

ULL Pre-processing Mitigation

January 13, 2025

1 Install

```
[1]: !pip install aif360
      !pip install fairlearn
```

Collecting aif360

Downloading aif360-0.6.1-py3-none-any.whl.metadata (5.0 kB)

Requirement already satisfied: numpy>=1.16 in /usr/local/lib/python3.10/dist-packages (from aif360) (1.26.4)

Requirement already satisfied: scipy>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from aif360) (1.13.1)

Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.10/dist-packages (from aif360) (2.2.2)

Requirement already satisfied: scikit-learn>=1.0 in /usr/local/lib/python3.10/dist-packages (from aif360) (1.6.0)

Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from aif360) (3.10.0)

Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24.0->aif360) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24.0->aif360) (2024.2)

Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24.0->aif360) (2024.2)

Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.0->aif360) (1.4.2)

Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.0->aif360) (3.5.0)

Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->aif360) (1.3.1)

Requirement already satisfied: cycycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->aif360) (0.12.1)

Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->aif360) (4.55.3)

Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->aif360) (1.4.8)

Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->aif360) (24.2)

Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.10/dist-

```

packages (from matplotlib->aif360) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->aif360) (3.2.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.2->pandas>=0.24.0->aif360) (1.17.0)
Downloading aif360-0.6.1-py3-none-any.whl (259 kB)
      259.7/259.7 kB
4.4 MB/s eta 0:00:00
Installing collected packages: aif360
Successfully installed aif360-0.6.1
Collecting fairlearn
  Downloading fairlearn-0.12.0-py3-none-any.whl.metadata (7.0 kB)
Requirement already satisfied: numpy>=1.24.4 in /usr/local/lib/python3.10/dist-
packages (from fairlearn) (1.26.4)
Requirement already satisfied: pandas>=2.0.3 in /usr/local/lib/python3.10/dist-
packages (from fairlearn) (2.2.2)
Requirement already satisfied: scikit-learn>=1.2.1 in
/usr/local/lib/python3.10/dist-packages (from fairlearn) (1.6.0)
Requirement already satisfied: scipy>=1.9.3 in /usr/local/lib/python3.10/dist-
packages (from fairlearn) (1.13.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=2.0.3->fairlearn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=2.0.3->fairlearn) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-
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packages (from scikit-learn>=1.2.1->fairlearn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.2.1->fairlearn)
(3.5.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.2->pandas>=2.0.3->fairlearn) (1.17.0)
Downloading fairlearn-0.12.0-py3-none-any.whl (240 kB)
      240.0/240.0 kB
3.7 MB/s eta 0:00:00
Installing collected packages: fairlearn
Successfully installed fairlearn-0.12.0

```

2 Imports

```

[3]: import os
import copy
import math
import json
import collections

```

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import OrdinalEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, cross_validate, \
    StratifiedKFold
from sklearn.metrics import get_scorer
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

from aif360.algorithms.preprocessing import LFR
from aif360.algorithms.inprocessing import MetaFairClassifier, \
    PrejudiceRemover, GerryFairClassifier
from fairlearn import metrics

```

/usr/local/lib/python3.10/dist-packages/scipy/__init__.py:146: UserWarning: A NumPy version >=1.17.3 and <1.25.0 is required for this version of SciPy (detected version 1.26.4

```
warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}")
```

WARNING:root:No module named 'inFairness': SenSeI and SenSR will be unavailable.
To install, run:
pip install 'aif360[inFairness]'

3 Settings

```
[36]: final_df_filename = "final_df_v1"
```

```
[63]: sensitive_feature = "f_ESCS"
favorable_sensitive_label = "ADVANTAGED"
unfavorable_sensitive_label = "DISADVANTAGED"

class_feature = "level_MAT"
favorable_class_label = "PASSED"
unfavorable_class_label = "NOT PASSED"

perf_metrics = ["balanced_accuracy", "precision", "recall", "roc_auc", "f1"]
fair_metrics = ["demographic_parity_ratio", "equalized_odds_ratio"]

```

4 Utils

```
[7]: from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder
from aif360.datasets import BinaryLabelDataset
from aif360.metrics import BinaryLabelDatasetMetric

```

