

```
! pip install evidently
```

```
Collecting mypy-extensions>=0.3.0 (from typing-inspect>=0.9.0->evidently)
  Downloading mypy_extensions-1.0.0-py3-none-any.whl.metadata (1.1 kB)
Requirement already satisfied: h11>=0.8 in /usr/local/lib/python3.10/dist-packages (from uvicorn>=0.22.0->uvicorn[standard]>=0.22.0->evidently) (0.14.0)
Collecting httptools>0.6.3 (from uvicorn[standard]>=0.22.0->evidently)
  Downloading httptools-0.6.4-cp310-cp310-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (3.6 kB)
Collecting python-dotenv>=0.13 (from uvicorn[standard]>=0.22.0->evidently)
  Downloading python_dotenv-1.0.1-py3-none-any.whl.metadata (23 kB)
Collecting uvloop!=0.15.0,!=0.15.1,>=0.14.0 (from uvicorn[standard]>=0.22.0->evidently)
  Downloading uvloop-0.21.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (4.9 kB)
Collecting watchfiles>=0.13 (from uvicorn[standard]>=0.22.0->evidently)
  Downloading watchfiles-1.0.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (4.9 kB)
Collecting websockets>=10.4 (from uvicorn[standard]>=0.22.0->evidently)
  Downloading websockets-14.1-cp310-cp310-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (6.7 kB)
Requirement already satisfied: sniffio>=1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp>3->litestar>=2.8.3->evidently) (1.3.1)
Requirement already satisfied: pycparser in /usr/local/lib/python3.10/dist-packages (from cffi>1.12->cryptography>=43.0.1->evidently) (2.22)
Requirement already satisfied: httpcore==1.* in /usr/local/lib/python3.10/dist-packages (from httpx>0.22->litestar>=2.8.3->evidently) (1.0.7)
Requirement already satisfied: mdurl~0.1 in /usr/local/lib/python3.10/dist-packages (from markdown-it-py>=2.2.0->rich>=13->evidently) (0.1.2)
Collecting faker (from polyfactory>=2.6.3->litestar>=2.8.3->evidently)
  Downloading Faker-33.1.0-py3-none-any.whl.metadata (15 kB)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas>=1.3.5->pandas[parquet]>=1.3.5->evidently) (1.16.0)
Downloading evidently-0.4.40-py3-none-any.whl (3.5 MB)
  3.5/3.5 MB 24.8 MB/s eta 0:00:00
Downloading deprecation-2.1.0-py2.py3-none-any.whl (11 kB)
  231.1/231.1 kB 17.5 MB/s eta 0:00:00
Downloading dynaconf-3.2.6-py2.py3-none-any.whl (231 kB)
  555.5/555.5 kB 30.3 MB/s eta 0:00:00
Downloading iterative_telemetry-0.0.9-py3-none-any.whl (10 kB)
  555.5 kB eta 0:00:00
Downloading litestar-2.13.0-py3-none-any.whl (555 kB)
  53.6/53.6 kB 4.1 MB/s eta 0:00:00
Downloading typing_inspect-0.9.0-py3-none-any.whl (8.8 kB)
  63.8/63.8 kB 5.3 MB/s eta 0:00:00
Downloading ujson-5.10.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (53 kB)
  79.1/79.1 kB 6.3 MB/s eta 0:00:00
Downloading httptools-0.6.4-cp310-cp310-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_64.whl (442 kB)
  442.1/442.1 kB 21.9 MB/s eta 0:00:00
Downloading litestar_htmx-0.3.0-py3-none-any.whl (8.9 kB)
  210.3/210.3 kB 16.0 MB/s eta 0:00:00
Downloading msgspec-0.18.6-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (210 kB)
  59.3/59.3 kB 4.9 MB/s eta 0:00:00
Downloading mypy_extensions-1.0.0-py3-none-any.whl (4.7 kB)
  3.8/3.8 kB 62.9 MB/s eta 0:00:00
Downloading python_dotenv-1.0.1-py3-none-any.whl (19 kB)
  442.6/442.6 kB 28.8 MB/s eta 0:00:00
Downloading uvloop-0.21.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (3.8 MB)
  168.2/168.2 kB 13.2 MB/s eta 0:00:00
Downloading appdirs-1.4.4-py2.py3-none-any.whl (9.6 kB)
  1.9/1.9 kB 58.9 MB/s eta 0:00:00
Installing collected packages: appdirs, websockets, watchdog, uvloop, unicorn, uuid6, ujson, python-dotenv, mypy-extensions, msgspec, httptools, dynaconf, deprecation, watchfiles, evidently
Successfully installed appdirs-1.4.4 deprecation-2.1.0 dynaconf-3.2.6 evidently-0.4.40 faker-33.1.0 httptools-0.6.4 iterative-telemetry-0.0.9 litestar-2.13.0 litestar-htmx-0.3.0 ms
```

```
! jupyter nbextension install --sys-prefix --symlink --overwrite --py evidently

→ Installing /usr/local/lib/python3.10/dist-packages/evidently/nbextension/static -> evidently
Symlinking: /usr/share/jupyter/nbextensions/evidently -> /usr/local/lib/python3.10/dist-packages/evidently/nbextension/static
- Validating: OK

To initialize this nbextension in the browser every time the notebook (or other app) loads:

jupyter nbextension enable evidently --py --sys-prefix

! jupyter nbextension enable evidently --py --sys-prefix

→ Enabling notebook extension evidently/extension...
Paths used for configuration of notebook:
/usr/etc/jupyter/nbconfig/notebook.json
Paths used for configuration of notebook:
- Validating: OK
Paths used for configuration of notebook:
/usr/etc/jupyter/nbconfig/notebook.json

try:
    import evidently
except:
    !pip install git+https://github.com/evidentlyai/evidently.git

import pandas as pd
import numpy as np

from sklearn import datasets, ensemble, model_selection

from evidently import ColumnMapping
from evidently.test_suite import TestSuite
from evidently.tests import *
from evidently.test_preset import NoTargetPerformanceTestPreset
from evidently.test_preset import DataQualityTestPreset
from evidently.test_preset import DataStabilityTestPreset
from evidently.test_preset import DataDriftTestPreset
from evidently.test_preset import RegressionTestPreset
from evidently.test_preset import MulticlassClassificationTestPreset
from evidently.test_preset import BinaryClassificationTopKTestPreset
from evidently.test_preset import BinaryClassificationTestPreset
from evidently.report import Report
from evidently.metric_preset import DataDriftPreset
from evidently.metric_preset import DataQualityPreset
from evidently.metric_preset import RegressionPreset
from evidently.metric_preset import ClassificationPreset
from evidently.metric_preset import TargetDriftPreset

import warnings
warnings.filterwarnings('ignore')
```

▼ 1. Dataset for Data Quality and Integrity

```
#Dataset for Data Quality and Integrity
```

```
adult_data = datasets.fetch_openml(name='adult', version=2, as_frame=True)
adult = adult_data.frame
```

```
adult.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	class
0	25	Private	226802	11th	7	Never-married	Machine-op-inspect	Own-child	Black	Male	0	0	40	United-States	<=50K
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-enriched	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K

Next steps: [Generate code with adult](#) [View recommended plots](#) [New interactive sheet](#)

```
adult.info()
```

```
→ <class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   age              48842 non-null   int64  
 1   workclass        46043 non-null   category
 2   fnlwgt           48842 non-null   int64  
 3   education        48842 non-null   category
 4   education-num    48842 non-null   int64  
 5   marital-status   48842 non-null   category
 6   occupation       46033 non-null   category
 7   relationship     48842 non-null   category
 8   race              48842 non-null   category
 9   sex               48842 non-null   category
 10  capital-gain    48842 non-null   int64  
 11  capital-loss    48842 non-null   int64  
 12  hours-per-week  48842 non-null   int64  
 13  native-country   47985 non-null   category
 14  class             48842 non-null   category
dtypes: category(9), int64(6)
memory usage: 2.7 MB
```

```
adult.education.value_counts()
```



count

education

HS-grad	15784
Some-college	10878
Bachelors	8025
Masters	2657
Assoc-voc	2061
11th	1812
Assoc-acdm	1601
10th	1389
7th-8th	955
Prof-school	834
9th	756
12th	657
Doctorate	594
5th-6th	509
1st-4th	247
Preschool	83

dtype: int64

```
adult_ref = adult[~adult.education.isin(['Some-college', 'HS-grad', 'Bachelors'])]
adult_cur = adult[adult.education.isin(['Some-college', 'HS-grad', 'Bachelors'])]

adult_cur.iloc[:2000, 3:5] = np.nan

adult_ref.shape , adult_cur.shape

((14155, 15), (34687, 15))

adult_cur.iloc[:2000 , 3:5]
```

	education	education-num
1	NaN	NaN
3	NaN	NaN
4	NaN	NaN
6	NaN	NaN
8	NaN	NaN
...
2813	NaN	NaN
2814	NaN	NaN
2815	NaN	NaN
2816	NaN	NaN
2817	NaN	NaN

2000 rows × 2 columns

▼ 2. Dataset for Regression

```
housing_data = datasets.fetch_california_housing(as_frame=True)
housing = housing_data.frame
```

```
housing.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	MedHouseVal
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422

Next steps: [Generate code with housing](#)

[View recommended plots](#)

[New interactive sheet](#)

```
housing.info()
```

```
↳ <class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   MedInc      20640 non-null   float64
 1   HouseAge    20640 non-null   float64
 2   AveRooms    20640 non-null   float64
 3   AveBedrms   20640 non-null   float64
 4   Population  20640 non-null   float64
```

```

5 AveOccup    20640 non-null   float64
6 Latitude     20640 non-null   float64
7 Longitude    20640 non-null   float64
8 MedHouseVal  20640 non-null   float64
dtypes: float64(9)
memory usage: 1.4 MB

```

```
housing.shape
```

```
(20640, 9)
```

```

housing.rename(columns={'MedHouseVal': 'target'}, inplace=True)
housing['prediction'] = housing_data['target'].values + np.random.normal(0, 3, housing.shape[0])

```

```
housing.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	target	prediction	
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526	6.567026	
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585	1.235988	
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521	0.777297	
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413	4.034504	
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422	-0.511835	

Next steps: [Generate code with housing](#)

[View recommended plots](#)

[New interactive sheet](#)

```

housing_ref = housing.sample(n=5000, replace=False)
housing_cur = housing.sample(n=5000, replace=False)

```

```
housing_ref.describe()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	target	prediction	
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	3.852558	28.444800	5.435699	1.097594	1451.12560	3.209105	35.617538	-119.550902	2.070375	2.058954	
std	1.912136	12.570416	2.774699	0.487576	1229.41989	17.581415	2.143159	2.006215	1.151730	3.207989	
min	0.499900	1.000000	1.130435	0.600000	17.00000	1.161290	32.550000	-124.300000	0.149990	-9.946500	
25%	2.544000	18.000000	4.433418	1.007015	785.75000	2.427801	33.930000	-121.760000	1.201000	-0.074769	
50%	3.515600	29.000000	5.220024	1.050188	1167.00000	2.822435	34.220000	-118.460000	1.804500	2.061700	
75%	4.746375	37.000000	6.065431	1.099508	1742.50000	3.291755	37.730000	-117.990000	2.657250	4.188197	
max	15.000100	52.000000	141.909091	25.636364	35682.00000	1243.333333	41.810000	-114.570000	5.000010	14.536211	

```
housing_cur.describe()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	target	prediction	grid
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	grid
mean	3.849595	28.676400	5.426195	1.098979	1416.916400	2.944566	35.625728	-119.563056	2.066844	2.030391	bar
std	1.906162	12.496468	2.769500	0.492697	1171.739456	1.469293	2.129458	2.003548	1.154078	3.166248	
min	0.499900	1.000000	1.130435	0.375000	3.000000	0.692308	32.550000	-124.250000	0.225000	-10.470058	
25%	2.549825	18.000000	4.446270	1.006025	792.750000	2.426918	33.940000	-121.792500	1.186750	-0.131569	
50%	3.522700	29.000000	5.210694	1.050584	1152.500000	2.809281	34.250000	-118.470000	1.792500	2.029548	
75%	4.690950	37.000000	6.042019	1.100228	1716.250000	3.277146	37.710000	-118.020000	2.654250	4.160654	
max	15.000100	52.000000	141.909091	25.636364	35682.000000	83.171429	41.950000	-114.560000	5.000010	14.345086	

3. Dataset for Binary Probabilistic Classification

