table view [Chart view](#)

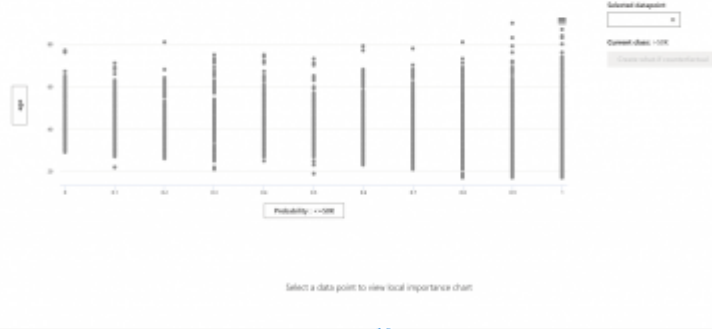
View the dataset in a table format for all features and rows.

| Index | TrueY | PredictedY | age | workclass | salary | education | education-num | sex |
|-------|-------|------------|-----|-----------|--------|--------------|---------------|------|
| 5 | ++00 | ++00 | 41 | Private | 20704 | Bachelors | 13 | Male |
| 10 | ++00 | ++00 | 34 | Private | 20004 | Some college | 16 | Male |
| 11 | ++00 | ++00 | 47 | Private | 40004 | HS grad | 9 | Male |
| 13 | ++00 | ++00 | 42 | Private | 17504 | Prof school | 10 | Male |
| 22 | ++00 | ++00 | 47 | Local gov | 17000 | Assoc voc | 10 | Male |
| 36 | ++00 | ++00 | 31 | Private | 16011 | HS grad | 9 | Male |
| 44 | ++00 | ++00 | 38 | Private | 20014 | Assoc voc | 11 | Male |
| 52 | ++00 | ++00 | 42 | Private | 12004 | Tech sch | 8 | Male |



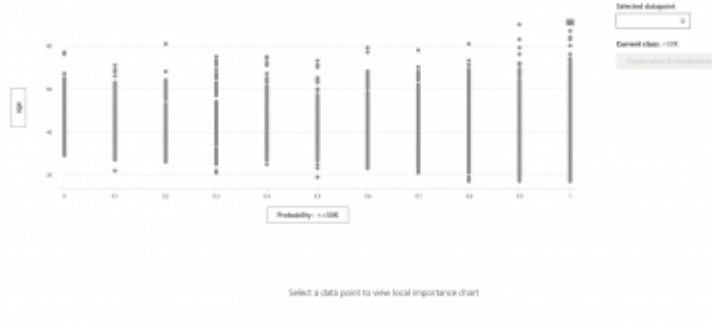
Counterfactuals

What if allow you to perturb features for any input and observe how the model's prediction changes. You can perturb features manually or specify the desired prediction (e.g. class) for a dataset to see a list of closest data points to the original input that would lead to the desired prediction. Also known as prediction counterfactuals, you can use them for exploring the relationships learned by the model, understanding important, necessary features for the model's predictions, or adding edge cases for the model. To start, choose input points from the data table or scatter plot.



Counterfactuals

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Causal analysis

The overall causal effects across all data

Aggregate causal effects Individual causal effect Treatment policy

Causal analysis assesses "what if" questions about learned relationships. Models learn how different policy options, such as different pricing strategies for a product or an alternative treatment for a patient, impact model predictions that identify important conditions. However, these tools help precisely the most important causal features that directly affect your outcome of interest. These models identify the causal effect of one feature (typically referred to as a "treatment"), holding other confounding features constant. For best results, make sure that the full dataset contains all available features that may confound with the outcome as confounders.

Select aggregate causal effect of each treatment with 95% confidence interval

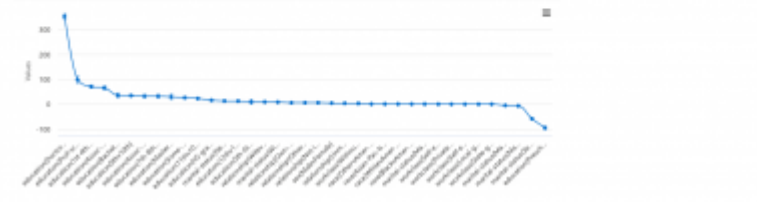
Why is it important to include confounding features?