```
[59]: class AIF360SkllearnWrapper(BaseEstimator, TransformerMixin):
    def __init__(
        self,
        aif360_model,
        sensitive_feature,
        favorable_class_label,
        unfavorable_class_label,
        favorable_sens_group,
        unfavorable_sens_group,
    ):
        self.aif360_model = aif360_model

        self.sensitive_feature = sensitive_feature
        self.favorable_sens_group = favorable_sens_group
        self.unfavorable_sens_group = unfavorable_sens_group

        self.class_feature = "label"
        self.favorable_class_label = favorable_class_label
        self.unfavorable_class_label = unfavorable_class_label

        self.ordinal_encoder = None

    def _encode_features(self, df, fit):

        df_encoded = df.copy()

        # Encode class
        if self.class_feature in df_encoded.columns:
            df_encoded[self.class_feature] = df_encoded[
                self.class_feature
            ].apply(lambda x: 1 if x == self.favorable_class_label else 0)
        else:
            df_encoded[self.class_feature] = 0 # or any constant value

        # Encode sensitive feature
        if self.sensitive_feature in df_encoded.columns:
            df_encoded[self.sensitive_feature] = df_encoded[
                self.sensitive_feature
            ].apply(lambda x: 1 if x == self.favorable_sens_group else 0)

        # Encode other columns
        categorical_cols = df_encoded.select_dtypes(include=['object', 'category']).columns
        numeric_cols = df_encoded.select_dtypes(exclude=['object', 'category']).columns
```

```

    if fit:
        self.ordinal_encoder = OrdinalEncoder()
        self.ordinal_encoder.fit(df_encoded[categorical_cols])

    if len(categorical_cols) > 0:
        df_encoded[categorical_cols] = self.ordinal_encoder.
→ transform(df_encoded[categorical_cols])
    if len(numeric_cols) > 0:
        df_encoded[numeric_cols] = df_encoded[numeric_cols]

    # Check missing values
    # print(df_encoded.isna().sum())
    # df_encoded = df_encoded.set_index(self.sensitive_feature)
    # print(df_encoded.isna().sum())
    # print(df_encoded)

    return df_encoded

def fit(self, X, y, **kwargs):
    if not self.sensitive_feature:
        raise ValueError("Protected attribute name must be specified.")

    df_encoded = self._encode_features(df=X.assign(label=y), fit=True)

    # print(df_encoded)
    dataset = BinaryLabelDataset(
        df=df_encoded,
        label_names=[self.class_feature],
        # sensitive_features=[self.sensitive_feature],
        protected_attribute_names=[self.sensitive_feature],
        favorable_label=1,
        unfavorable_label=0
    )
    self.aif360_model = self.aif360_model.fit(dataset, **kwargs)
    return self

def transform(self, X, decode=False):
    X_encoded = self._encode_features(df=X, fit=False)
    dataset = BinaryLabelDataset(
        df=X_encoded,
        label_names=[self.class_feature],
        # sensitive_features=[self.sensitive_feature],
        protected_attribute_names=[self.sensitive_feature],
        favorable_label=1,
        unfavorable_label=0
    )

```

```

        new_X = self.aif360_model.transform(dataset).convert_to_dataframe()[0]
        new_X[self.sensitive_feature] = new_X[self.sensitive_feature].
        ↪apply(lambda x: self.favorable_sens_group if x == 1 else self.
        ↪unfavorable_sens_group) if decode else new_X[self.sensitive_feature]
        return new_X

```

```

[9]: def encode_feature(df, feature, favorable_label):

```

```

    df_encoded = df.copy()

    # Encode class
    if feature in df_encoded.columns:
        df_encoded[feature] = df_encoded[
            feature
        ].apply(lambda x: 1 if x == favorable_label else 0)
    return df_encoded

```

```

[10]: def decode_feature(df, feature, favorable_label, unfavorable_label):

```

```

    df_decoded = df.copy()

    # Encode class
    if feature in df_decoded.columns:
        df_decoded[feature] = df_decoded[
            feature
        ].apply(lambda x: favorable_label if x == 1 else unfavorable_label)
    return df_decoded

```