```
bcancer_data = datasets.load_breast_cancer(as_frame=True)
bcancer = bcancer_data.frame
```

```
bcancer.head()
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	worst perimeter	worst area	worst smoothness	worst compactness	worst concavity	worst concave points	syr
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	17.33	184.60	2019.0	0.1622	0.6656	0.7119	0.2654	(
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	23.41	158.80	1956.0	0.1238	0.1866	0.2416	0.1860	(
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	25.53	152.50	1709.0	0.1444	0.4245	0.4504	0.2430	(
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	...	26.50	98.87	567.7	0.2098	0.8663	0.6869	0.2575	(
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	...	16.67	152.20	1575.0	0.1374	0.2050	0.4000	0.1625	(

5 rows × 31 columns

```
bcancer.target.value_counts()
```

	count
target	
1	357
0	212

dtype: int64

```
bcancer.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
```

```
Data columns (total 31 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   mean radius       569 non-null    float64
 1   mean texture      569 non-null    float64
 2   mean perimeter    569 non-null    float64
 3   mean area         569 non-null    float64
 4   mean smoothness   569 non-null    float64
 5   mean compactness  569 non-null    float64
 6   mean concavity   569 non-null    float64
 7   mean concave points 569 non-null  float64
 8   mean symmetry    569 non-null    float64
 9   mean fractal dimension 569 non-null  float64
 10  radius error     569 non-null    float64
 11  texture error    569 non-null    float64
 12  perimeter error  569 non-null    float64
 13  area error       569 non-null    float64
 14  smoothness error 569 non-null    float64
 15  compactness error 569 non-null    float64
 16  concavity error  569 non-null    float64
 17  concave points error 569 non-null  float64
 18  symmetry error   569 non-null    float64
 19  fractal dimension error 569 non-null  float64
 20  worst radius     569 non-null    float64
 21  worst texture    569 non-null    float64
 22  worst perimeter  569 non-null    float64
 23  worst area        569 non-null    float64
 24  worst smoothness 569 non-null    float64
 25  worst compactness 569 non-null    float64
 26  worst concavity  569 non-null    float64
 27  worst concave points 569 non-null  float64
 28  worst symmetry   569 non-null    float64
 29  worst fractal dimension 569 non-null  float64
 30  target           569 non-null    int64 

dtypes: float64(30), int64(1)
memory usage: 137.9 KB
```

```
bcancer_ref = bcancer.sample(n=300, replace=False)
bcancer_cur = bcancer.sample(n=200, replace=False)
```

```
bcancer_label_ref = bcancer_ref.copy(deep=True)
bcancer_label_cur = bcancer_cur.copy(deep=True)
```

```
bcancer_data.feature_names.tolist()
```

```
['mean radius',
 'mean texture',
 'mean perimeter',
 'mean area',
 'mean smoothness',
 'mean compactness',
 'mean concavity',
 'mean concave points',
 'mean symmetry',
 'mean fractal dimension',
 'radius error',
 'texture error',
 'perimeter error',
 'area error',
 'smoothness error',
 'compactness error',
```

```
'concavity error',
'concave points error',
'symmetry error',
'fractal dimension error',
'worst radius',
'worst texture',
'worst perimeter',
'worst area',
'worst smoothness',
'worst compactness',
'worst concavity',
'worst concave points',
'worst symmetry',
'worst fractal dimension']
```

```
model = ensemble.RandomForestClassifier(random_state=1, n_estimators=10)
model.fit(bcancer_ref[bcancer_data.feature_names.tolist()], bcancer_ref.target)
```

A screenshot of a Jupyter Notebook cell. The code `RandomForestClassifier(n_estimators=10, random_state=1)` is being typed into the cell. A tooltip or dropdown menu is open above the cursor, showing the class definition for `RandomForestClassifier` with its parameters: `n_estimators` and `random_state`. The cell has a progress bar at the bottom.

```
bcancer_ref['prediction'] = model.predict_proba(bcancer_ref[bcancer_data.feature_names.tolist()])[:, 1]
bcancer_cur['prediction'] = model.predict_proba(bcancer_cur[bcancer_data.feature_names.tolist()])[:, 1]
```

```
bcancer_ref.head()
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst perimeter	worst area	worst smoothness	worst compactness	worst concavity	worst concave points	worst symmetry	...
111	12.63	20.76	82.15	480.4	0.09933	0.12090	0.106500	0.060210	0.1735	0.07070	...	89.00	527.4	0.12870	0.22500	0.221600	0.11050	0.2226	
8	13.00	21.82	87.50	519.8	0.12730	0.19320	0.185900	0.093530	0.2350	0.07389	...	106.20	739.3	0.17030	0.54010	0.539000	0.20600	0.4378	
333	11.25	14.78	71.38	390.0	0.08306	0.04458	0.000974	0.002941	0.1773	0.06081	...	82.08	492.7	0.11660	0.09794	0.005518	0.01667	0.2815	
397	12.80	17.46	83.05	508.3	0.08044	0.08895	0.073900	0.040830	0.1574	0.05750	...	90.72	591.0	0.09534	0.18120	0.190100	0.08296	0.1988	
90	14.62	24.02	94.57	662.7	0.08974	0.08606	0.031020	0.029570	0.1685	0.05866	...	102.90	803.7	0.11150	0.17660	0.091890	0.06946	0.2522	

5 rows × 32 columns

```
bcancer_cur.head()
```



	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst perimeter	worst area	worst smoothness	worst compactness	worst concavity	worst concave points	worst symmetry	d:
397	12.800	17.46	83.05	508.3	0.08044	0.08895	0.07390	0.04083	0.1574	0.05750	...	90.72	591.0	0.09534	0.18120	0.19010	0.08296	0.1988	
158	12.060	12.74	76.84	448.6	0.09311	0.05241	0.01972	0.01963	0.1590	0.05907	...	84.08	532.8	0.12750	0.12320	0.08636	0.07025	0.2514	
149	13.740	17.91	88.12	585.0	0.07944	0.06376	0.02881	0.01329	0.1473	0.05580	...	97.19	725.9	0.09711	0.18240	0.15640	0.06019	0.2350	
471	12.040	28.14	76.85	449.9	0.08752	0.06000	0.02367	0.02377	0.1854	0.05698	...	87.24	567.6	0.10410	0.09726	0.05524	0.05547	0.2404	
416	9.405	21.70	59.60	271.2	0.10440	0.06159	0.02047	0.01257	0.2025	0.06601	...	68.73	359.4	0.15260	0.11930	0.06141	0.03770	0.2872	

5 rows × 32 columns

```
bcancer_label_ref['prediction'] = model.predict(bcancer_label_ref[bcancer_data.feature_names.tolist()])
bcancer_label_cur['prediction'] = model.predict(bcancer_label_cur[bcancer_data.feature_names.tolist()])
```

bcancer_label_ref.head()



	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst perimeter	worst area	worst smoothness	worst compactness	worst concavity	worst concave points	worst symmetry	d:
111	12.63	20.76	82.15	480.4	0.09933	0.12090	0.106500	0.060210	0.1735	0.07070	...	89.00	527.4	0.12870	0.22500	0.221600	0.11050	0.2226	
8	13.00	21.82	87.50	519.8	0.12730	0.19320	0.185900	0.093530	0.2350	0.07389	...	106.20	739.3	0.17030	0.54010	0.539000	0.20600	0.4378	
333	11.25	14.78	71.38	390.0	0.08306	0.04458	0.000974	0.002941	0.1773	0.06081	...	82.08	492.7	0.11660	0.09794	0.005518	0.01667	0.2815	
397	12.80	17.46	83.05	508.3	0.08044	0.08895	0.073900	0.040830	0.1574	0.05750	...	90.72	591.0	0.09534	0.18120	0.190100	0.08296	0.1988	
90	14.62	24.02	94.57	662.7	0.08974	0.08606	0.031020	0.029570	0.1685	0.05866	...	102.90	803.7	0.11150	0.17660	0.091890	0.06946	0.2522	

5 rows × 32 columns

bcancer_label_cur.head()



	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst perimeter	worst area	worst smoothness	worst compactness	worst concavity	worst concave points	worst symmetry	d:
397	12.800	17.46	83.05	508.3	0.08044	0.08895	0.07390	0.04083	0.1574	0.05750	...	90.72	591.0	0.09534	0.18120	0.19010	0.08296	0.1988	
158	12.060	12.74	76.84	448.6	0.09311	0.05241	0.01972	0.01963	0.1590	0.05907	...	84.08	532.8	0.12750	0.12320	0.08636	0.07025	0.2514	
149	13.740	17.91	88.12	585.0	0.07944	0.06376	0.02881	0.01329	0.1473	0.05580	...	97.19	725.9	0.09711	0.18240	0.15640	0.06019	0.2350	
471	12.040	28.14	76.85	449.9	0.08752	0.06000	0.02367	0.02377	0.1854	0.05698	...	87.24	567.6	0.10410	0.09726	0.05524	0.05547	0.2404	
416	9.405	21.70	59.60	271.2	0.10440	0.06159	0.02047	0.01257	0.2025	0.06601	...	68.73	359.4	0.15260	0.11930	0.06141	0.03770	0.2872	

5 rows × 32 columns

✓ 4. Dataset for Multiclass Classification

```
iris_data = datasets.load_iris(as_frame=True)
iris = iris_data.frame
```

```
iris.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	grid
0	5.1	3.5	1.4	0.2	0	blue
1	4.9	3.0	1.4	0.2	0	light blue
2	4.7	3.2	1.3	0.2	0	light green
3	4.6	3.1	1.5	0.2	0	light green
4	5.0	3.6	1.4	0.2	0	light green

Next steps: [Generate code with iris](#) [View recommended plots](#) [New interactive sheet](#)

```
iris.target.value_counts()
```

	count
target	
0	50
1	50
2	50

```
dtype: int64
```

```
iris_ref = iris.sample(n=75, replace=False)
iris_cur = iris.sample(n=75, replace=False)
```

```
model = ensemble.RandomForestClassifier(random_state=1, n_estimators=3)
model.fit(iris_ref[iris_data.feature_names], iris_ref.target)
```

```
RandomForestClassifier
RandomForestClassifier(n_estimators=3, random_state=1)
```

```
iris_ref['prediction'] = model.predict(iris_ref[iris_data.feature_names])
iris_cur['prediction'] = model.predict(iris_cur[iris_data.feature_names])
```

```
iris_ref.head()
```

iris_ref

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	prediction	grid icon
76	6.8	2.8	4.8	1.4	1	1	info icon
14	5.8	4.0	1.2	0.2	0	0	
87	6.3	2.3	4.4	1.3	1	1	
44	5.1	3.8	1.9	0.4	0	0	
55	5.7	2.8	4.5	1.3	1	1	

Next steps: [Generate code with iris_ref](#) [View recommended plots](#) [New interactive sheet](#)

iris_cur.head()

iris_cur

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	prediction	grid icon
17	5.1	3.5	1.4	0.3	0	0	info icon
44	5.1	3.8	1.9	0.4	0	0	
8	4.4	2.9	1.4	0.2	0	0	
63	6.1	2.9	4.7	1.4	1	1	
30	4.8	3.1	1.6	0.2	0	0	

Next steps: [Generate code with iris_cur](#) [View recommended plots](#) [New interactive sheet](#)

5. Leveraging Test presets and List of Tests

✓ A. Data stability

```
data_stability = TestSuite(tests=[
    DataStabilityTestPreset(),
])
data_stability.run(reference_data=adult_ref, current_data=adult_cur)
data_stability
```



39

Tests

29

Success

0

Warning

10

Fail

0

Error

All tests ▾

⚠ Number of Rows

The number of rows is 34687. The test threshold is $\text{eq}=1.42\text{e}+04 \pm 1.42\text{e}+03$.