| Feature | Effect estimate | Standard error | Z score | P-value | Confidence interval | Confidence interval upper |
|---------------|-----------------|----------------|---------|----------|---------------------|---------------------------|
| education[0] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[1] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[2] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[3] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[4] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[5] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[6] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[7] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[8] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[9] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[10] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[11] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[12] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[13] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[14] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[15] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[16] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[17] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[18] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[19] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[20] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[21] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[22] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[23] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[24] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[25] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[26] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[27] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[28] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[29] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[30] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[31] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[32] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[33] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[34] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[35] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[36] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[37] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[38] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[39] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[40] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[41] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[42] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[43] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[44] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[45] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[46] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[47] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[48] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[49] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[50] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[51] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[52] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[53] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[54] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
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| education[58] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[59] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[60] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[61] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[62] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[63] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[64] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[65] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[66] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[67] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[68] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[69] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
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| education[72] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[73] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[74] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[75] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[76] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[77] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[78] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[79] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[80] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[81] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[82] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[83] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[84] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[85] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[86] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[87] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[88] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[89] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[90] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[91] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[92] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[93] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[94] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[95] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[96] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[97] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[98] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |
| education[99] | 0.023e+1 | 1.88e+0 | 4.33e+0 | 0.000e+0 | 0.023e+1 | 0.023e+1 |

Confidence intervals: On average in this sample, increasing this feature by 1 unit will cause the probability of class/label "+100%" to increase by 0 units.

Binary treatments: On average in this sample, turning on this feature will cause the probability of class/label "+100%" to increase by 0 units.

A linear fit logistic regression $P(y)$ is fitted with fit to predict y from X, and a least-sqr logistic regression $\beta(X)$ is computed with fit to predict X(y) from X(y). The causal effect can be viewed as the average contribution of the non-distributive variable of the non-probabilistic variable. Learn more about [Responsible Machine Learning](#).



Global cohort: All data (default) Switch cohort New cohort

Error analysis

Tree map Heat map

With the heat map you can focus on specific interactions between filters and compare disaggregated error rates. Start with low-impact features to compare.

Cohort: All data

Cells: Error coverage: 100.00% Error rate: 15.88%

Select metrics:

Select one feature by using the dropdown. Below, you can change and filter your data along two dimensions.

Row: Position 1

Column: Feature 2

Basic information

All data
All data (2 filters)

Instances in global cohort

Total: 1000
Correct: 836
Incorrect: 164

Instances in the selected cohort

Total: 1000
Correct: 836
Incorrect: 164

Prediction path (filter)

Model overview

Evaluate the performance of your model by exploring the distribution of your predictor values and the values of your model performance metrics. Use the "Global cohort" tab to investigate your model's testing at a comparative analysis of its performance across different pre-built or newly created cohort filters. Use the "Feature cohort" to investigate your model by testing at a comparative analysis of its performance across categorical, high-impact feature subgroups (e.g. performance across different genders, income levels).

Dataset cohorts:

Metrics:

| Cohort | Sample size | Accuracy score | False positive rate | False negative rate | Information |
|----------|-------------|----------------|---------------------|---------------------|-------------|
| All data | 1,000 | 0.84 | 0.07 | 0.07 | 0.93% |

Probability distribution **Metrics visualizations** **Confusion matrix**

See split chart

Data analysis

Table view Chart view

View the dataset in a table format for all features and rows.

| ID | trust | predict | age | workclass | fnagi | education | education-num | sex |
|----|-------|---------|-----|-----------|-------|--------------|---------------|------|
| 0 | 1 | 1 | 41 | Never | 20704 | Bachelor | 16 | Male |
| 10 | 1 | 1 | 34 | Never | 20884 | Some college | 16 | Male |
| 11 | 1 | 1 | 47 | Never | 18863 | HS grad | 9 | Male |
| 12 | 1 | 1 | 42 | Never | 17562 | Prof school | 16 | Male |
| 22 | 1 | 1 | 47 | Self emp | 11020 | Assoc voc | 12 | Male |
| 36 | 1 | 1 | 31 | Never | 16671 | HS grad | 9 | Male |
| 41 | 1 | 1 | 31 | Never | 20023 | Assoc voc | 11 | Male |
| 53 | 1 | 1 | 33 | Never | 13004 | No sen | 4 | Male |

AI Knowledge