```

[11]: def compute_fair_metric(
    fair_metric_name, sensitive_feature, X, y_true, y_pred
):

```

```

    # metrics_module = __import__("metrics")
    metrics_module = globals()["metrics"]
    fair_metric_scorer = getattr(metrics_module, fair_metric_name)

    X_sensitive = encode_feature(X, sensitive_feature,
        ↪favorable_label=favorable_sensitive_label)
    X_sensitive = X_sensitive[sensitive_feature]

    return fair_metric_scorer(
        y_true=y_true,
        y_pred=y_pred,
        sensitive_features=X_sensitive,
    )

```

5 Src

```
[39]: final_df = pd.read_csv(f"{final_df_filename}.csv").set_index("id_questionnaire")
final_df
```

```
[39]:          s_frequency_of_work_with_teachers \
```

id_questionnaire	
1	0.733333
3	0.833333
5	0.566667
6	0.533333
8	0.633333
...	...
20421	0.566667
20422	0.700000
20423	0.400000
20424	0.500000
20427	0.666667

	s_frequency_of_evaluations	s_frequency_of_internet_usage \
id_questionnaire		
1	0.740741	0.066667
3	0.750000	0.666667
5	0.888889	0.133333
6	0.851852	0.133333
8	0.703704	0.266667
...
20421	0.777778	0.600000
20422	0.518519	0.266667
20423	0.555556	0.400000
20424	0.555556	0.200000
20427	0.740741	0.133333

	s_frequency_of_materials_in_class	f_ESCS \
id_questionnaire		
1	0.380952	0.235340
3	1.000000	0.261451
5	0.666667	3.151773
6	0.380952	-1.627731
8	0.666667	-0.358498
...
20421	0.476190	-0.764891
20422	0.380952	-0.048524
20423	0.571429	0.072922
20424	0.523810	2.755881
20427	0.476190	1.372627

id_questionnaire	s_extent_of_classmates_affinity \
1	0.714286
3	0.833333
5	0.952381
6	0.761905
8	0.857143
...	...
20421	0.904762
20422	0.952381
20423	0.809524
20424	0.904762
20427	0.857143

id_questionnaire	s_extent_of_teacher_performance	s_extent_of_class_env \
1	0.833333	0.791667
3	0.800000	0.833333
5	1.000000	1.000000
6	0.866667	1.000000
8	0.966667	0.833333
...
20421	1.000000	1.000000
20422	0.888889	0.916667
20423	1.000000	0.666667
20424	0.766667	0.791667
20427	0.900000	0.916667

id_questionnaire	f_mother_age	s_frequency_of_computer_usage \
1	43.0	0.111111
3	45.0	0.666667
5	39.0	0.000000
6	25.0	0.222222
8	37.0	0.333333
...
20421	41.0	0.111111
20422	36.0	0.222222
20423	46.0	0.111111
20424	41.0	0.111111
20427	37.0	0.000000

id_questionnaire	f_number_of_homework_hours_a_week \
1	14.0
3	9.0
5	6.0

6	5.0
8	10.0
...	...
20421	14.0
20422	2.0
20423	8.0
20424	2.0
20427	1.0

	s_extent_of_school_satisfaction	f_mother_education_level \
id_questionnaire		
1	0.944444	7.0
3	0.888889	3.0
5	1.000000	9.0
6	1.000000	3.0
8	0.833333	7.0
...
20421	1.000000	5.0
20422	0.944444	4.0
20423	1.000000	3.0
20424	0.833333	9.0
20427	1.000000	5.0

	f_extent_of_family_satisfaction	f_number_of_tech_at_home \
id_questionnaire		
1	0.700000	3.0
3	0.291667	4.0
5	0.833333	7.0
6	0.833333	3.0
8	1.000000	3.0
...
20421	1.000000	4.0
20422	0.708333	5.0
20423	0.833333	10.0
20424	0.666667	10.0
20427	0.291667	5.0

	f_frequency_of_books_at_home \
id_questionnaire	
1	1.000000
3	0.444444
5	0.555556
6	0.333333
8	0.555556
...	...
20421	0.222222
20422	0.555556

20423	0.444444
20424	0.555556
20427	0.444444

	f_frequency_of_parent_involved_in_school_activities \
id_questionnaire	
1	0.333333
3	0.166667
5	0.250000
6	0.083333
8	0.333333
...	...
20421	0.333333
20422	0.000000
20423	0.000000
20424	0.416667
20427	0.000000

	s_gender	level_MAT
id_questionnaire		
1	FEMALE	NOT PASSED
3	FEMALE	NOT PASSED
5	FEMALE	PASSED
6	FEMALE	NOT PASSED
8	MALE	NOT PASSED
...
20421	MALE	NOT PASSED
20422	FEMALE	NOT PASSED
20423	MALE	NOT PASSED
20424	MALE	NOT PASSED
20427	FEMALE	NOT PASSED

[10735 rows x 19 columns]

