Module 4 - Reducing unfairness in learning algorithm applications

Assignment overview

In this assignment, you are tasked to create a classifer to predict the estimated income of individuals in the Kaggle Adult Income Dataset. This dataset is known to be biased towards certain groups. You will try some strategies to create a more fair classifier.

For this assignment, it is possible to work in **groups of up to 2 students**. Read the instructions carefully, as they may assign tasks to specific students.

Group members

Leave blanks if group has less than 2 members:

- Student 1: Jingyuan Liu (S.N. 69763183)
- Student 2: Nicholas Tam (S.N. 45695970)

Learning Goals:

After completing this week's lecture and tutorial work, you will be able to:

1. Discuss the consequences of erroneous (biased) data on the training of learning algorithms and how it impacts its end users
2. Discuss potential ethical implications in errors in feature selection, model selection
3. Describe strategies for reducing algorithmic bias
4. Apply strategies to reduce unfairness in a predictive model trained on an unbalanced dataset
5. Describe advantages and limitations of the strategies used to reduce unfairness in predictive models

Libraries

Here are some libraries you will need for this assignment. `imblearn` and `aif360` are new ones, you can install it by running the cell below. Comment out this line after one execution:

In [1]:

```
# !pip install imblearn
# !pip install aif360

# !conda install imblearn -n DSCI430
# !conda install aif360 -n DSCI430
```

In [2]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler
from imblearn.over_sampling import SMOTENC
import matplotlib.pyplot as plt
from aif360.algorithms.postprocessing import EqOddsPostprocessing
from aif360.datasets import BinaryLabelDataset

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

```
WARNING:root:No module named 'tensorflow': AdversarialDebiasing will be unavailab
le. To install, run:
pip install 'aif360[AdversarialDebiasing]'
WARNING:root:No module named 'tensorflow': AdversarialDebiasing will be unavailab
le. To install, run:
pip install 'aif360[AdversarialDebiasing]'
WARNING:root:No module named 'fairlearn': ExponentiatedGradientReduction will be
unavailable. To install, run:
pip install 'aif360[Reductions]'
WARNING:root:No module named 'fairlearn': GridSearchReduction will be unavailabl
e. To install, run:
pip install 'aif360[Reductions]'
WARNING:root:No module named 'inFairness': SenSeI and SenSR will be unavailable.
To install, run:
pip install 'aif360[inFairness]'
WARNING:root:No module named 'fairlearn': GridSearchReduction will be unavailabl
e. To install, run:
pip install 'aif360[Reductions]'
```

Dataset

The dataset you will use for this assignment is the Kaggle Adult Income Dataset. You may visit the source page for more information about this dataset.

The dataset includes 15 columns: 14 of them are demographics and other features to describe a person, and one (the target variable), is their income. The income variable is binary and has the two possible values `<=50K` or `>50K`.

Let's start by importing the dataset and taking a look (you are free to add other lines if you want more details):

In [3]:

```
df = pd.read_csv("adult.csv")
df.head()
```

Out[3]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relation
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husb
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husb
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husb
4	18	?	103497	Some-college	10	Never-married	?	Own-

Unfortunately, this dataset is notoriously biased in the association between income and other demographic information, such as race and gender. Let's see how.

Question 1

Create the following 3 bar charts:

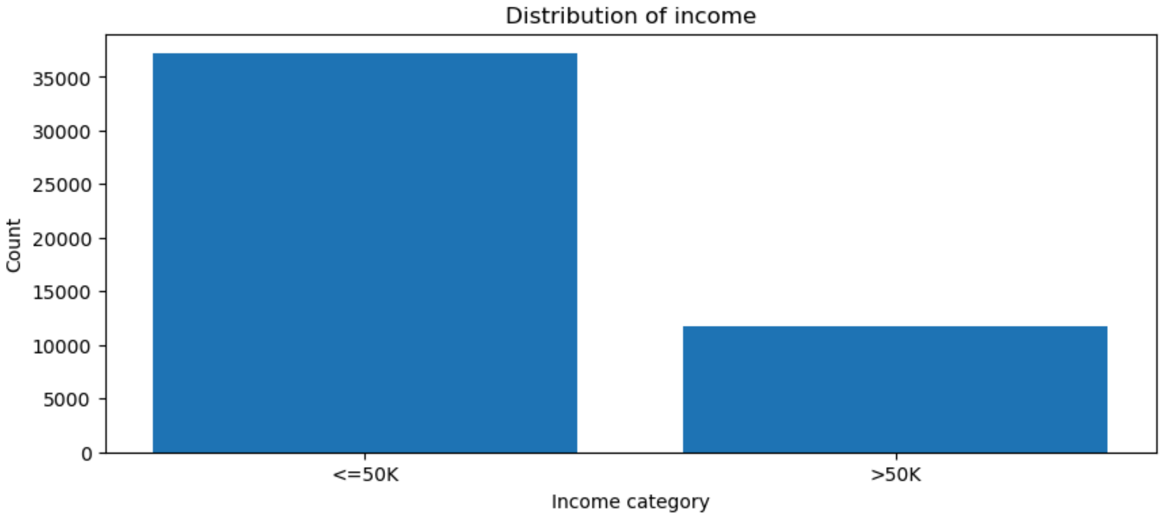
- A global bar chart of the target variable
- A bar chart of the target variable divided by gender
- A bar chart of the target variable divided by race

Comment on the results. Is the target variable balanced? Is the target variable balanced across protected groups?