✓ Number of Columns

[Details](#)

The number of columns is 15. The test threshold is $\text{eq}=15$.

⚠ Column Types

[Details](#)

The number of columns with a type mismatch is 1 out of 15.

✓ The Share of Missing Values in a Column

The share of missing values in the column **capital-gain** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e}-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **hours-per-week** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e}-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **age** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e}-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **fnlwgt** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e}-12$.

⚠ The Share of Missing Values in a Column

The share of missing values in the column **education-num** is 0.0577. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **capital-loss** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **relationship** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **race** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **native-country** is 0.0162. The test threshold is $\text{lte}=0.0208 \pm 0.00208$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **workclass** is 0.0549. The test threshold is $\text{lte}=0.0633 \pm 0.00633$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **occupation** is 0.055. The test threshold is $\text{lte}=0.0637 \pm 0.00637$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **class** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

❗ The Share of Missing Values in a Column

The share of missing values in the column **education** is 0.0577. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **marital-status** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **sex** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ Share of Out-of-Range Values

Details

The share of values out of range in the column **capital-gain** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

✓ Share of Out-of-Range Values

Details

The share of values out of range in the column **hours-per-week** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

✓ Share of Out-of-Range Values

Details

The share of values out of range in the column **age** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

❗ Share of Out-of-Range Values

Details

The share of values out of range in the column **fnlwgt** is 0.000115 (4 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

✓ Share of Out-of-Range Values

Details

The share of values out of range in the column **education-num** is 0 (0 out of 32687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

❗ Share of Out-of-Range Values

Details

The share of values out of range in the column **capital-loss** is 8.65e-05 (3 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

✓ Share of Out-of-List Values

Details

The share of values out of list in the column **relationship** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

✓ Share of Out-of-List Values

Details

The share of values out of list in the column **race** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

❗ Share of Out-of-List Values

Details

The share of values out of list in the column **native-country** is 0.0163 (564 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

Share of Out-of-List Values Details

The share of values out of list in the column **workclass** is 0.0549 (1903 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

 Share of Out-of-List Values Details

The share of values out of list in the column **occupation** is 0.055 (1907 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

 Share of Out-of-List Values Details

The share of values out of list in the column **class** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

 Share of Out-of-List Values Details

The share of values out of list in the column **education** is 1 (34687 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

 Share of Out-of-List Values Details

The share of values out of list in the column **marital-status** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

 Share of Out-of-List Values Details

The share of values out of list in the column **sex** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1\text{e-}12$.

 Mean Value Stability Details

The mean value of the column **capital-gain** is 844. The expected range is from $-1.82\text{e+}04$ to $2.15\text{e+}04$

 Mean Value Stability Details

The mean value of the column **hours-per-week** is 40.5. The expected range is from 13.4 to 67

 Mean Value Stability Details

The mean value of the column **age** is 38. The expected range is from 11.3 to 69.3

 Mean Value Stability Details

The mean value of the column **education** is 1.000000. The expected range is from 0.11044 to 4.014105

The mean value of the column **fnlwgt** is 1.89e+05. The expected range is from -2.1e+04 to 4.04e+05

Mean Value Stability

[Details](#)

The mean value of the column **education-num** is 10.2. The expected range is from 1.56 to 17.8

Mean Value Stability

[Details](#)

The mean value of the column **capital-loss** is 83.3. The expected range is from -763 to 958

```
#test preset in a JSON format
data_stability.json()

→ {"version": "0.4.40", "tests": [{"name": "Number of Rows", "description": "The number of rows is 34687. The test threshold is eq=1.42e+04 \u00b1 1.42e+03.", "status": "FAIL", "group": "data_integrity", "parameters": {"condition": {"eq": {"value": 14155, "relative": 0.1, "absolute": 1e-12}}, "value": 34687.0}, {"name": "Number of Columns", "description": "The number of columns is 15. The test threshold is eq=15.", "status": "SUCCESS", "group": "data_integrity", "parameters": {"condition": {"eq": 15}, "value": 15.0}}, {"name": "Column Types", "description": "The number of columns with a type mismatch is 1 out of 15.", "status": "FAIL", "group": "data_integrity", "parameters": {"columns": [{"actual_type": "int64", "column_name": "age", "expected_type": "int64"}, {"actual_type": "CategoricalDtypeType", "column_name": "workclass", "expected_type": "CategoricalDtypeType"}, {"actual_type": "int64", "column_name": "fnlwgt", "expected_type": "int64"}]}]
```

#test preset as a python object
data_stability.as_dict()

```
'status': 'SUCCESS',
'group': 'data_quality',
'parameters': {'column_name': 'hours-per-week',
  'current_mean': 40.51,
  'n_sigmas': 2,
  'reference_mean': 40.21,
  'reference_std': 13.42},
{'name': 'Mean Value Stability',
'description': 'The mean value of the column **age** is 38. The expected range is from 11.3 to 69.3',
'data_type': 'numerical'}
```

✓ B. Data Quality

```
data_quality = TestSuite(tests=[
    DataQualityTestPreset(),
])
data_quality.run(reference_data=adult_ref, current_data=adult_cur)
data_quality
```



33

Tests

25

Success

0

Warning

8

Fail

0

Error

All tests ▾

✓ The Share of Missing Values in a Column

The share of missing values in the column **capital-gain** is 0. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **hours-per-week** is 0. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **age** is 0. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **fnlwgt** is 0. The test threshold is $\text{lte}=0 \pm 1e-12$.

❗ The Share of Missing Values in a Column

The share of missing values in the column **education-num** is 0.0577. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **capital-loss** is 0. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **relationship** is 0. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **race** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **native-country** is 0.0162. The test threshold is $\text{lte}=0.0208 \pm 0.00208$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **workclass** is 0.0549. The test threshold is $\text{lte}=0.0633 \pm 0.00633$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **occupation** is 0.055. The test threshold is $\text{lte}=0.0637 \pm 0.00637$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **class** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

⚠ The Share of Missing Values in a Column

The share of missing values in the column **education** is 0.0577. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **marital-status** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ The Share of Missing Values in a Column

The share of missing values in the column **sex** is 0. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

✓ Share of the Most Common Value

Details

The most common value in the column **capital-gain** is 0. Its share is 0.923. The test threshold is $\text{eq}=0.903 \pm 0.0903$.

✓ Share of the Most Common Value

Details

The most common value in the column **hours-per-week** is 40. Its share is 0.479. The test threshold is $\text{eq}=0.438 \pm 0.0438$.

! Share of the Most Common Value[Details](#)

The most common value in the column **age** is 23. Its share is 0.0312. The test threshold is $\text{eq}=0.0407 \pm 0.00407$.

! Share of the Most Common Value[Details](#)

The most common value in the column **fnlwgt** is 203488. Its share is 0.0006. The test threshold is $\text{eq}=0.0005 \pm 5e-05$.

! Share of the Most Common Value[Details](#)

The most common value in the column **education-num** is 9.0. Its share is 0.429. The test threshold is $\text{eq}=0.188 \pm 0.0188$.

✓ Share of the Most Common Value[Details](#)

The most common value in the column **capital-loss** is 0. Its share is 0.955. The test threshold is $\text{eq}=0.949 \pm 0.0949$.

✓ Share of the Most Common Value[Details](#)

The most common value in the column **relationship** is Husband. Its share is 0.394. The test threshold is $\text{eq}=0.426 \pm 0.0426$.

✓ Share of the Most Common Value[Details](#)

The most common value in the column **race** is White. Its share is 0.857. The test threshold is $\text{eq}=0.851 \pm 0.0851$.

✓ Share of the Most Common Value[Details](#)

The most common value in the column **native-country** is United-States. Its share is 0.918. The test threshold is $\text{eq}=0.847 \pm 0.0847$.

✓ Share of the Most Common Value[Details](#)

The most common value in the column **workclass** is Private. Its share is 0.707. The test threshold is $\text{eq}=0.663 \pm 0.0663$.

! Share of the Most Common Value[Details](#)

The most common value in the column **occupation** is Adm-clerical. Its share is 0.135. The test threshold is $\text{eq}=0.209 \pm 0.0209$.

✓ Share of the Most Common Value[Details](#)

The most common value in the column **class** is <=50K. Its share is 0.773. The test threshold is $\text{eq}=0.731 \pm 0.0731$.

⚠ Share of the Most Common Value

[Details](#)

The most common value in the column **education** is HS-grad. Its share is 0.429. The test threshold is $\text{eq}=0.188 \pm 0.0188$.

✓ Share of the Most Common Value

[Details](#)

The most common value in the column **marital-status** is Married-civ-spouse. Its share is 0.449. The test threshold is $\text{eq}=0.482 \pm 0.0482$.

✓ Share of the Most Common Value

[Details](#)

The most common value in the column **sex** is Male. Its share is 0.661. The test threshold is $\text{eq}=0.686 \pm 0.0686$.

✓ Number of Constant Columns

[Details](#)

The number of constant columns is 0. The test threshold is $\text{lte}=0$.

✓ Number of Duplicate Columns

The number of duplicate columns is 0. The test threshold is $\text{lte}=0$.

⚠ Number of Duplicate Rows

The number of duplicate rows is 38. The test threshold is $\text{eq}=27 \pm 2.7$.

✓ C. Data Drift

```
data_drift = TestSuite(tests=[  
    DataDriftTestPreset(stattest='psi'),  
])  
  
data_drift.run(reference_data=adult_ref, current_data=adult_cur)  
data_drift
```



16

Tests

13

Success

0

Warning

3

Fail

0

Error

All tests ▾

Share of Drifted Columns Details

The drift is detected for 20% features (3 out of 15). The test threshold is $\text{lt}=0.3$

Drift per Column Details

The drift score for the feature **relationship** is 0.008. The drift detection method is PSI. The drift detection threshold is 0.1.

Drift per Column Details

The drift score for the feature **race** is 0.003. The drift detection method is PSI. The drift detection threshold is 0.1.

Drift per Column Details

The drift score for the feature **native-country** is 0.1. The drift detection method is PSI. The drift detection threshold is 0.1.

Drift per Column Details

The drift score for the feature **workclass** is 0.013. The drift detection method is PSI. The drift detection threshold is 0.1.

Drift per Column Details

The drift score for the feature **occupation** is 0.192. The drift detection method is PSI. The drift detection threshold is 0.1.

Drift per Column Details

The drift score for the feature **class** is 0.009. The drift detection method is PSI. The drift detection threshold is 0.1.

Drift per Column Details

The drift score for the feature **education** is 15. The drift detection method is PSI. The drift detection threshold is 0.1.

ⓘ Drift per Column

Details

The drift score for the feature **marital-status** is 0.01. The drift detection method is PSI. The drift detection threshold is 0.1.

ⓘ Drift per Column

Details

The drift score for the feature **sex** is 0.003. The drift detection method is PSI. The drift detection threshold is 0.1.

ⓘ Drift per Column

Details

The drift score for the feature **capital-gain** is 0.029. The drift detection method is PSI. The drift detection threshold is 0.1.

ⓘ Drift per Column

Details

The drift score for the feature **hours-per-week** is 0.016. The drift detection method is PSI. The drift detection threshold is 0.1.

ⓘ Drift per Column

Details

The drift score for the feature **age** is 0.055. The drift detection method is PSI. The drift detection threshold is 0.1.

ⓘ Drift per Column

Details

The drift score for the feature **fnlwgt** is 0.004. The drift detection method is PSI. The drift detection threshold is 0.1.

! Drift per Column

Details

The drift score for the feature **education-num** is 15. The drift detection method is PSI. The drift detection threshold is 0.1.

ⓘ Drift per Column

Details

The drift score for the feature **capital-loss** is 0.006. The drift detection method is PSI. The drift detection threshold is 0.1.

✓ D. test suite to monitor a model's performance without actual target values (labels)

```
no_target_performance = TestSuite(tests=[  
    NoTargetPerformanceTestPreset(columns=['education-num', 'hours-per-week'], num_stattest='ks', cat_stattest='psi'),  
])  
  
no_target_performance.run(reference_data=adult_ref, current_data=adult_cur)  
no_target_performance
```



8
Tests

5
Success

0
Warning

3
Fail

0
Error

All tests ▾

⚠ Share of Drifted Columns Details

The drift is detected for 46.7% features (7 out of 15). The test threshold is $\text{lt}=0.3$.