```
[65]: final_df[sensitive_feature] = final_df[sensitive_feature].apply(lambda x:
    ↪favorable_sensitive_label if x > 1.5 else unfavorable_sensitive_label)
final_df
```

```
[65]: s_frequency_of_work_with_teachers \
id_questionnaire
1          0.733333
3          0.833333
5          0.566667
6          0.533333
8          0.633333
...
20421      0.566667
```

20422	0.700000
20423	0.400000
20424	0.500000
20427	0.666667

	s_frequency_of_evaluations	s_frequency_of_internet_usage \
id_questionnaire		
1	0.740741	0.066667
3	0.750000	0.666667
5	0.888889	0.133333
6	0.851852	0.133333
8	0.703704	0.266667
...
20421	0.777778	0.600000
20422	0.518519	0.266667
20423	0.555556	0.400000
20424	0.555556	0.200000
20427	0.740741	0.133333

	s_frequency_of_materials_in_class	f_ESCS \
id_questionnaire		
1	0.380952	DISADVANTAGED
3	1.000000	DISADVANTAGED
5	0.666667	ADVANTAGED
6	0.380952	DISADVANTAGED
8	0.666667	DISADVANTAGED
...
20421	0.476190	DISADVANTAGED
20422	0.380952	DISADVANTAGED
20423	0.571429	DISADVANTAGED
20424	0.523810	ADVANTAGED
20427	0.476190	DISADVANTAGED

	s_extent_of_classmates_affinity \
id_questionnaire	
1	0.714286
3	0.833333
5	0.952381
6	0.761905
8	0.857143
...	...
20421	0.904762
20422	0.952381
20423	0.809524
20424	0.904762
20427	0.857143

id_questionnaire	s_extent_of_teacher_performance	s_extent_of_class_env \
1	0.833333	0.791667
3	0.800000	0.833333
5	1.000000	1.000000
6	0.866667	1.000000
8	0.966667	0.833333
...
20421	1.000000	1.000000
20422	0.888889	0.916667
20423	1.000000	0.666667
20424	0.766667	0.791667
20427	0.900000	0.916667

id_questionnaire	f_mother_age	s_frequency_of_computer_usage \
1	43.0	0.111111
3	45.0	0.666667
5	39.0	0.000000
6	25.0	0.222222
8	37.0	0.333333
...
20421	41.0	0.111111
20422	36.0	0.222222
20423	46.0	0.111111
20424	41.0	0.111111
20427	37.0	0.000000

id_questionnaire	f_number_of_homework_hours_a_week \
1	14.0
3	9.0
5	6.0
6	5.0
8	10.0
...	...
20421	14.0
20422	2.0
20423	8.0
20424	2.0
20427	1.0

id_questionnaire	s_extent_of_school_satisfaction	f_mother_education_level \
1	0.944444	7.0
3	0.888889	3.0
5	1.000000	9.0

6	1.000000	3.0
8	0.833333	7.0
...
20421	1.000000	5.0
20422	0.944444	4.0
20423	1.000000	3.0
20424	0.833333	9.0
20427	1.000000	5.0

id_questionnaire	f_extent_of_family_satisfaction	f_number_of_tech_at_home \
1	0.700000	3.0
3	0.291667	4.0
5	0.833333	7.0
6	0.833333	3.0
8	1.000000	3.0
...
20421	1.000000	4.0
20422	0.708333	5.0
20423	0.833333	10.0
20424	0.666667	10.0
20427	0.291667	5.0

id_questionnaire	f_frequency_of_books_at_home \
1	1.000000
3	0.444444
5	0.555556
6	0.333333
8	0.555556
...	...
20421	0.222222
20422	0.555556
20423	0.444444
20424	0.555556
20427	0.444444

id_questionnaire	f_frequency_of_parent_involved_in_school_activities \
1	0.333333
3	0.166667
5	0.250000
6	0.083333
8	0.333333
...	...
20421	0.333333
20422	0.000000

20423	0.000000
20424	0.416667
20427	0.000000

id_questionnaire	s_gender	level_MAT
1	FEMALE	NOT PASSED
3	FEMALE	NOT PASSED
5	FEMALE	PASSED
6	FEMALE	NOT PASSED
8	MALE	NOT PASSED
...
20421	MALE	NOT PASSED
20422	FEMALE	NOT PASSED
20423	MALE	NOT PASSED
20424	MALE	NOT PASSED
20427	FEMALE	NOT PASSED

[10735 rows x 19 columns]