In [4]:

```
# Your answer here

display(df["income"].value_counts(normalize=True).sort_index())

plt.figure(figsize=(10,4))
frame = df["income"].astype("string").value_counts().sort_index()
plt.bar(frame.index, frame)
plt.xlabel("Income category")
plt.ylabel("Count")
plt.title("Distribution of income")
plt.show()
```

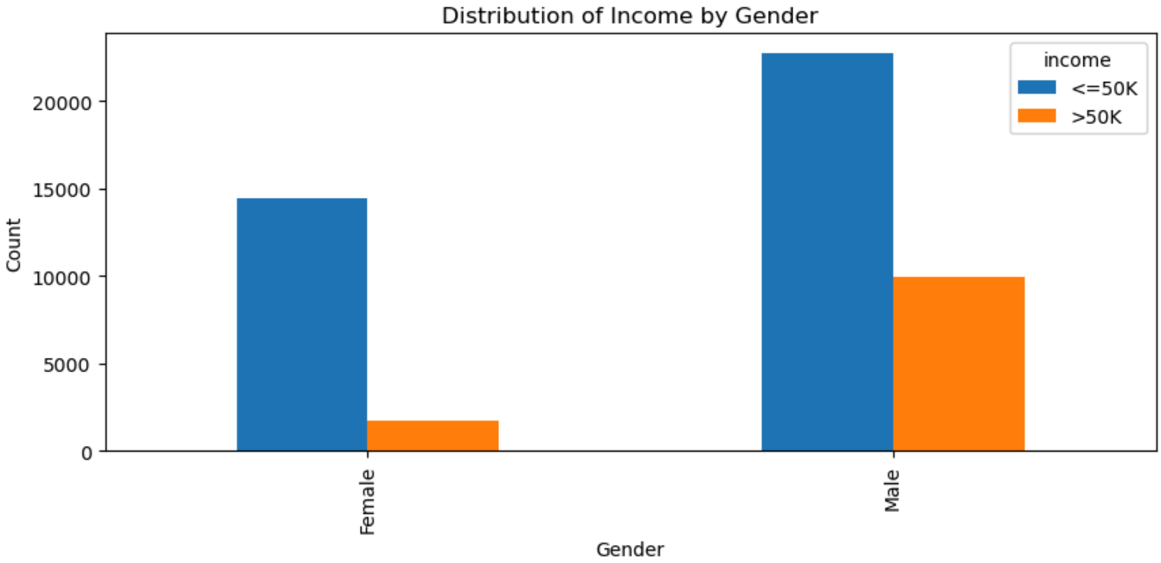
```
income
<=50K    0.760718
>50K     0.239282
Name: proportion, dtype: float64
```



Across the entire dataset, the target variable `income` is not balanced, with 0.760718 of the samples having `income == "<=50K"`, and 0.239282 of the samples having `income == ">50K"`; we have much more individuals with `income == "<=50K"` than people with `income == ">50K"` in the dataset. As a result, the model may have biased predictive results in favor of the more frequent class of the target variable.

In [5]:
```
genders = df["gender"].astype("string").value_counts().sort_index().index

# for gen in genders:
#     data = df[df["gender"] == gen]
#     print("Distribution of income for " + gen.lower())
#     display(data["income"].value_counts(normalize=True).sort_index())

#     plt.figure(figsize=(10,4))
#     frame = data["income"].astype("string")
#     f_cats = frame.value_counts().sort_index()
#     plt.bar(f_cats.index, f_cats)
#     plt.xlabel(gen)
#     plt.ylabel("Count")
#     plt.title("Distribution of income for " + gen.lower())
#     plt.show()

grouped_data_gender = df.groupby(["gender", "income"]).size().unstack()
plt.figure(figsize=(10, 4))
grouped_data_gender.plot(kind="bar", stacked=False, figsize=(10, 4))
plt.xlabel("Gender")
plt.ylabel("Count")
plt.title("Distribution of Income by Gender")
plt.show()

for gen in genders:
    data = df[df["gender"] == gen]
    display(gen,data["income"].value_counts(normalize=True))
```

```
<Figure size 1000x400 with 0 Axes>
```