⚠ Column Types Details

The number of columns with a type mismatch is 1 out of 15.

⚠ The Share of Missing Values in a Column Details

The share of missing values in the column **education-num** is 0.0577. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ The Share of Missing Values in a Column Details

The share of missing values in the column **hours-per-week** is 0. The test threshold is $\text{lte}=0 \pm 1e-12$.

✓ Share of Out-of-Range Values Details

The share of values out of range in the column **education-num** is 0 (0 out of 32687). The test threshold is $\text{eq}=0 \pm 1e-12$.

✓ Share of Out-of-Range Values Details

The share of values out of range in the column **hours-per-week** is 0 (0 out of 34687). The test threshold is $\text{eq}=0 \pm 1e-12$.

✓ Mean Value Stability Details

The mean value of the column **education-num** is 10.2. The expected range is from 1.56 to 17.8

✓ Mean Value Stability Details

The mean value of the column **hours-per-week** is 40.5. The expected range is from 13.4 to 67

▼ E. Regression model performance

```
regression_performance = TestSuite(tests=[  
    RegressionTestPreset()  
])  
  
regression_performance.run(reference_data=housing_ref, current_data=housing_cur)  
regression_performance
```



All tests ▾

Mean Error (ME) Details

The ME is -0.0365. The test threshold is $\text{eq}=0 \pm 0.295$.

Mean Absolute Error (MAE) Details

The MAE is 2.34. The test threshold is $\text{eq}=2.36 \pm 0.236$

Root Mean Square Error (RMSE) Details

The RMSE is 2.95. The test threshold is $\text{eq}=2.96 \pm 0.296$.

Mean Absolute Percentage Error (MAPE) Details

The MAPE is 1.57e+02. The test threshold is $\text{eq}=157 \pm 15.7$.

✓ F. Multiclass Classification Model Performance

```
classification_performance = TestSuite(tests=[  
    MulticlassClassificationTestPreset(stattest='psi')  
])  
  
classification_performance.run(reference_data=iris_ref, current_data=iris_cur)  
classification_performance
```



10
Tests

10
Success

0
Warning

0
Fail

0
Error

All tests ▾

Accuracy Score Details

The Accuracy Score is 0.947. The test threshold is $\text{eq}=0.973 \pm 0.195$

F1 Score Details

The F1 Score is 0.951. The test threshold is $\text{eq}=0.971 \pm 0.194$

Precision Score by Class Details

The precision score of the label **0** is 1. The test threshold is $\text{eq}=1 \pm 0.2$

Precision Score by Class Details

The precision score of the label **1** is 0.893. The test threshold is $\text{eq}=0.964 \pm 0.193$

Precision Score by Class Details

The precision score of the label **2** is 0.963. The test threshold is $\text{eq}=0.95 \pm 0.19$

Recall Score by Class Details

The recall score of the label **0** is 1. The test threshold is $\text{eq}=1 \pm 0.2$

Recall Score by Class Details

The recall score of the label **1** is 0.962. The test threshold is $\text{eq}=0.964 \pm 0.193$

Recall Score by Class Details

The recall score of the label **2** is 0.897. The test threshold is $\text{eq}=0.95 \pm 0.19$

Number of Rows

The number of rows is 75. The test threshold is $\text{eq}=75 \pm 7.5$.

Details

Drift per Column

The drift score for the feature **target** is 0.075. The drift detection method is PSI. The drift detection threshold is 0.1.

▼ G. Binary Classification Model Performance

```
label_binary_classification_performance = TestSuite(tests=[  
    BinaryClassificationTestPreset(),  
])  
  
label_binary_classification_performance.run(reference_data=bcancer_label_ref, current_data=bcancer_label_cur)  
label_binary_classification_performance
```



5
Tests

5
Success

0
Warning

0
Fail

0
Error

All tests ▾

Drift per Column Details

The drift score for the feature **target** is 0.513. The drift detection method is Z-test p_value. The drift detection threshold is 0.05.

Precision Score Details

The Precision Score is 0.971. The test threshold is $\text{eq}=1 \pm 0.2$

Recall Score Details

The Recall Score is 0.978. The test threshold is $\text{eq}=1 \pm 0.2$

F1 Score Details

The F1 Score is 0.974. The test threshold is $\text{eq}=1 \pm 0.2$

Accuracy Score Details

The Accuracy Score is 0.965. The test threshold is $\text{eq}=1 \pm 0.2$

```
prob_binary_classification_performance = TestSuite(tests=[  
    BinaryClassificationTestPreset(stattest='psi', probas_threshold=0.89),  
])  
  
prob_binary_classification_performance.run(reference_data=bcancer_ref, current_data=bcancer_cur)  
prob_binary_classification_performance
```



6
Tests

6
Success

0
Warning

0
Fail

0
Error

All tests ▾

Drift per Column Details

The drift score for the feature **target** is 0.004. The drift detection method is PSI. The drift detection threshold is 0.1.

ROC AUC Score Details

The ROC AUC Score is 0.98. The test threshold is $\text{eq}=1 \pm 0.2$

Precision Score Details

The Precision Score is 0.976. The test threshold is $\text{eq}=1 \pm 0.2$

Recall Score Details

The Recall Score is 0.919. The test threshold is $\text{eq}=0.948 \pm 0.19$

Accuracy Score Details

The Accuracy Score is 0.93. The test threshold is $\text{eq}=0.967 \pm 0.193$

F1 Score Details

The F1 Score is 0.947. The test threshold is $\text{eq}=0.974 \pm 0.195$

```
binary_topK_classification_performance = TestSuite(tests=[  
    BinaryClassificationTopKTestPreset(k=10, stattest='psi'),  
])  
  
binary_topK_classification_performance.run(reference data=bcancer ref. current data=bcancer cur)  
https://colab.research.google.com/drive/1JP1nUmAYPBINDsFwpeA6g-oIxvhv9i3y#scrollTo=KwyUUvxCATtd&printMode=true
```

```
binary_topK_classification_performance
```



7
Tests

6
Success

0
Warning

1
Fail

0
Error

All tests ▾

Accuracy Score Details

The Accuracy Score is 0.905. The test threshold is $\text{eq}=0.89 \pm 0.178$

Precision Score Details

The Precision Score is 0.983. The test threshold is $\text{eq}=1 \pm 0.2$

Recall Score Details

The Recall Score is 0.874. The test threshold is $\text{eq}=0.83 \pm 0.166$

F1 Score Details

The F1 Score is 0.925. The test threshold is $\text{eq}=0.907 \pm 0.181$

Drift per Column Details

The drift score for the feature **target** is 0.004. The drift detection method is PSI. The drift detection threshold is 0.1.

ROC AUC Score Details

The ROC AUC Score is 0.98. The test threshold is $\text{eq}=1 \pm 0.2$

Logarithmic Loss Details

The Logarithmic Loss is 0.429. The test threshold is $\text{eq}=0.0422 \pm 0.00845$

✓ H. List of all Data Integrity Test

```
#dataset-level tests

data_integrity_dataset_tests = TestSuite(tests=[  
    TestNumberOfColumns(),  
    TestNumberOfRows(),  
    TestNumberOfMissingValues(),  
    TestShareOfMissingValues(),  
    TestNumberOfColumnsWithMissingValues(),  
    TestNumberOfRowsWithMissingValues(),  
    TestShareOfColumnsWithMissingValues(),  
    TestShareOfRowsWithMissingValues(),  
    TestNumberOfDifferentMissingValues(),  
    TestNumberOfConstantColumns(),  
    TestNumberOfEmptyRows(),  
    TestNumberOfEmptyColumns(),  
    TestNumberOfDuplicatedRows(),  
    TestNumberOfDuplicatedColumns(),  
    TestColumnsType(),  
  
])  
  
data_integrity_dataset_tests.run(reference_data=adult_ref, current_data=adult_cur)  
data_integrity_dataset_tests
```



15
Tests

6
Success

0
Warning

9
Fail

0
Error

All tests ▾

Number of Columns

[Details](#)

The number of columns is 15. The test threshold is $\text{eq}=15$.

Number of Rows

[Details](#)

The number of rows is 34687. The test threshold is $\text{eq}=1.42\text{e}+04 \pm 1.42\text{e}+03$.

The Number of Missing Values

[Details](#)

The number of missing values is 8373. The test threshold is $\text{lte}=5.13\text{e}+03 \pm 513$.

Share of Missing Values

[Details](#)

The share of missing values is 0.0161. The test threshold is $\text{lte}=0.00985 \pm 0.000985$.

The Number of Columns With Missing Values

[Details](#)

The number of columns with missing values is 5. The test threshold is $\text{lte}=3$.

The Number Of Rows With Missing Values

[Details](#)

The number of rows with missing values is 4281. The test threshold is $\text{lte}=2.9\text{e}+03 \pm 290$.

The Share of Columns With Missing Values

[Details](#)

The share of columns with missing values is 0.333. The test threshold is $\text{lte}=0.2$.

The Share of Rows With Missing Values

The share of rows with missing values is 0.123. The test threshold is $\text{lte}=0.0837 \pm 0.00837$.

Different Types of Missing Values

Details

The number of differently encoded types of missing values is 1. The test threshold is $\text{eq}=1$.

Number of Constant Columns

Details

The number of constant columns is 0. The test threshold is $\text{lte}=0$.

Number of Empty Rows

Number of Empty Rows is 0. The test threshold is $\text{eq}=0 \pm 1e-12$.

Number of Empty Columns

Details

Number of Empty Columns is 0. The test threshold is $\text{lte}=0$.

Number of Duplicate Rows

The number of duplicate rows is 38. The test threshold is $\text{eq}=27 \pm 2.7$.

Number of Duplicate Columns

The number of duplicate columns is 0. The test threshold is $\text{lte}=0$.

Column Types

Details

The number of columns with a type mismatch is 1 out of 15.

```
#column-level tests

data_integrity_column_tests = TestSuite(tests=[
    TestColumnNumberOfMissingValues(column_name='education'),
    TestColumnShareOfMissingValues(column_name='education'),
    TestColumnNumberOfDifferentMissingValues(column_name='education'),
    TestColumnAllConstantValues(column_name='education'),
    TestColumnAllUniqueValues(column_name='education'),
    TestColumnRegExp(column_name='education', reg_exp='^[0..9]'),
   TestCategoryShare(column_name='education', category='Some-college', lt=0.5),
   TestCategoryShare(column_name='age', category=27., lt=0.5)
])

data_integrity_column_tests.run(reference_data=adult_ref, current_data=adult_cur)
data_integrity_column_tests
```



8
Tests

4
Success

0
Warning

4
Fail

0
Error

All tests ▾

❗ The Number of Missing Values in a Column

The number of missing values in the column **education** is 2000. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

❗ The Share of Missing Values in a Column

The share of missing values in the column **education** is 0.0577. The test threshold is $\text{lte}=0 \pm 1\text{e-}12$.

❗ Different Types of Missing Values in a Column

Details

The number of differently encoded types of missing values in the column **education** is 1. The test threshold is $\text{lte}=0$.

✅ All Constant Values in a Column

Details

The number of the unique values in the column **education** is 3 out of 34687

❗ All Unique Values in a Column

Details

The number of the unique values in the column **education** is 3 out of 34687

✅ RegExp Match

Details

The number of the mismatched values in the column **education** is 32687. The test threshold is $\text{eq}=3.28\text{e+}04 \pm 3.28\text{e+}03$.

✅ Share of category

Details

The share of category 'Some-college' in the column **education** is 0.296 (10260 out of 34687). The test threshold is $\text{lt}=0.5$.

✅ Share of category

Details

The share of category '27.0' in the column **age** is 0.0271 (941 out of 34687). The test threshold is lt=0.5.