```
[66]: get_features = lambda curr_df: [col for col in curr_df.columns if not col.
    ↳startswith("level_")]
```

```
X, y = final_df[get_features(final_df)], final_df[class_feature]
```

```
# y = y.apply(lambda elem: favorable_class_label if elem >= 3.5 else
    ↳unfavorable_class_label)
```

```
[95]: my_conf = {
    "k": 5,
    "Ax": 0.01,
    "Ay": 1.0,
    "Az": 50.0
}
mitigator = LFR(
    unprivileged_groups=[{sensitive_feature: 1}],
    privileged_groups=[{sensitive_feature: 0}],
    **my_conf
)
wrapper = AIF360SklearnWrapper(
    aif360_model=mitigator,
    sensitive_feature=sensitive_feature,
    favorable_sens_group=favorable_sensitive_label,
    unfavorable_sens_group=unfavorable_sensitive_label,
    favorable_class_label=favorable_class_label,
    unfavorable_class_label=unfavorable_class_label,
)
```

```

# Fit the model
wrapper.fit(X, y)
X_t = wrapper.transform(X, decode=True)
transformed_df = pd.concat([X_t.reset_index(drop=True).drop("label", axis=1), y.
    ↪reset_index(drop=True)], axis=1)
# X_t = decode_feature(X_t, sensitive_feature, favorable_sensitive_label, ↪
    ↪unfavorable_sensitive_label)
# X_t = decode_feature(X_t, "label", favorable_class_label, ↪
    ↪unfavorable_class_label)
transformed_df

```

```

[95]:      s_frequency_of_work_with_teachers  s_frequency_of_evaluations  \
0                0.603402                0.718262
1                0.603402                0.718262
2                0.603402                0.718262
3                0.603414                0.718256
4                0.603402                0.718262
...                ...                ...
10730            0.603402                0.718262
10731            0.603402                0.718262
10732            0.603402                0.718262
10733            0.603402                0.718262
10734            0.603402                0.718262

      s_frequency_of_internet_usage  s_frequency_of_materials_in_class  \
0                0.366703                0.499796
1                0.366703                0.499796
2                0.366703                0.499796
3                0.366722                0.499819
4                0.366703                0.499796
...                ...                ...
10730            0.366703                0.499796
10731            0.366703                0.499796
10732            0.366703                0.499796
10733            0.366703                0.499796
10734            0.366703                0.499796