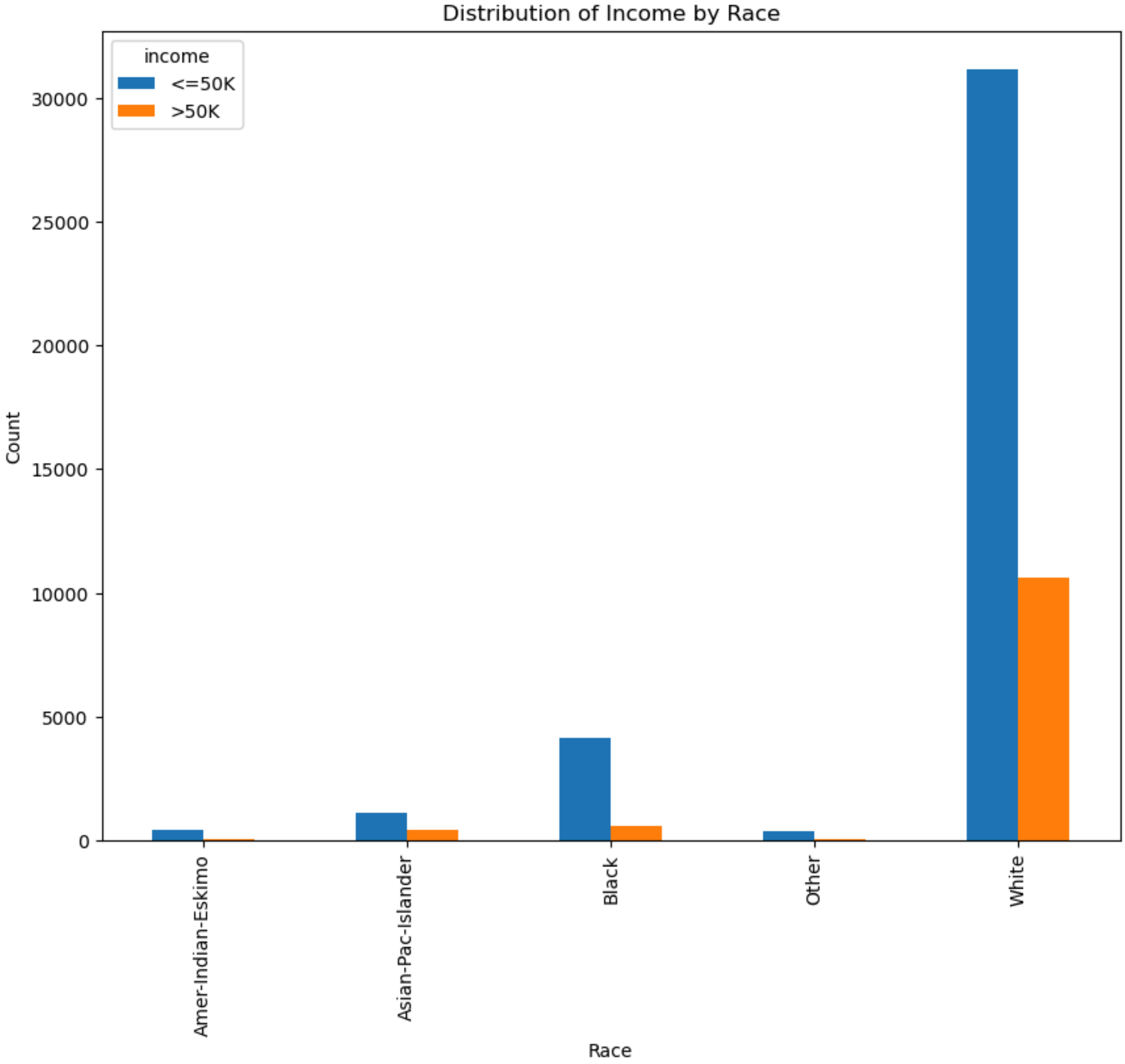


```
'Female'
income
<=50K    0.890749
>50K     0.109251
Name: proportion, dtype: float64
'Male'
income
<=50K    0.696233
>50K     0.303767
Name: proportion, dtype: float64
```

The target variable `income` is not balanced across each `gender` groups, nor are the distributions of each `income` category equal across each level of `gender`. For instance, the proportion of `income == "<=50K"` samples is 0.890749 among female individuals and only 0.696233 among male individuals. This runs the risk of differential treatment and classification of `income` between categories of protected characteristics and increases the predictive bias and the possibility of unfairness against certain groups under protected characteristics.

In [6]:
```
races = df["race"].astype("string").value_counts().sort_index().index

# for gen in races:
#     data = df[df["race"] == gen]
#     print("Distribution of income for " + gen.lower())
#     display(data["income"].value_counts(normalize=True).sort_index())

#     plt.figure(figsize=(10,4))
#     frame = data["income"].astype("string")
#     f_cats = frame.value_counts().sort_index()
#     plt.bar(f_cats.index, f_cats)
#     plt.xlabel(gen)
#     plt.ylabel("Count")
#     plt.title("Distribution of income for " + gen.lower())
#     plt.show()

grouped_data_race = df.groupby(["race", "income"]).size().unstack()
plt.figure(figsize=(10, 8))
grouped_data_race.plot(kind="bar", stacked=False, figsize=(10, 8))
plt.xlabel("Race")
plt.ylabel("Count")
plt.title("Distribution of Income by Race")
plt.show()

for race in races:
    data = df[df["race"] == race]
    display(race,data["income"].value_counts(normalize=True))
```

```
<Figure size 1000x800 with 0 Axes>
```



```
'Amer-Indian-Eskimo'
income
<=50K    0.882979
>50K     0.117021
Name: proportion, dtype: float64
'Asian-Pac-Islander'
income
<=50K    0.730744
>50K     0.269256
Name: proportion, dtype: float64
'Black'
income
<=50K    0.879189
>50K     0.120811
Name: proportion, dtype: float64
'Other'
income
<=50K    0.876847
>50K     0.123153
Name: proportion, dtype: float64
```

```
'White'
income
<=50K    0.746013
>50K     0.253987
Name: proportion, dtype: float64
```

The target variable `income` is not balanced across each `race` groups either, nor are the distributions of each `income` category equal across each level of `race`. For instance, the proportion of `income == "<=50K"` samples is 0.882979 among amer-indian-eskimo individuals and 0.746013 among white individuals. This runs the risk of differential treatment and classification of `income` between categories of protected characteristics and increases the predictive bias and the possibility of unfairness against certain groups under protected characteristics.

A biased classifier

We can expect that a classifier trained on this kind of data will show some problematic behaviors when assigning an individual to a predicted income level. Let's visualize this using a random forest classifier.

In [7]:

```
# STEP 1
# Run this cell create training and test sets
train_df, test_df = train_test_split(df, test_size=0.3, random_state=123)

X_train, y_train = (
    train_df.drop(columns=["income"]),
    train_df["income"],
)
X_test, y_test = (
    test_df.drop(columns=["income"]),
    test_df["income"],
)
```

In [8]:

```
test_df.shape
```

Out[8]:

```
(14653, 15)
```

In [9]:

```
# STEP 2
# Run this cell to do the necessary dataset preprocessing (encoding of categoric
# Note that, since we are using a tree based classifier, we don't need to scale
# numerical features.

categorical_feats = ["workclass",
                     "education",
                     "marital-status",
                     "occupation",
                     "relationship",
                     "race",
                     "gender",
                     "native-country",
                     ]  # Apply one-hot encoding
passthrough_feats = ["age",
                "fnlwgt",
                "educational-num",
                "capital-gain",
                 "capital-loss",
                 "hours-per-week"
                 ]  # Numerical - no need to scale
target = "income"

ct = make_column_transformer(
    (
        make_pipeline(OneHotEncoder(handle_unknown="ignore",drop="if_binary")),
        categorical_feats,
    ),  # OHE on categorical features
    ("passthrough", passthrough_feats)  # no transformations on numerical featur
)

X_train_transformed = ct.fit_transform(X_train).toarray()

column_names = list(
    ct.named_transformers_["pipeline"].get_feature_names_out(
        categorical_feats
    )
) + passthrough_feats

X_test_transformed = ct.transform(X_test).toarray()
```