⌄ I. List of all Data Quality Tests

```
#dataset-level tests

data_quality_dataset_tests = TestSuite(tests=[
    TestConflictTarget(),
    TestConflictPrediction(),
    TestTargetPredictionCorrelation(),
    TestHighlyCorrelatedColumns(),
    TestTargetFeaturesCorrelations(),
    TestPredictionFeaturesCorrelations(),
    TestCorrelationChanges(),
])
data_quality_dataset_tests.run(reference_data=iris_ref, current_data=iris_cur)
data_quality_dataset_tests
```



7
Tests

7
Success

0
Warning

0
Fail

0
Error

All tests ▾

Test number of conflicts in target

Target is stable

Test number of conflicts in prediction

Prediction is stable

Correlation between Target and Prediction

The correlation between the target and prediction is 0.931. The test threshold is $\text{eq}=0.958 \pm 0.25$.

Highly Correlated Columns

[Details](#)

The maximum correlation is 0.952. The test threshold is $\text{eq}=0.972 \pm 0.0972$.

Correlation between Target and Features

[Details](#)

The maximum correlation is 0.931. The test threshold is $\text{eq}=0.958 \pm 0.0958$.

Correlation between Prediction and Features

[Details](#)

The maximum correlation is 0.931. The test threshold is $\text{eq}=0.958 \pm 0.0958$.

Change in Correlation

[Details](#)

The number of correlation violations is 0. The test threshold is $\text{eq}=0$.

```
#column-level tests

data_quality_column_tests = TestSuite(tests=[
    TestColumnValueMin(column_name='education-num'),
    TestColumnValueMax(column_name='education-num'),
    TestColumnValueMean(column_name='education-num'),
    TestColumnValueMedian(column_name='education-num'),
    TestColumnValueStd(column_name='education-num'),
    TestNumberOfUniqueValues(column_name='education'),
    TestUniqueValuesShare(column_name='education'),
    TestMostCommonValueShare(column_name='education'),
    TestMeanInNSigmas(column_name='education-num'),
    TestValueRange(column_name='education-num'),
    TestNumberOfOutOfRangeValues(column_name='education-num'),
    TestShareOfOutOfRangeValues(column_name='education-num'),
    TestValueList(column_name='education'),
    TestNumberOfOutListValues(column_name='education'),
    TestShareOfOutListValues(column_name='education'),
    TestColumnQuantile(column_name='education-num', quantile=0.25),
    TestShareOfOutListValues(column_name='education-num'),
])
data_quality_column_tests.run(reference_data=adult_ref, current_data=adult_cur)
data_quality_column_tests
```



17

Tests

8

Success

0

Warning

9

Fail

0

Error

All tests ▾

 Min Value

Details

The minimum value of the column **education-num** is 9.0. The test threshold is gte=1.

 Max Value

Details

The maximum value of the column **education-num** is 13.0. The test threshold is lte=16.

 Mean Value

Details

The mean value of the column **education-num** is 10.2. The test threshold is eq=9.68 ± 0.968.

 Median Value

Details

The median value of the column **education-num** is 10. The test threshold is eq=11 ± 1.1.

 Standard Deviation (SD)

Details

The standard deviation of the column **education-num** is 1.57. The test threshold is eq=4.06 ± 0.406.

 Number of Unique Values

Details

The number of the unique values in the column **education** is 3. The test threshold is eq=13 ± 1.3.

 Share of Unique Values

Details

The share of the unique values in the column **education** is 0.0001. The test threshold is eq=0.0009 ± 9e-05.

 Share of the Most Common Value

Details

The most common value in the column **education** is HS-grad. Its share is 0.429. The test threshold is eq=0.188 ± 0.0188.

✓ Mean Value Stability

Details

The mean value of the column **education-num** is 10.2. The expected range is from 1.56 to 17.8

✓ Value Range

Details

All values in the column **education-num** are within range

✓ Number of Out-of-Range Values

Details

The number of values out of range in the column **education-num** is 0. The test threshold is eq=0 ± 1e-12.

✓ Share of Out-of-Range Values

Details

The share of values out of range in the column **education-num** is 0 (0 out of 32687). The test threshold is eq=0 ± 1e-12.

❗ Out-of-List Values

Details

The column **education** has values out of list.

❗ Number Out-of-List Values

Details

The number of values out of list in the column **education** is 34687. The test threshold is eq=0 ± 1e-12.

❗ Share of Out-of-List Values

Details

The share of values out of list in the column **education** is 1 (34687 out of 34687). The test threshold is eq=0 ± 1e-12.

❗ Quantile Value

Details

The 0.25 quantile value of the column **education-num** is 9. The test threshold is eq=6 ± 0.6.

❗ Share of Out-of-List Values

Details

The share of values out of list in the column **education-num** is 1 (34687 out of 34687). The test threshold is eq=0 ± 1e-12.



✓ J. List of all Data Drift Tests

```
#dataset-level tests

data_drift_dataset_tests = TestSuite(tests=[
    TestNumberOfDriftedColumns(),
    TestShareOfDriftedColumns(),
])

data_drift_dataset_tests.run(reference_data=adult_ref, current_data=adult_cur)
data_drift_dataset_tests
```



Tests	Success	Warning	Fail	Error
2	0	0	2	0

All tests ▾

⚠ Number of Drifted Features

[Details](#)

The drift is detected for 5 out of 15 features. The test threshold is $lt=5$.

⚠ Share of Drifted Columns

[Details](#)

The drift is detected for 33.3% features (5 out of 15). The test threshold is $lt=0.3$.

```
#column-level tests

data_drift_column_tests = TestSuite(tests=[
    TestColumnDrift(column_name='education-num', stattest='psi', stattest_threshold=0.3)
])

data_drift_column_tests.run(reference_data=adult_ref, current_data=adult_cur)
data_drift_column_tests
```



1
Tests

0
Success

0
Warning

1
Fail

0
Error

All tests ▾

! Drift per Column Details

The drift score for the feature **education-num** is 15. The drift detection method is PSI. The drift detection threshold is 0.3.

✗ K. List of all Regression Performance Test

```
#dataset-level tests
regression_performance_dataset_tests = TestSuite(tests=[
    TestValueMAE(),
    TestValueRMSE(),
    TestValueMeanError(),
    TestValueMAPE(),
    TestValueAbsMaxError(),
    TestValueR2Score()
])

regression_performance_dataset_tests.run(reference_data=housing_ref, current_data=housing_cur)
regression_performance_dataset_tests
```



6
Tests

6
Success

0
Warning

0
Fail

0
Error

All tests ▾

Mean Absolute Error (MAE)

Details

The MAE is 2.34. The test threshold is $\text{eq}=2.36 \pm 0.236$

Root Mean Square Error (RMSE)

Details

The RMSE is 2.95. The test threshold is $\text{eq}=2.96 \pm 0.296$.

Mean Error (ME)

Details

The ME is -0.0365. The test threshold is $\text{eq}=0 \pm 0.295$.

Mean Absolute Percentage Error (MAPE)

Details

The MAPE is $1.57\text{e}+02$. The test threshold is $\text{eq}=157 \pm 15.7$.

Max Absolute Error

Details

The Max Absolute Error is 11.5. The test threshold is $\text{lte}=10.6 \pm 1.06$.

R2 Score

Details

The R2 score is -5.54. The test threshold is $\text{eq}=-5.62 \pm 0.562$.

⌄ L. List of all Multiclass classification performance test

```
#dataset-level tests
```

```
classification_performance_dataset_tests = TestSuite(tests=[  
    TestAccuracyScore(),  
    TestPrecisionScore(),  
    TestRecallScore(),  
    TestF1Score(),  
    TestPrecisionByClass(label=0),  
    TestPrecisionByClass(label=1),  
    TestPrecisionByClass(label=2),  
    TestRecallByClass(label=0),  
    TestRecallByClass(label=1),  
    TestRecallByClass(label=2),  
    TestF1ByClass(label=0),  
    TestF1ByClass(label=1),  
    TestF1ByClass(label=2),  
])  
  
classification_performance_dataset_tests.run(reference_data=iris_ref, current_data=iris_cur)  
classification_performance_dataset_tests
```



13

Tests

13

Success

0

Warning

0

Fail

0

Error

All tests ▾

Accuracy Score Details

The Accuracy Score is 0.947. The test threshold is $\text{eq}=0.973 \pm 0.195$

Precision Score Details

The Precision Score is 0.952. The test threshold is $\text{eq}=0.971 \pm 0.194$

Recall Score Details

The Recall Score is 0.953. The test threshold is $\text{eq}=0.971 \pm 0.194$

F1 Score Details

The F1 Score is 0.951. The test threshold is $\text{eq}=0.971 \pm 0.194$

Precision Score by Class Details

The precision score of the label **0** is 1. The test threshold is $\text{eq}=1 \pm 0.2$

Precision Score by Class Details

The precision score of the label **1** is 0.893. The test threshold is $\text{eq}=0.964 \pm 0.193$

Precision Score by Class Details

The precision score of the label **2** is 0.963. The test threshold is $\text{eq}=0.95 \pm 0.19$

Recall Score by Class Details

The recall score of the label **0** is 1. The test threshold is $\text{eq}=1 \pm 0.2$

Recall Score by Class

[Details](#)

The recall score of the label **1** is 0.962. The test threshold is $\text{eq}=0.964 \pm 0.193$

Recall Score by Class

[Details](#)

The recall score of the label **2** is 0.897. The test threshold is $\text{eq}=0.95 \pm 0.19$

F1 Score by Class

[Details](#)

The F1 score of the label **0** is 1. The test threshold is $\text{eq}=1 \pm 0.2$

F1 Score by Class

[Details](#)

The F1 score of the label **1** is 0.926. The test threshold is $\text{eq}=0.964 \pm 0.193$

F1 Score by Class

[Details](#)

The F1 score of the label **2** is 0.929. The test threshold is $\text{eq}=0.95 \pm 0.19$

✓ M. List of all Binary Classification performance test

```
#dataset-level tests

prob_classification_performance_dataset_tests = TestSuite(tests=[
    TestAccuracyScore(),
    TestPrecisionScore(),
    TestRecallScore(),
    TestF1Score(),
    TestRocAuc(),
    TestLogLoss(),
    TestPrecisionByClass(label=0),
    TestPrecisionByClass(label=1),
    TestRecallByClass(label=0),
    TestRecallByClass(label=1),
    TestF1ByClass(label=0),
    TestF1ByClass(label=1),
])

prob_classification_performance_dataset_tests.run(reference_data=bcancer_ref, current_data=bcancer_cur)
prob_classification_performance_dataset_tests
```



12

Tests

11

Success

0

Warning

1

Fail

0

Error

All tests ▾

✓ Accuracy Score Details

The Accuracy Score is 0.97. The test threshold is $\text{eq}=0.99 \pm 0.198$

✓ Precision Score Details

The Precision Score is 0.957. The test threshold is $\text{eq}=0.985 \pm 0.197$

✓ Recall Score Details

The Recall Score is 1. The test threshold is $\text{eq}=1 \pm 0.2$

✓ F1 Score Details

The F1 Score is 0.978. The test threshold is $\text{eq}=0.992 \pm 0.198$

✓ ROC AUC Score Details

The ROC AUC Score is 0.98. The test threshold is $\text{eq}=1 \pm 0.2$

❗ Logarithmic Loss Details

The Logarithmic Loss is 0.429. The test threshold is $\text{eq}=0.0422 \pm 0.00845$

✓ Precision Score by Class Details

The precision score of the label 0 is 1. The test threshold is $\text{eq}=1 \pm 0.2$

✓ Precision Score by Class Details

The precision score of the label **1** is 0.957. The test threshold is eq=0.985 ± 0.197

✓ Recall Score by Class

Details

The recall score of the label **0** is 0.908. The test threshold is eq=0.972 ± 0.194

✓ Recall Score by Class

Details

The recall score of the label **1** is 1. The test threshold is eq=1 ± 0.2

✓ F1 Score by Class

Details

The F1 score of the label **0** is 0.952. The test threshold is eq=0.986 ± 0.197

✓ F1 Score by Class

Details

The F1 score of the label **1** is 0.978. The test threshold is eq=0.992 ± 0.198

6. Metric Preset and List of Metrics

✓ A. Create the Data Drift Metric Report

```
data_drift_report = Report(metrics=[  
    DataDriftPreset(num_statetest='ks', cat_statetest='psi', num_statetest_threshold=0.2, cat_statetest_threshold=0.2),  
])  
  
data_drift_report.run(reference_data=adult_ref, current_data=adult_cur)  
data_drift_report
```