      f_ESCS  s_extent_of_classmates_affinity  \
0  DISADVANTAGED                0.84255
1  DISADVANTAGED                0.84255
2    ADVANTAGED                0.84255
3  DISADVANTAGED                0.84253
4  DISADVANTAGED                0.84255
...                ...                ...
10730  DISADVANTAGED                0.84255
10731  DISADVANTAGED                0.84255

```

10732	DISADVANTAGED	0.84255
10733	ADVANTAGED	0.84255
10734	DISADVANTAGED	0.84255

	s_extent_of_teacher_performance	s_extent_of_class_env	f_mother_age	\
0	0.900597	0.805209	40.753695	
1	0.900597	0.805209	40.753695	
2	0.900597	0.805209	40.753695	
3	0.900560	0.805217	40.751982	
4	0.900597	0.805209	40.753695	
...	
10730	0.900597	0.805209	40.753695	
10731	0.900597	0.805209	40.753695	
10732	0.900597	0.805209	40.753695	
10733	0.900597	0.805209	40.753695	
10734	0.900597	0.805209	40.753695	

	s_frequency_of_computer_usage	f_number_of_homework_hours_a_week	\
0	0.251157	7.348350	
1	0.251157	7.348350	
2	0.251157	7.348350	
3	0.251180	7.348001	
4	0.251157	7.348350	
...	
10730	0.251157	7.348350	
10731	0.251157	7.348350	
10732	0.251157	7.348350	
10733	0.251157	7.348350	
10734	0.251157	7.348350	

	s_extent_of_school_satisfaction	f_mother_education_level	\
0	0.942216	5.435752	
1	0.942216	5.435752	
2	0.942216	5.435752	
3	0.942182	5.435626	
4	0.942216	5.435752	
...	
10730	0.942216	5.435752	
10731	0.942216	5.435752	
10732	0.942216	5.435752	
10733	0.942216	5.435752	
10734	0.942216	5.435752	

	f_extent_of_family_satisfaction	f_number_of_tech_at_home	\
0	0.829478	5.056625	
1	0.829478	5.056625	
2	0.829478	5.056625	

3	0.829471	5.056480
4	0.829478	5.056625
...
10730	0.829478	5.056625
10731	0.829478	5.056625
10732	0.829478	5.056625
10733	0.829478	5.056625
10734	0.829478	5.056625

	f_frequency_of_books_at_home \
0	0.570457
1	0.570457
2	0.570457
3	0.570437
4	0.570457
...	...
10730	0.570457
10731	0.570457
10732	0.570457
10733	0.570457
10734	0.570457

	f_frequency_of_parent_involved_in_school_activities	s_gender \
0	0.359890	0.496403
1	0.359890	0.496403
2	0.359890	0.496403
3	0.359889	0.496395
4	0.359890	0.496403
...
10730	0.359890	0.496403
10731	0.359890	0.496403
10732	0.359890	0.496403
10733	0.359890	0.496403
10734	0.359890	0.496403

	level_MAT
0	NOT PASSED
1	NOT PASSED
2	PASSED
3	NOT PASSED
4	NOT PASSED
...	...
10730	NOT PASSED
10731	NOT PASSED
10732	NOT PASSED
10733	NOT PASSED
10734	NOT PASSED

[10735 rows x 19 columns]

```
[99]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Suppose 's_gender' is your sensitive feature (e.g., "MALE"/"FEMALE"),
# and 'label' is binary (0/1) in both dataframes.
pre = encode_feature(final_df, sensitive_feature, favorable_sensitive_label)
post = encode_feature(transformed_df, sensitive_feature,
    ↪ favorable_sensitive_label)

pre = encode_feature(pre, class_feature, favorable_class_label)
post = encode_feature(post, class_feature, favorable_class_label)

groups = pre[sensitive_feature].unique() # or X_t["s_gender"].unique()

# 1) Compute selection rates in the original data
original_rates = []
for grp in groups:
    mask = (pre[sensitive_feature] == grp)
    group_data = pre[mask]
    if len(group_data) > 0:
        sel_rate = group_data[class_feature].mean() # fraction of label=1
    else:
        sel_rate = np.nan
    original_rates.append(sel_rate)

# 2) Compute selection rates in the transformed data
transformed_rates = []
for grp in groups:
    mask = (post[sensitive_feature] == grp)
    group_data = post[mask]
    if len(group_data) > 0:
        sel_rate = group_data[class_feature].mean()
    else:
        sel_rate = np.nan
    transformed_rates.append(sel_rate)

# 3) Build a single DataFrame for plotting
df_plot = pd.DataFrame({
    "group": groups,
    "original_rate": original_rates,
    "transformed_rate": transformed_rates
})
```