In [10]:

```
# You may use this lines to check the result
pd.DataFrame(X_train_transformed, columns=column_names).head()
# pd.DataFrame(X_test_transformed, columns=column_names)
```

Out[10]:

	workclass_?	workclass_Federal-gov	workclass_Local-gov	workclass_Never-worked	workclass_P
0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	
3	0.0	0.0	1.0	0.0	
4	0.0	0.0	0.0	0.0	

5 rows × 106 columns

In [11]:

```
# STEP 3
# Run this cell to train a random forest classifer. The hyperparameters have bee

from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(random_state=0, max_depth = 19, n_estimators = 100)
```

How good is this classifier? Let's check its accuracy, by running the cells below:

In [12]:

```
clf.score(X_train_transformed, y_train)
```

Out[12]:

```
0.9064318932990143
```

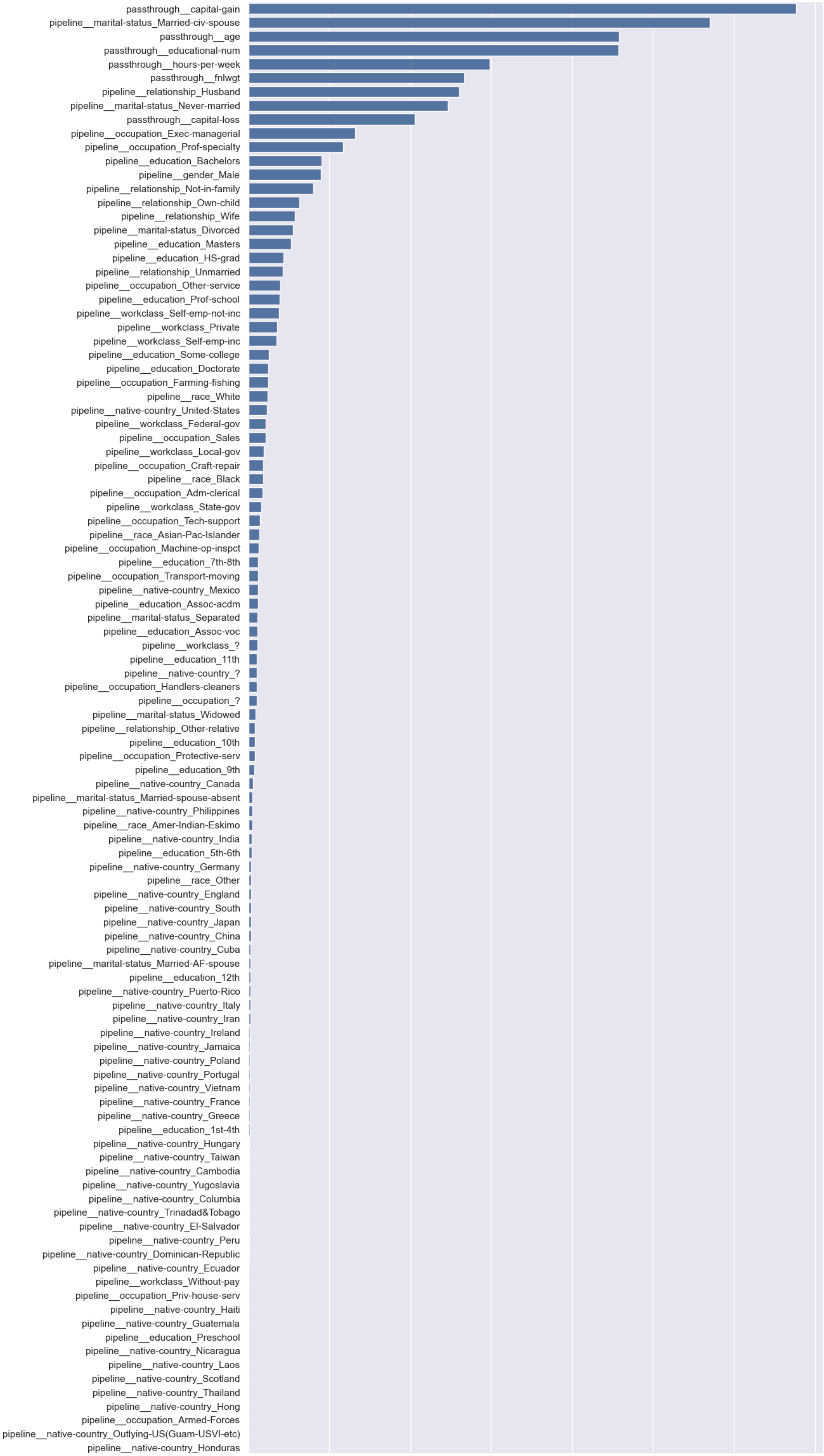
```
In [13]: clf.score(X_test_transformed, y_test)
```

```
Out[13]: 0.8624172524397734
```