Dataset Drift

Dataset Drift is NOT detected. Dataset drift detection threshold is 0.5

15

Columns

6

Drifted Columns

0.4

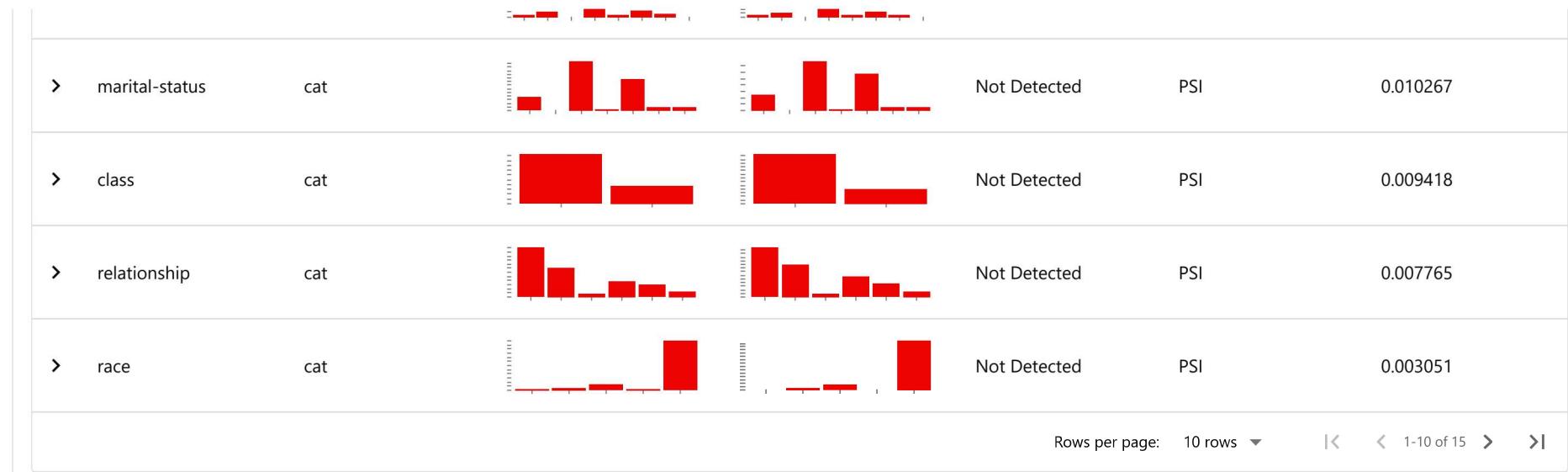
Share of Drifted Columns

Data Drift Summary

Drift is detected for 40.0% of columns (6 out of 15).

Search

Column	Type	Reference Distribution	Current Distribution	Data Drift	Stat Test	Drift Score
> education	cat			Detected	PSI	15.016729
> capital-loss	num			Not Detected	K-S p_value	0.346362
> occupation	cat			Not Detected	PSI	0.191829
> native-country	cat			Not Detected	PSI	0.099832
> fnlwgt	num			Detected	K-S p_value	0.027831
> workclass	cat			Not Detected	PSI	0.013186



```
data_drift_report.save_html('data_drift_report.html')
```

```
data_drift_report.json()
```

```
→ {"version": "0.4.40", "metrics": [{"metric": "DatasetDriftMetric", "result": {"drift_share": 0.5, "number_of_columns": 15, "number_of_drifted_columns": 6, "share_of_drifted_column": 0.4, "dataset_drift": false}}, {"metric": "DataDriftTable", "result": {"number_of_columns": 15, "number_of_drifted_columns": 6, "share_of_drifted_columns": 0.4, "dataset_drift": false, "drift_by_columns": {"age": {"column_name": "age", "column_type": "num", "stattest_name": "K-S p_value", "stattest_threshold": 0.2, "drift_score": 2.704668436775831e-60, "drift_detected": true, "current": {"small_distribution": {"x": [17.0, 24.3, 31.6, 38.9, 46.2, 53.5, 60.8, 68.1, 75.4, 82.7, 90.0], "y": [0.02471021672878118, 0.025839691234843417, 0.0262859521410848, 0.025211766596857754, 0.015942967066340047, 0.010173168977679455, 0.0061528716099474344, 0.0018640278561586543, 0.000568686464590777, 0.0002369526935794904]}}, "referenc": {"small_distribution": {"x": [17.0, 24.3, 31.6, 38.9, 46.2, 53.5, 60.8, 68.1, 75.4, 82.7]}}}}
```

```
data_drift_report.save_json('data_drift_report.json')
```

```
data_drift_report.as_dict()
```

```
→ {'metrics': [{}{'metric': 'DatasetDriftMetric', 'result': {'drift_share': 0.5, 'number_of_columns': 15, 'number_of_drifted_columns': 6, 'share_of_drifted_columns': 0.4, 'dataset_drift': False}}, {}{'metric': 'DataDriftTable', 'result': {'number_of_columns': 15, 'number_of_drifted_columns': 6, 'share_of_drifted_columns': 0.4, 'dataset_drift': False, 'drift_by_columns': {'age': {'column_name': 'age', 'column_type': 'num', 'stattest_name': 'K-S p_value', 'stattest_threshold': 0.2, 'drift_score': 2.704668436775831e-60, 'drift_detected': True, 'current': {'small_distribution': {'x': [17.0, 24.3, 31.6, 38.9, 46.2, 53.5, 60.8, 68.1, 75.4, 82.7]}}}}}}
```

```
24.3,
31.6,
38.9,
46.2,
53.5,
60.8,
68.1,
75.4,
82.7,
90.0],
'y': [0.02471021672878118,
0.025839691234843417,
0.0262859521410848,
0.025211766596857754,
0.015942967066340047,
0.010173168977679455,
0.0061528716099474344,
0.0018640278561586543,
0.000568686464590777,
0.0002369526935794904]}},
'reference': {'small_distribution': {'x': [17.0,
24.3,
31.6,
38.9,
46.2,
53.5,
60.8,
68.1,
75.4,
82.7,
90.0],
'y': [0.02104876054252575,
0.020739077628796638,
0.02384558435714183,
0.026835959992838568,
0.018658395552179158,
0.012580868370245284,
0.00869047676652328,
0.0029516652714806184,
0.001227110610126622
data_drift_report = Report(metrics=[
    DataDriftPreset(num_stattest='ks',
                    cat_stattest='psi',
                    num_stattest_threshold=0.2,
                    cat_stattest_threshold=0.2),
],
options={"render": {"raw_data": True}}
        )
data_drift_report.run(reference_data=adult_ref, current_data=adult_cur)
data_drift_report
```



Dataset Drift

Dataset Drift is NOT detected. Dataset drift detection threshold is 0.5

15

Columns

6

Drifted Columns

0.4

Share of Drifted Columns

Data Drift Summary

Drift is detected for 40.0% of columns (6 out of 15).

Search

Column	Type	Reference Distribution	Current Distribution	Data Drift	Stat Test	Drift Score
> education	cat			Detected	PSI	15.016729
> capital-loss	num			Not Detected	K-S p_value	0.346362
> occupation	cat			Not Detected	PSI	0.191829
> native-country	cat			Not Detected	PSI	0.099832
> fnlwgt	num			Detected	K-S p_value	0.027831
> workclass	cat			Not Detected	PSI	0.013186



▼ B. Create the Data Quality Metric Report

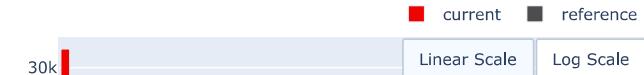
```
data_quality_report = Report(metrics=[  
    DataQualityPreset(),  
])  
  
data_quality_report.run(reference_data=adult_ref, current_data=adult_cur)  
data_quality_report
```



Dataset Summary

Metric	Current	Reference
id column	None	None
target column	None	None
prediction column	None	None
date column	None	None
number of columns	15	15
number of rows	34687	14155
missing values	8373	2092
categorical columns	9	9
numeric columns	6	6
text columns	0	0
datetime columns	0	0
empty columns	0	0
constant columns	0	0
almost constant features	1	0
duplicated columns	0	0
almost duplicated features	0	0

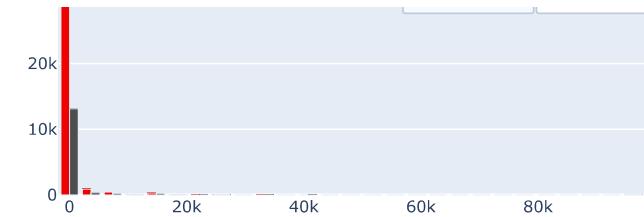
	current	reference
count	34687	14155
mean	844.27	1654.45
std	6159.97	9908.08
min	0.0	0.0
25%	0.0	0.0



capital-gain

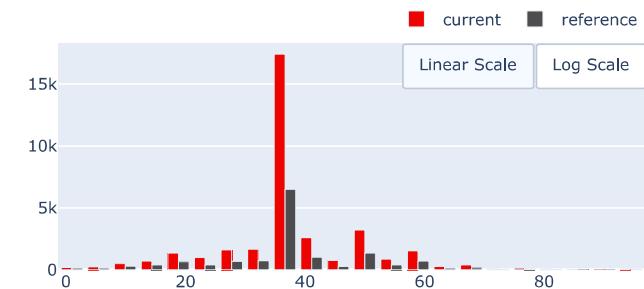
num

50%	0.0	0.0
75%	0.0	0.0
max	99999.0	99999.0
unique	117 (0.34%)	114 (0.81%)
most common	0.0 (92.33%)	0.0 (90.3%)
missing	0 (0.0%)	0 (0.0%)
infinite	0 (0.0%)	0 (0.0%)

**hours-per-week**

num

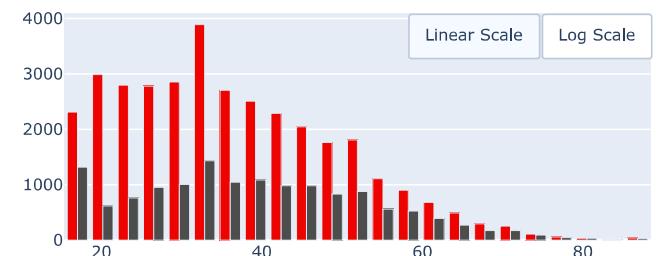
	current	reference
count	34687	14155
mean	40.51	40.21
std	11.94	13.42
min	1.0	1.0
25%	40.0	38.0
50%	40.0	40.0
75%	45.0	45.0
max	99.0	99.0
unique	95 (0.27%)	84 (0.59%)
most common	40.0 (47.88%)	40.0 (43.77%)
missing	0 (0.0%)	0 (0.0%)



infinite	0 (0.0%)	0 (0.0%)
----------	----------	----------

	current	reference
count	34687	14155
mean	37.97	40.3
std	13.31	14.52
min	17.0	17.0
25%	27.0	29.0
50%	36.0	39.0
75%	47.0	50.0
max	90.0	90.0
unique	73 (0.21%)	73 (0.52%)
most common	23.0 (3.12%)	17.0 (4.07%)
missing	0 (0.0%)	0 (0.0%)
infinite	0 (0.0%)	0 (0.0%)

■ current ■ reference



	current	reference
count	34687	14155
mean	188997.37	191298.05
std	105374.9	106149.45
min	12285.0	13769.0