```

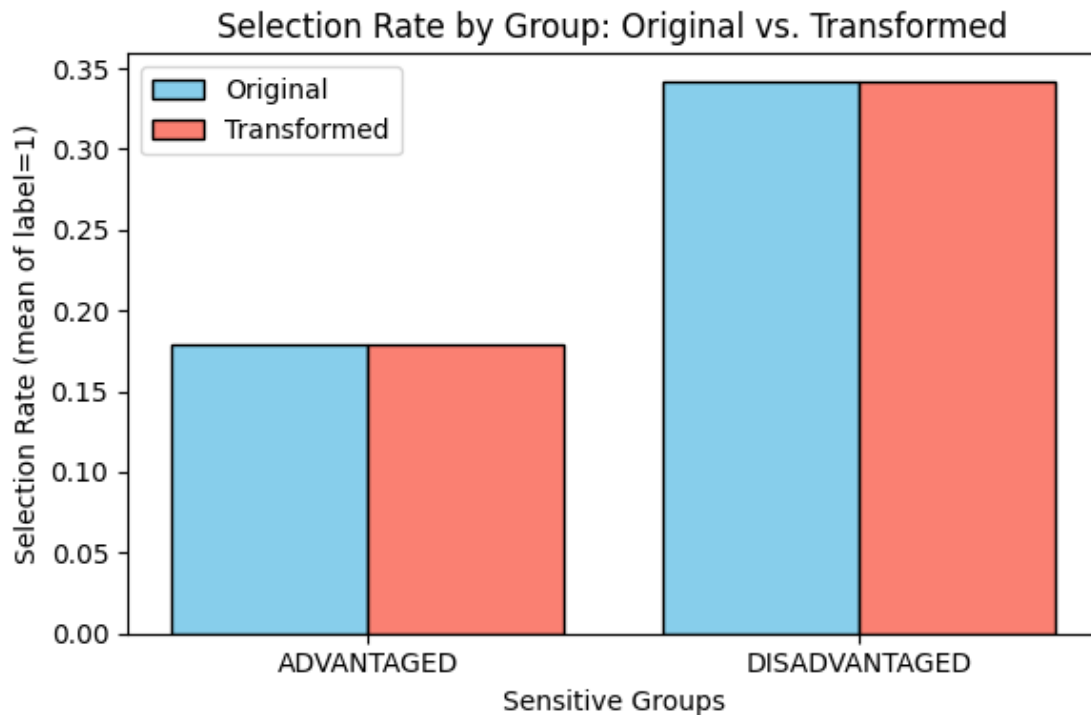
get_actual_elem = lambda elem: unfavorable_sensitive_label if elem == 1 else_
    favorable_sensitive_label
# 4) Plot side-by-side bars
plt.figure(figsize=(6, 4))

bar_width = 0.4
x_positions = np.arange(len(groups))

plt.bar(x_positions - bar_width/2, df_plot["original_rate"],
        width=bar_width, label="Original", color="skyblue", edgecolor="black")
plt.bar(x_positions + bar_width/2, df_plot["transformed_rate"],
        width=bar_width, label="Transformed", color="salmon", edgecolor="black")

plt.xticks(x_positions, [get_actual_elem(elem) for elem in df_plot["group"]])
plt.xlabel("Sensitive Groups")
plt.ylabel("Selection Rate (mean of label=1)")
plt.title("Selection Rate by Group: Original vs. Transformed")
plt.legend()
plt.tight_layout()
plt.show()

```



```

[97]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pandas.plotting import parallel_coordinates

# 1) Identify numeric columns (excluding the label).
numeric_cols = final_df.select_dtypes(include=[np.number]).columns
if class_feature in numeric_cols:
    numeric_cols = numeric_cols.drop(class_feature)

# 2) (Optional) sample rows to avoid clutter if data is large
SAMPLE_SIZE = 200
final_sample = (
    final_df[numeric_cols]
    .reset_index(drop=True)
    .sample(n=min(SAMPLE_SIZE, len(final_df)), random_state=42)
    .copy()
)
trans_sample = (
    transformed_df[numeric_cols]
    .reset_index(drop=True)
    .sample(n=min(SAMPLE_SIZE, len(transformed_df)), random_state=42)
    .copy()
)