Finally, let's see what features are considered important by the classifier.

```
In [14]: import seaborn as sns

         feature_importances = clf.feature_importances_

         # Sort the feature importances from greatest to least using the sorted indices
         sorted_indices = feature_importances.argsort()[::-1]
         sorted_feature_names = ct.get_feature_names_out()[sorted_indices]
         sorted_importances = feature_importances[sorted_indices]

         # # Create a bar plot of the feature importances
         sns.set(rc={'figure.figsize':(11.7,30)})
         sns.barplot(x=sorted_importances, y=sorted_feature_names)
```

```
Out[14]: <Axes: >
```


passthrough__capital-gain
pipeline__marital-status_Married-civ-spouse
passthrough__age
passthrough__educational-num
passthrough__hours-per-week
passthrough__fnlwgt
pipeline__relationship_Husband
pipeline__marital-status_Never-married
passthrough__capital-loss
pipeline__occupation_Exec-managerial
pipeline__occupation_Prof-specialty
pipeline__education_Bachelors
pipeline__gender_Male
pipeline__relationship_Not-in-family
pipeline__relationship_Own-child
pipeline__relationship_Wife
pipeline__marital-status_Divorced
pipeline__education_Masters
pipeline__education_HS-grad
pipeline__relationship_Unmarried
pipeline__occupation_Other-service
pipeline__education_Prof-school
pipeline__workclass_Self-emp-not-inc
pipeline__workclass_Private
pipeline__workclass_Self-emp-inc
pipeline__education_Some-college
pipeline__education_Doctorate
pipeline__occupation_Farming-fishing
pipeline__race_White
pipeline__native-country_United-States
pipeline__workclass_Federal-gov
pipeline__occupation_Sales
pipeline__workclass_Local-gov
pipeline__occupation_Craft-repair
pipeline__race_Black
pipeline__occupation_Adm-clerical
pipeline__workclass_State-gov
pipeline__occupation_Tech-support
pipeline__race_Asian-Pac-Islander
pipeline__occupation_Machine-op-inspct
pipeline__education_7th-8th
pipeline__occupation_Transport-moving
pipeline__native-country_Mexico
pipeline__education_Assoc-acdm
pipeline__marital-status_Separated
pipeline__education_Assoc-voc
pipeline__workclass_?
pipeline__education_11th
pipeline__native-country_?
pipeline__occupation_Handlers-cleaners
pipeline__occupation_?
pipeline__marital-status_Widowed
pipeline__relationship_Other-relative
pipeline__education_10th
pipeline__occupation_Protective-serv
pipeline__education_9th
pipeline__native-country_Canada
pipeline__marital-status_Married-spouse-absent
pipeline__native-country_Philippines
pipeline__race_Amer-Indian-Eskimo
pipeline__native-country_India
pipeline__education_5th-6th
pipeline__native-country_Germany
pipeline__race_Other
pipeline__native-country_England
pipeline__native-country_South
pipeline__native-country_Japan
pipeline__native-country_China
pipeline__native-country_Cuba
pipeline__marital-status_Married-AF-spouse
pipeline__education_12th
pipeline__native-country_Puerto-Rico
pipeline__native-country_Italy
pipeline__native-country_Iran
pipeline__native-country_Ireland
pipeline__native-country_Jamaica
pipeline__native-country_Poland
pipeline__native-country_Portugal
pipeline__native-country_Vietnam
pipeline__native-country_France
pipeline__native-country_Greece
pipeline__education_1st-4th
pipeline__native-country_Hungary
pipeline__native-country_Taiwan
pipeline__native-country_Cambodia
pipeline__native-country_Yugoslavia
pipeline__native-country_Columbia
pipeline__native-country_Trinadad&Tobago
pipeline__native-country_El-Salvador
pipeline__native-country_Peru
pipeline__native-country_Dominican-Republic
pipeline__native-country_Ecuador
pipeline__workclass_Without-pay
pipeline__occupation_Priv-house-serv
pipeline__native-country_Haiti
pipeline__native-country_Guatemala
pipeline__education_Preschool
pipeline__native-country_Nicaragua
pipeline__native-country_Laos
pipeline__native-country_Scotland
pipeline__native-country_Thailand
pipeline__native-country_Hong
pipeline__occupation_Armed-Forces
pipeline__native-country_Outlying-US(Guam-USVI-etc)
pipeline__native-country_Honduras