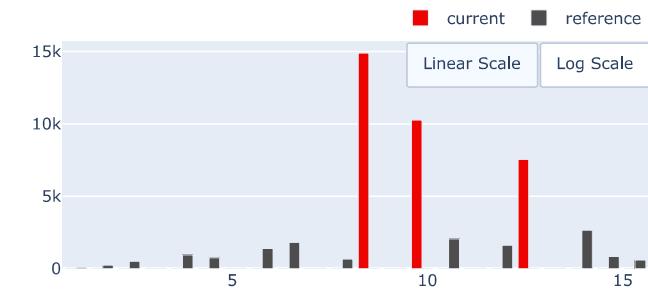
fnlwgt
num

25%	117618.0	117295.0
50%	177675.0	179973.0
75%	236393.5	240462.5
max	1490400.0	1455435.0
unique	22172 (63.92%)	11585 (81.84%)
most common	203488.0 (0.06%)	238917.0 (0.05%)
missing	0 (0.0%)	0 (0.0%)
infinite	0 (0.0%)	0 (0.0%)



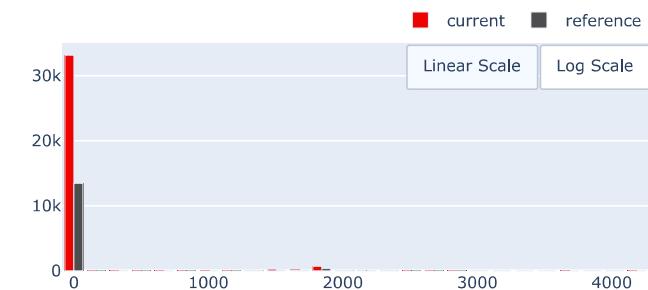
education-num
num

	current	reference
count	32687	14155
mean	10.24	9.68
std	1.57	4.06
min	9.0	1.0
25%	9.0	6.0
50%	10.0	11.0
75%	10.0	14.0
max	13.0	16.0
unique	3 (0.01%)	13 (0.09%)
most common	9.0 (42.93%)	14.0 (18.77%)

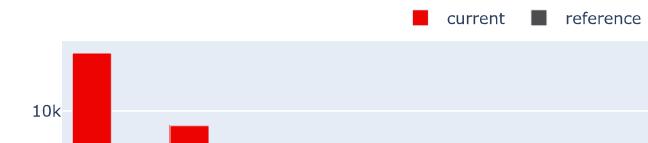


missing	2000 (5.77%)	0 (0.0%)
infinite	0 (0.0%)	0 (0.0%)

	current	reference
count	34687	14155
mean	83.32	97.74
std	391.26	430.27
min	0.0	0.0
25%	0.0	0.0
50%	0.0	0.0
75%	0.0	0.0
max	4356.0	3900.0
unique	92 (0.27%)	85 (0.6%)
most common	0.0 (95.5%)	0.0 (94.9%)
missing	0 (0.0%)	0 (0.0%)
infinite	0 (0.0%)	0 (0.0%)



	current	reference
count	34687	14155
unique	6 (0.02%)	6 (0.04%)
most common	Husband (39.44%)	Husband (42.62%)



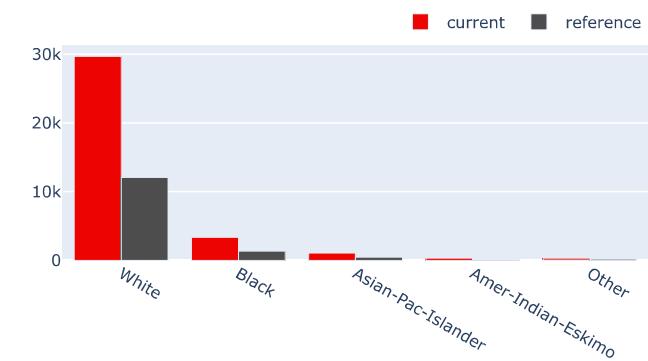
ML Monitoring Test and Reports (Data - Stability , Quality , Drift , Model perf - regression , binary & multiclass classification) - Colab

cat

	most common	median (33.44%)	median (42.00%)
missing	0 (0.0%)	0 (0.0%)	
new categories	0		
missing categories	0		

race
cat

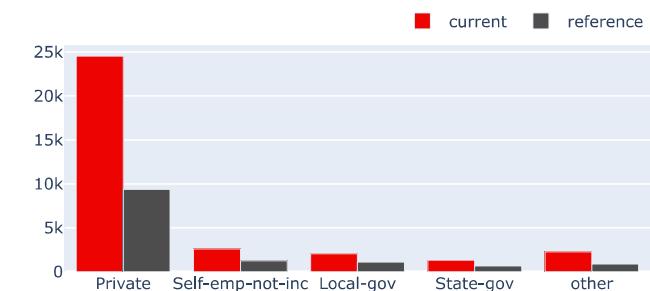
	current	reference
count	34687	14155
unique	5 (0.01%)	5 (0.04%)
most common	White (85.65%)	White (85.14%)
missing	0 (0.0%)	0 (0.0%)
new categories	0	
missing categories	0	

native-country
cat

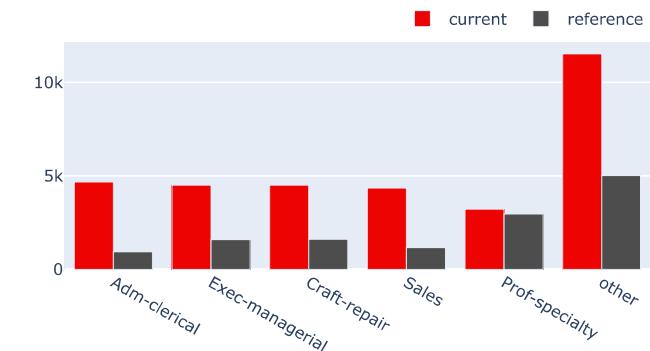
	current	reference
count	34124	13861
unique	41 (0.12%)	40 (0.28%)
most common	United-States (91.82%)	United-States (84.66%)
missing	563 (1.62%)	294 (2.08%)
new categories	1	
missing categories	0	



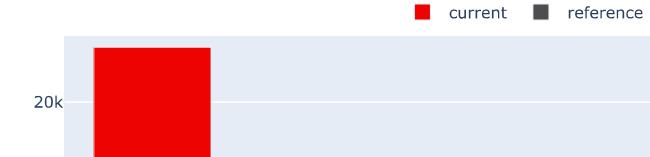
	current	reference
workclass cat	count	32784
	unique	8 (0.02%)
	most common	Private (70.69%)
	missing	1903 (5.49%)
	new categories	0
	missing categories	0



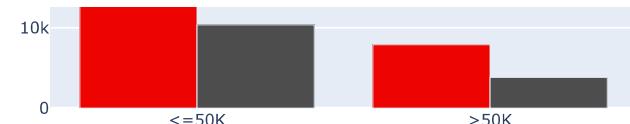
	current	reference
occupation cat	count	32780
	unique	14 (0.04%)
	most common	Adm-clerical (13.46%)
	missing	1907 (5.5%)
	new categories	0
	missing categories	0



	current	reference
class cat	count	14155
	unique	2 (0.01%)
	most common	<=50K (77.29%)
		<=50K (73.1%)

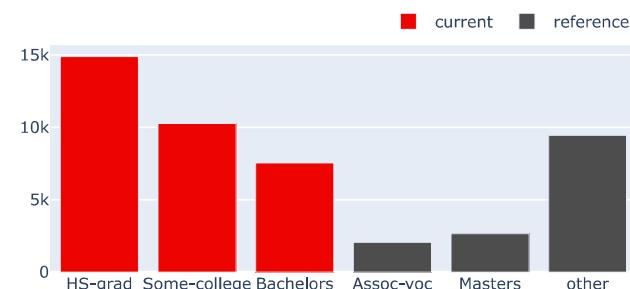


missing	0 (0.0%)	0 (0.0%)
new categories	0	
missing categories	0	



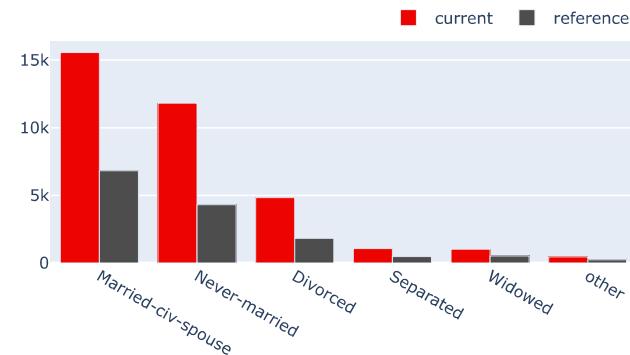
education
cat

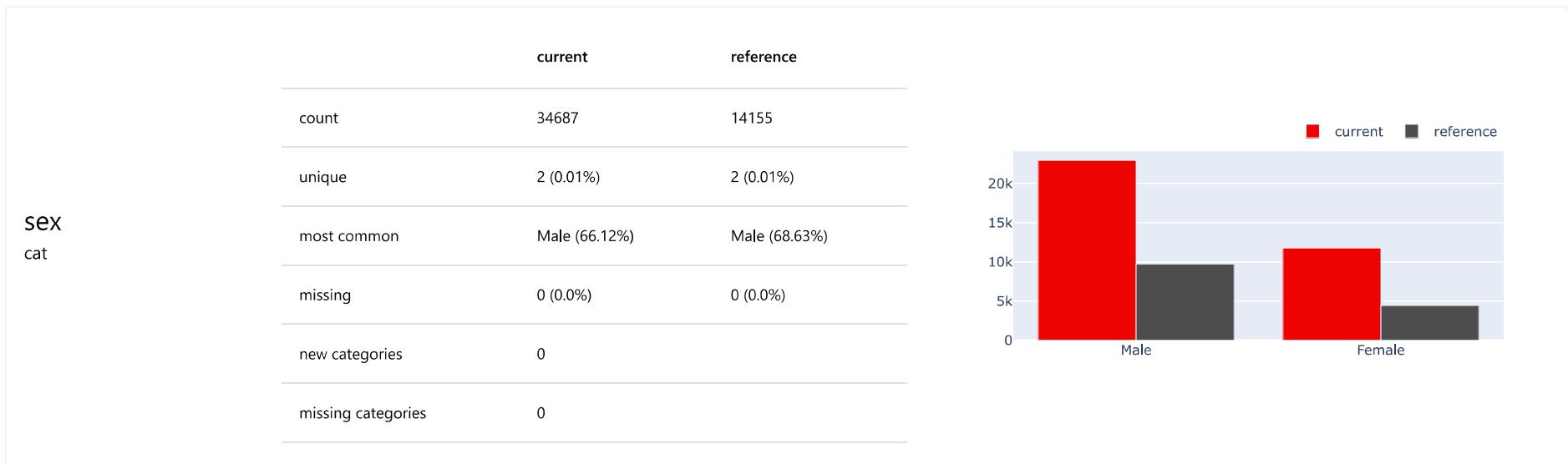
	current	reference
count	32687	14155
unique	3 (0.01%)	13 (0.09%)
most common	HS-grad (42.93%)	Masters (18.77%)
missing	2000 (5.77%)	0 (0.0%)
new categories	4	
missing categories	13	



marital-status
cat

	current	reference
count	34687	14155
unique	7 (0.02%)	7 (0.05%)
most common	Married-civ-spouse (44.85%)	Married-civ-spouse (48.19%)
missing	0 (0.0%)	0 (0.0%)
new categories	0	
missing categories	0	





Dataset Missing Values

8373 (1.609%)

Missing values (Current data)

2092 (0.985%)

Missing values (Reference data)

Current dataset

Table Histogram

Value	Count
education	2000
education-num	2000
occupation	1907
workclass	1903
native-country	563
age	0
fnlwgt	0

marital-status	0
relationship	0
race	0
sex	0
capital-gain	0
capital-loss	0
hours-per-week	0
class	0

Reference dataset

Table **Histogram**

Value	Count
occupation	902
workclass	896
native-country	294
age	0
fnlwgt	0
education	0
education-num	0
marital-status	0
relationship	0
race	0
sex	0
capital-gain	0
capital-loss	0
hours-per-week	0
class	0

```
data_quality_report.save_html('data_quality_report.html')
```

✓ C. Create the Regression Performance Metric Report

```
regression_performance_report = Report(metrics=[  
    RegressionPreset(),  
])  
  
regression_performance_report.run(reference_data=housing_ref.sort_index(), current_data=housing_cur.sort_index())  
regression_performance_report
```