# 3) Tag each subset with a "source"
final_sample["source"] = "Original"
trans_sample["source"] = "Transformed"

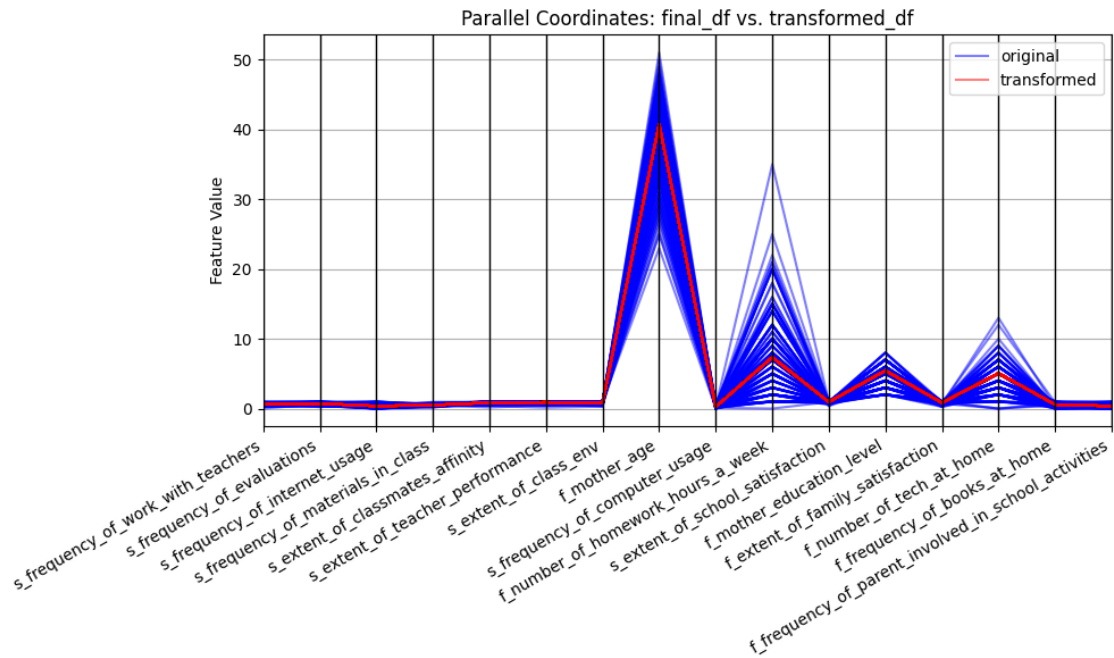
# 4) Concatenate them
combined = pd.concat([final_sample, trans_sample], ignore_index=True)

# 5) Parallel Coordinates expects one categorical column (here "source") to
    ↪ color the lines
plt.figure(figsize=(10, 6))
parallel_coordinates(
    combined,
    class_column="source",
    color=["blue", "red"], # or other color palette
    alpha=0.5
)
plt.title("Parallel Coordinates: final_df vs. transformed_df")
plt.ylabel("Feature Value")

# Make feature names vertical to avoid overlap
plt.xticks(rotation=30, ha="right")
plt.tight_layout()

```

```
plt.show()
```



```
[98]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pandas.plotting import andrews_curves

# 1) Identify numeric columns (excluding the label if it's numeric)
numeric_cols = final_df.select_dtypes(include=[np.number]).columns
if class_feature in numeric_cols:
    numeric_cols = numeric_cols.drop(class_feature)

# 2) Subset each DataFrame + add a "source" column
orig_numeric = final_df[numeric_cols].copy()
orig_numeric["source"] = "original"

trans_numeric = transformed_df[numeric_cols].copy()
trans_numeric["source"] = "transformed"

# 3) Concatenate them
combined = pd.concat([orig_numeric, trans_numeric], ignore_index=True)

# 4) Andrews Curves
plt.figure(figsize=(10, 6))
andrews_curves(
```

```

frame=combined,
class_column="source",
alpha=0.7,
colormap=plt.cm.Set2 # or another colormap
)
plt.title("Andrews Curves: final_df vs. transformed_df")
plt.grid(True)
plt.tight_layout()
plt.show()

```