In [15]:

```
sorted_feature_names
```

```
Out[15]: array(['passthrough__capital-gain',
               'pipeline__marital-status_Married-civ-spouse', 'passthrough__age',
               'passthrough__educational-num', 'passthrough__hours-per-week',
               'passthrough__fnlwgt', 'pipeline__relationship_Husband',
               'pipeline__marital-status_Never-married',
               'passthrough__capital-loss',
               'pipeline__occupation_Exec-managerial',
               'pipeline__occupation_Prof-specialty',
               'pipeline__education_Bachelors', 'pipeline__gender_Male',
               'pipeline__relationship_Not-in-family',
               'pipeline__relationship_Own-child', 'pipeline__relationship_Wife',
               'pipeline__marital-status_Divorced', 'pipeline__education_Masters',
               'pipeline__education_HS-grad', 'pipeline__relationship_Unmarried',
               'pipeline__occupation_Other-service',
               'pipeline__education_Prof-school',
               'pipeline__workclass_Self-emp-not-inc',
               'pipeline__workclass_Private', 'pipeline__workclass_Self-emp-inc',
               'pipeline__education_Some-college',
               'pipeline__education_Doctorate',
               'pipeline__occupation_Farming-fishing', 'pipeline__race_White',
               'pipeline__native-country_United-States',
               'pipeline__workclass_Federal-gov', 'pipeline__occupation_Sales',
               'pipeline__workclass_Local-gov',
               'pipeline__occupation_Craft-repair', 'pipeline__race_Black',
               'pipeline__occupation_Adm-clerical',
               'pipeline__workclass_State-gov',
               'pipeline__occupation_Tech-support',
               'pipeline__race_Asian-Pac-Islander',
               'pipeline__occupation_Machine-op-inspct',
               'pipeline__education_7th-8th',
               'pipeline__occupation_Transport-moving',
               'pipeline__native-country_Mexico',
               'pipeline__education_Assoc-acdm',
               'pipeline__marital-status_Separated',
               'pipeline__education_Assoc-voc', 'pipeline__workclass_?',
               'pipeline__education_11th', 'pipeline__native-country_?',
               'pipeline__occupation_Handlers-cleaners', 'pipeline__occupation_?',
               'pipeline__marital-status_Widowed',
               'pipeline__relationship_Other-relative',
               'pipeline__education_10th', 'pipeline__occupation_Protective-serv',
               'pipeline__education_9th', 'pipeline__native-country_Canada',
               'pipeline__marital-status_Married-spouse-absent',
               'pipeline__native-country_Philippines',
               'pipeline__race_Amer-Indian-Eskimo',
               'pipeline__native-country_India', 'pipeline__education_5th-6th',
               'pipeline__native-country_Germany', 'pipeline__race_Other',
               'pipeline__native-country_England',
               'pipeline__native-country_South', 'pipeline__native-country_Japan',
               'pipeline__native-country_China', 'pipeline__native-country_Cuba',
               'pipeline__marital-status_Married-AF-spouse',
               'pipeline__education_12th', 'pipeline__native-country_Puerto-Rico',
               'pipeline__native-country_Italy', 'pipeline__native-country_Iran',
               'pipeline__native-country_Ireland',
               'pipeline__native-country_Jamaica',
               'pipeline__native-country_Poland',
               'pipeline__native-country_Portugal',
               'pipeline__native-country_Vietnam',
               'pipeline__native-country_France',
               'pipeline__native-country_Greece', 'pipeline__education_1st-4th',
               'pipeline__native-country_Hungary',
               'pipeline__native-country_Taiwan',
               'pipeline__native-country_Cambodia',
               'pipeline__native-country_Yugoslavia',
               'pipeline__native-country_Columbia',
               'pipeline__native-country_Trinadad&Tobago',
               'pipeline__native-country_El-Salvador',
               'pipeline__native-country_Peru',
               'pipeline__native-country_Dominican-Republic',
               'pipeline__native-country_Ecuador',
               'pipeline__workclass_Without-pay',
               'pipeline__occupation_Priv-house-serv',
               'pipeline__native-country_Haiti',
               'pipeline__native-country_Guatemala',
               'pipeline__education_Preschool',
               'pipeline__native-country_Nicaragua',
               'pipeline__native-country_Laos',
               'pipeline__native-country_Scotland',
               'pipeline__native-country_Thailand',
               'pipeline__native-country_Hong',
               'pipeline__occupation_Armed-Forces',
               'pipeline__native-country_Outlying-US(Guam-USVI-etc)',
               'pipeline__native-country_Honduras',
               'pipeline__workclass_Never-worked'], dtype=object)
```

Question 2

What are the most important features for this classifier? Do they include protected characteristics, such as race or gender?

Based on the figure above, the top most important features for the classifier with scores greater than approximately 0.01 are `passthrough__capital-gain`, `pipeline__marital-status_Married-civ-spouse`, `passthrough__age`, `passthrough__educational-num`, `passthrough__hours-per-week`, `passthrough__fnlwgt`, `pipeline__relationship_Husband`, `pipeline__marital_status_Never-married`, `passthrough__capital-loss`, `passthrough__occupation_Exec-managerial`, `pipeline__occupation_Prof-specialty`, `pipeline__education_Bachelors`, `pipeline__gender_Male`, `pipeline__relationship_Not-in-family`, `pipeline__relationship_Own-child', 'pipeline__relationship_Wife`, `pipeline__marital-status_Divorced`, and `pipeline__education_Masters`. There are many protected characteristics among the most important features, most notably `pipeline__marital-status_Married-civ-spouse`, `passthrough__age`, `pipeline__relationship_Husband`, and `pipeline__marital_status_Never-married`, `pipeline__gender_Male`, `pipeline__relationship_Not-in-family`, `pipeline__relationship_Own-child', 'pipeline__relationship_Wife`, and `pipeline__marital-status_Divorced`. These protected characteristics belong to features such as `marital status`, `age`, `relationship`, `gender`.

Question 3

From Assignment 3, we have learned that a classifier may perform well in terms of accuracy, but being unfair to protected groups in the dataset. Use what you have learned in Assignment 3 and **evaluate this classifier for fairness in treating the two gender groups included in this dataset.** In particular, do the following:

- Compute the 6 fairness metrics and the Average Distance from the Reference on training and test sets. You may reuse portions of code you have included in Assignment 3.
- Comment on the results, providing an interpretation for each computed metric; how different is the treatment of the two groups? Is one (or more) of the metrics particularly concerning?

Here is a recap of the fairness metrics:

1. *Predicted Positive Rate Disparity (PPRD)*, whether the numbers of positive predictions are on par across groups.
2. *Predicted Positive Group Rate Disparity (PPGRD)*, whether the rates of positive predictions are on par across groups.
3. *False Discovery Rate Disparity (FDRD)*, whether the ratios of false positives to predicted positives are on par across groups.
4. *False Positive Rate Disparity (FPRD)*, whether the ratios of false positives to actual negatives are on par across groups.
5. *False Omission Rate Disparity (FORD)*, whether the ratios of false negatives to predicted negatives are on par across groups.
6. *False Negative Rate Disparity (FNRD)*, whether the ratios of false negatives to actual positives are on par across groups.