Regression Model Performance. Target: 'target'

Current: Model Quality (+/- std)

-0.04 (2.95)

ME

2.34 (1.8)

MAE

156.62 (1.7)

MAPE

Reference: Model Quality (+/- std)

-0.01 (2.96)

ME

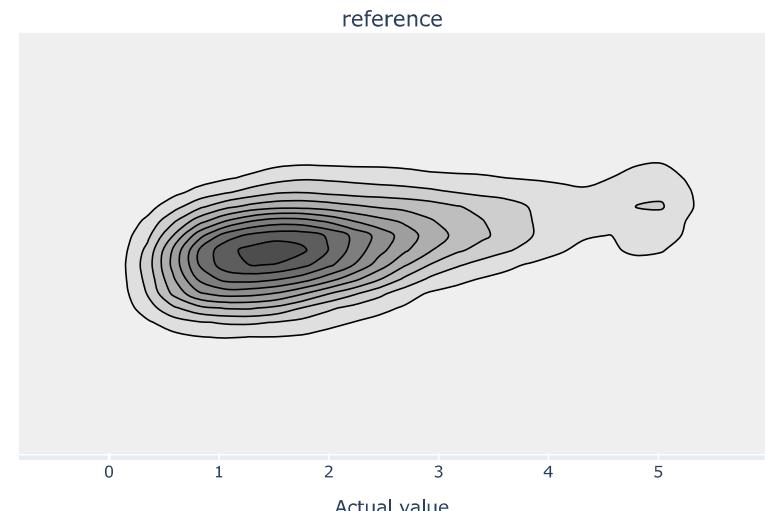
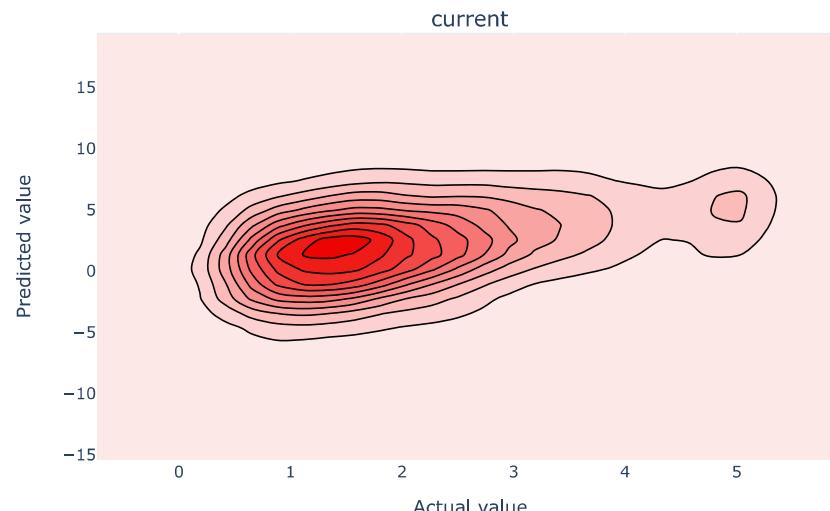
2.36 (1.8)

MAE

156.7 (1.74)

MAPE

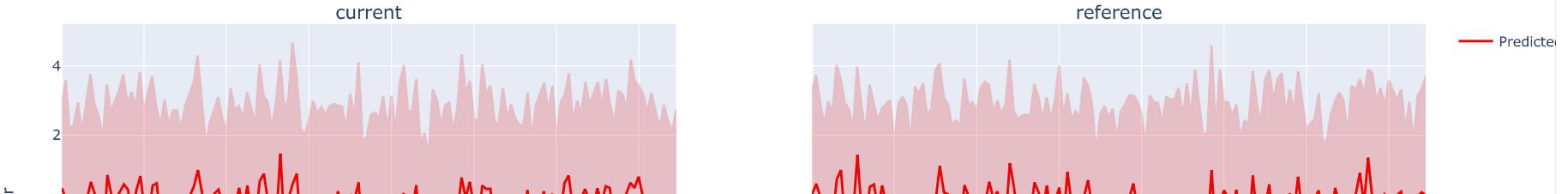
Predicted vs Actual

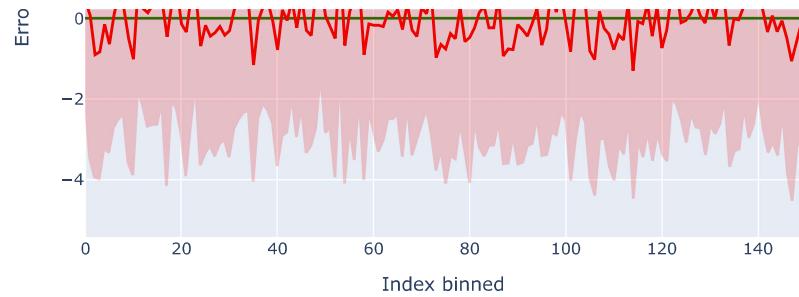


Predicted vs Actual in Time

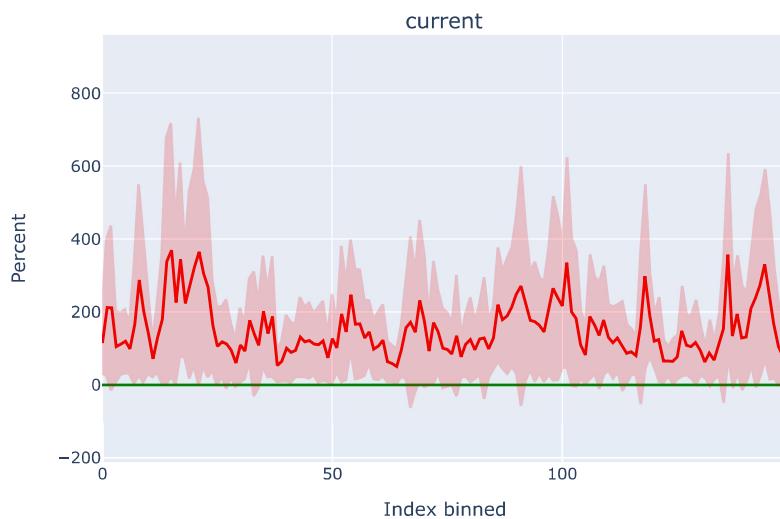


Error (Predicted - Actual)



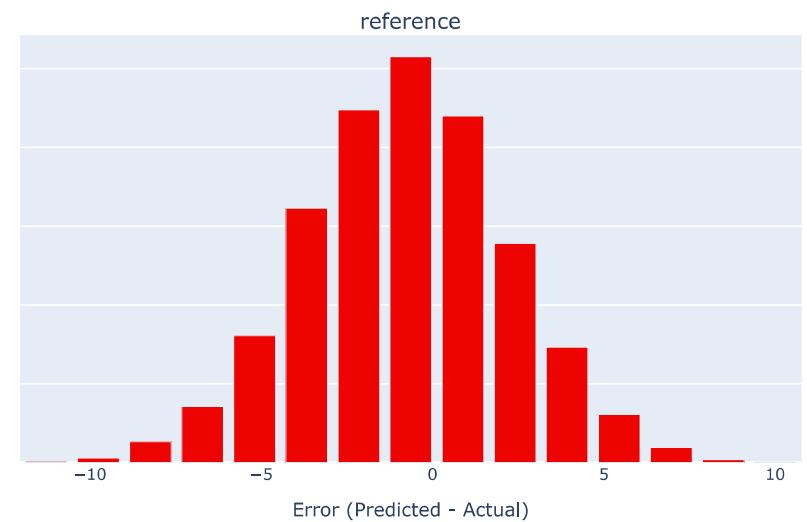
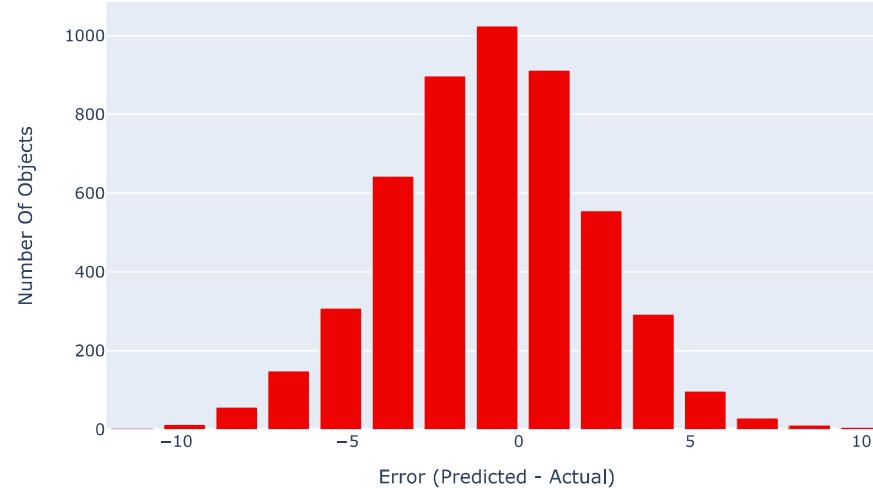


Absolute Percentage Error

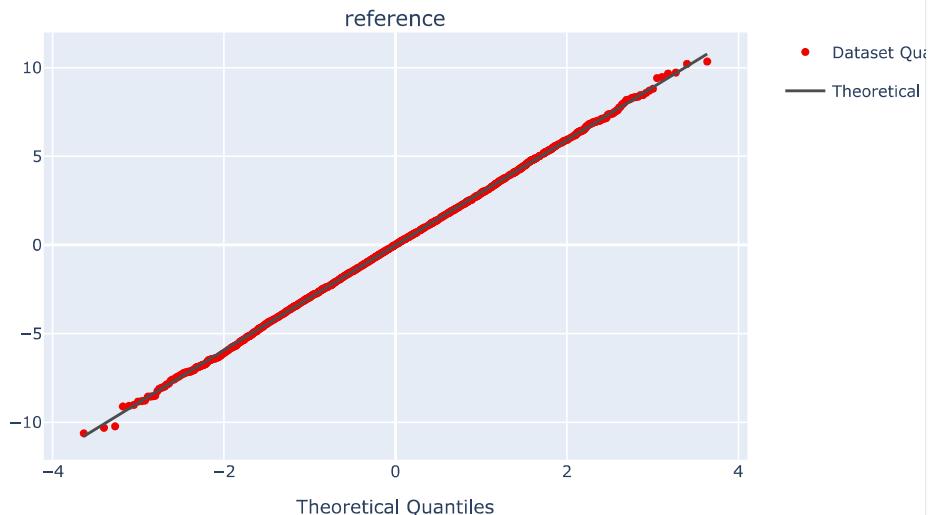
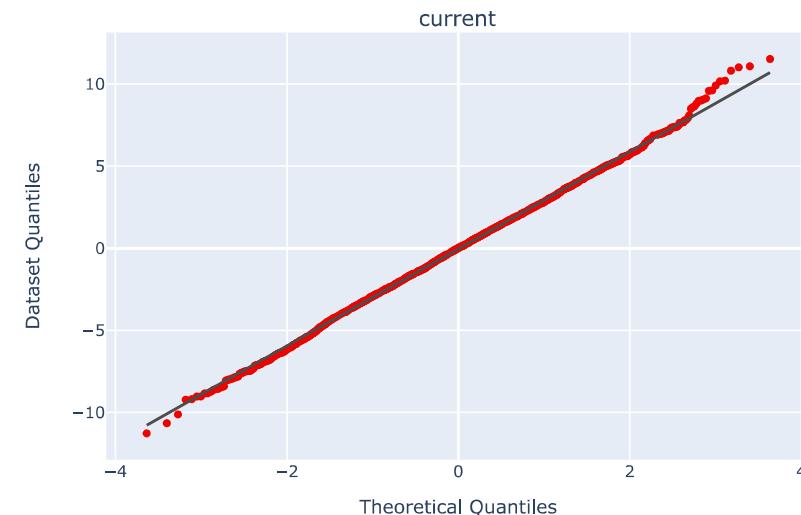


Error Distribution

abs



Error Normality



Error Bias Table

Current: Mean Error per Group (+/- std)

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