In [16]:

```
# Your answer here (you may add more cells)
# Add as many cells as needed to compute the required metrics for every classifi
# also add markdown cells if you want to add comments or notes about your result

# Splitting datasets by gender
train_df_m = train_df[train_df["gender"] == "Male"]
train_df_f = train_df[train_df["gender"] == "Female"]
test_df_m = test_df[test_df["gender"] == "Male"]
test_df_f = test_df[test_df["gender"] == "Female"]
# train_df_m.head()

# Creating training and test sets and separating features and target
X_train_m, y_train_m = (
    train_df_m.drop(columns=["income"]),
    train_df_m["income"],
)
X_test_m, y_test_m = (
    test_df_m.drop(columns=["income"]),
    test_df_m["income"],
)
X_train_f, y_train_f = (
    train_df_f.drop(columns=["income"]),
    train_df_f["income"],
)
X_test_f, y_test_f = (
    test_df_f.drop(columns=["income"]),
    test_df_f["income"],
)
```

```
# xsets = [X_train_m, X_test_m, X_train_f, X_test_f]
# ysets = [y_train_m, y_test_m, y_train_f, y_test_f]

# Do not need to refit due to both ultimately training on the same set as a whol
X_train_transformed_m = pd.DataFrame(ct.transform(X_train_m).toarray(), columns=
X_train_transformed_f = pd.DataFrame(ct.transform(X_train_f).toarray(), columns=

X_test_transformed_m = pd.DataFrame(ct.transform(X_test_m).toarray(), columns=cc
X_test_transformed_f = pd.DataFrame(ct.transform(X_test_f).toarray(), columns=cc
```

In [17]:

```
fairness_mets = {
    "model": [],
    "PPRD": [],
    "PPGRD": [],
    "FDRD": [],
    "FPRD": [],
    "FORD": [],
    "FNRD": [],
    # "PPRD_dfr": [],
    # "PPGRD_dfr": [],
    # "FDRD_dfr": [],
    # "FPRD_dfr": [],
    # "FORD_dfr": [],
    # "FNRD_dfr": [],
    "adfr": [],
}
```

In [18]:

```
# confusion_matrix(y_m, model.predict(X_m))
```

In [19]:

```
# https://datascience.stackexchange.com/questions/28493/confusion-matrix-get-ite

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

def fairness_metrics(modelname, X_m_pred, y_m, X_f_pred, y_f, name):
# def fairness_metrics(modelname, model, X_m, y_m, X_f, y_f, name):
    # cm_m = confusion_matrix(y_m, model.predict(X_m))
    # cm_f = confusion_matrix(y_f, model.predict(X_f))
    cm_m = confusion_matrix(y_m, X_m_pred)
    cm_f = confusion_matrix(y_f, X_f_pred)

    # TP_m = cm_m[0][0]
    # FP_m = cm_m[0][1]
    # FN_m = cm_m[1][0]
    # TN_m = cm_m[1][1]

    # TP_f = cm_f[0][0]
    # FP_f = cm_f[0][1]
    # FN_f = cm_f[1][0]
    # TN_f = cm_f[1][1]

    TP_m = cm_m[1][1]
    FP_m = cm_m[0][1]
    FN_m = cm_m[1][0]
    TN_m = cm_m[0][0]

    TP_f = cm_f[1][1]
    FP_f = cm_f[0][1]
    FN_f = cm_f[1][0]
    TN_f = cm_f[0][0]

    PPRD = (TP_f + FP_f)/(TP_m + FP_m)
    PPGRD = ((TP_f + FP_f)/(TP_f + FP_f + FN_f + TN_f))/((TP_m + FP_m)/(TP_m + F
    FDRD = (FP_f/(TP_f + FP_f))/(FP_m/(TP_m + FP_m))
    FPRD = (FP_f/(TN_f + FP_f))/(FP_m/(TN_m + FP_m))
    FORD = (FN_f/(TN_f + FN_f))/(FN_m/(TN_m + FN_m))
    FNRD = (FN_f/(TP_f + FN_f))/(FN_m/(TP_m + FN_m))

    PPRD_adfr = abs(PPRD - 1)
    PPGRD_adfr = abs(PPGRD - 1)
    FDRD_adfr = abs(FDRD - 1)
    FPRD_adfr = abs(FPRD - 1)
    FORD_adfr = abs(FORD - 1)
    FNRD_adfr = abs(FNRD - 1)
    adfr = np.mean([PPRD_adfr, PPGRD_adfr, FDRD_adfr, FPRD_adfr, FORD_adfr, FNRD

    fairness_mets["model"].append(str(modelname) + " (" + str(name) + ")")
    fairness_mets["PPRD"].append(PPRD)
    fairness_mets["PPGRD"].append(PPGRD)
    fairness_mets["FDRD"].append(FDRD)
    fairness_mets["FPRD"].append(FPRD)
    fairness_mets["FORD"].append(FORD)
    fairness_mets["FNRD"].append(FNRD)
    # fairness_mets["PPRD_adfr"].append(PPRD_adfr)
    # fairness_mets["PPGRD_adfr"].append(PPGRD_adfr)
    # fairness_mets["FDRD_adfr"].append(FDRD_adfr)
    # fairness_mets["FPRD_adfr"].append(FPRD_adfr)
    # fairness_mets["FORD_adfr"].append(FORD_adfr)
    # fairness_mets["FNRD_adfr"].append(FNRD_adfr)
    fairness_mets["adfr"].append(adfr)
```

In [20]:

```
display(train_df["gender"].value_counts(normalize=False).sort_index().sort_index
display(test_df["gender"].value_counts(normalize=False).sort_index().sort_index(

# fairness_metrics("Random Forest", clf, X_train_transformed_m, y_train_m, X_tra
# fairness_metrics("Random Forest", clf, X_test_transformed_m, y_test_m, X_test_
fairness_metrics("Random Forest", clf.predict(X_train_transformed_m), y_train_m,
fairness_metrics("Random Forest", clf.predict(X_test_transformed_m), y_test_m, c

fairness_mets_df = pd.DataFrame(fairness_mets)
fairness_mets_df = fairness_mets_df.set_index(["model"])
fairness_mets_df
```

```
gender
Female    11323
Male      22866
Name: count, dtype: int64
gender
Female    4869
Male      9784
Name: count, dtype: int64
```

Out[20]:

	PPRD	PPGRD	FDRD	FPRD	FORD	FNRD	adfr
model							
Random Forest (Training)	0.175265	0.353936	0.389925	0.107931	0.255968	0.852545	0.644072
Random Forest (Testing)	0.143736	0.288830	0.837058	0.188731	0.351694	1.211745	0.566949

~~The model exhibits extreme amounts of bias against female individuals, where every fairness metric except `FNRD` on the testing set is less than 1, indicate bias against female individuals. Most notably, the `FPRD` metric for the training and testing sets provides values of 0.107931 and 0.188731 respectively, indicating an extremely high false positive rate for male individuals compared to female individuals. The `FORD` for the training and testing sets provides values of 0.255968 and 0.351694 respectively, indicating an extremely high ratio of false negatives to predicted negatives for male individuals compared to female individuals. The value of `adfr` is relatively high, indicating the classifier is relatively unfair.~~

Refined answer:

The model exhibits extreme amounts of bias against female individuals, where every fairness metric (except `FNRD`) on the testing set significantly deviates from the base value of 1, most of which indicate bias against female individuals. Most notably, the `FPRD` metric for the training and testing sets provides values of 0.107931 and 0.188731 respectively, indicating an extremely high false positive rate for male individuals compared to female individuals. The `FORD` for the training and testing sets provides values of 0.255968 and 0.351694 respectively. These smaller values may occur because the denominator of `FORD` for females is higher, indicating females group has more predicted negatives, which is also suggested by the high values of `FNRD`, indicating females group has few predictive positives, which we now is true because this dataset is inherently imbalanced against females.

Debiasing techniques: dropping protected characteristics

A first idea to fix this issue could be dropping the protected characteristics from our dataset before training the classifier. Let's try this out and see if there is any improvement.

Question 4

1. Drop race, gender and native country from training and test set (we are focusing on gender but we will drop race and native country for good

measure).

2. Transform the cleaned dataset using one-hot encoding.
3. Re-train the random forest classifier.
4. Compare accuracy and fairness of this new classifier to the previous one. Do we see any improvement? How do you explain the changes you see (or lack thereof)? Note that, to compare fairness, you will need to have a way to identify the gender of each sample, even though you are not using this feature for classification.
5. Create a new plot of the feature importance according to this classifier. Do you see any changes from the first one?

Hint: steps 2, 3 and 5 can be completed by tweaking the starting code given at the beginning of this assignment. Ask a TA or instructor if you need help in doing that.

In [21]:

```
# Your answer here (you may add more cells)
# Step 1
X_train_new = X_train.drop(columns = ["race", "gender", "native-country"])
X_test_new = X_test.drop(columns = ["race", "gender", "native-country"])
# X_train_new
```

In [22]:

```
# Step 2
categorical_feats_new = ["workclass",
                     "education",
                     "marital-status",
                     "occupation",
                     "relationship",
                     ]  # Apply one-hot encoding
passthrough_feats_new = ["age",
                    "fnlwgt",
                    "educational-num",
                    "capital-gain",
                    "capital-loss",
                    "hours-per-week"
                    ]  # Numerical - no need to scale
target = "income"

ct_new = make_column_transformer(
    (
        make_pipeline(OneHotEncoder(handle_unknown="ignore",drop="if_binary")),
        categorical_feats_new,
    ),  # OHE on categorical features
    ("passthrough", passthrough_feats_new)  # no transformations on numerical fe
)

X_train_transformed_new = ct_new.fit_transform(X_train_new).toarray()

column_names_new = list(
    ct_new.named_transformers_["pipeline"].get_feature_names_out(
        categorical_feats_new
    )
) + passthrough_feats_new

X_test_transformed_new = ct_new.transform(X_test_new).toarray()
```

```
X_train_transformed_new_df = pd.DataFrame(X_train_transformed_new, columns=colum
X_test_transformed_new_df = pd.DataFrame(X_test_transformed_new, columns=column_
```

In [23]:

```
# Step 3
clf_new = RandomForestClassifier(random_state=0, max_depth = 19, n_estimators =
```

In [24]:

```
# Step 4.1
print("Training accuracy: " + str(clf.score(X_train_transformed, y_train)))
print("Testing accuracy: " + str(clf.score(X_test_transformed, y_test)))
print("Training accuracy (New): " + str(clf_new.score(X_train_transformed_new, y
print("Testing accuracy (New): " + str(clf_new.score(X_test_transformed_new, y_t
```

```
Training accuracy: 0.9064318932990143
Testing accuracy: 0.8624172524397734
Training accuracy (New): 0.9185410512153032
Testing accuracy (New): 0.860301644714393
```

In [25]:

```
# Step 4.2
# Splitting datasets by gender (Despite the variable being removed)

train_groups = train_df["gender"]
test_groups = test_df["gender"]

X_train_transformed_new_m_df = pd.DataFrame(X_train_transformed_new[train_groups
X_train_transformed_new_f_df = pd.DataFrame(X_train_transformed_new[train_groups
X_test_transformed_new_m_df = pd.DataFrame(X_test_transformed_new[test_groups ==
X_test_transformed_new_f_df = pd.DataFrame(X_test_transformed_new[test_groups ==
# display(X_train_transformed_new_m_df.head())

# fairness_metrics("Random Forest", clf_new, X_train_transformed_new_m_df, y_tra
# fairness_metrics("Random Forest", clf_new, X_test_transformed_new_m_df, y_test
fairness_metrics("Random Forest", clf_new.predict(X_train_transformed_new_m_df),
fairness_metrics("Random Forest", clf_new.predict(X_test_transformed_new_m_df),
fairness_mets_df = pd.DataFrame(fairness_mets)
fairness_mets_df = fairness_mets_df.set_index(["model"])
fairness_mets_df
```

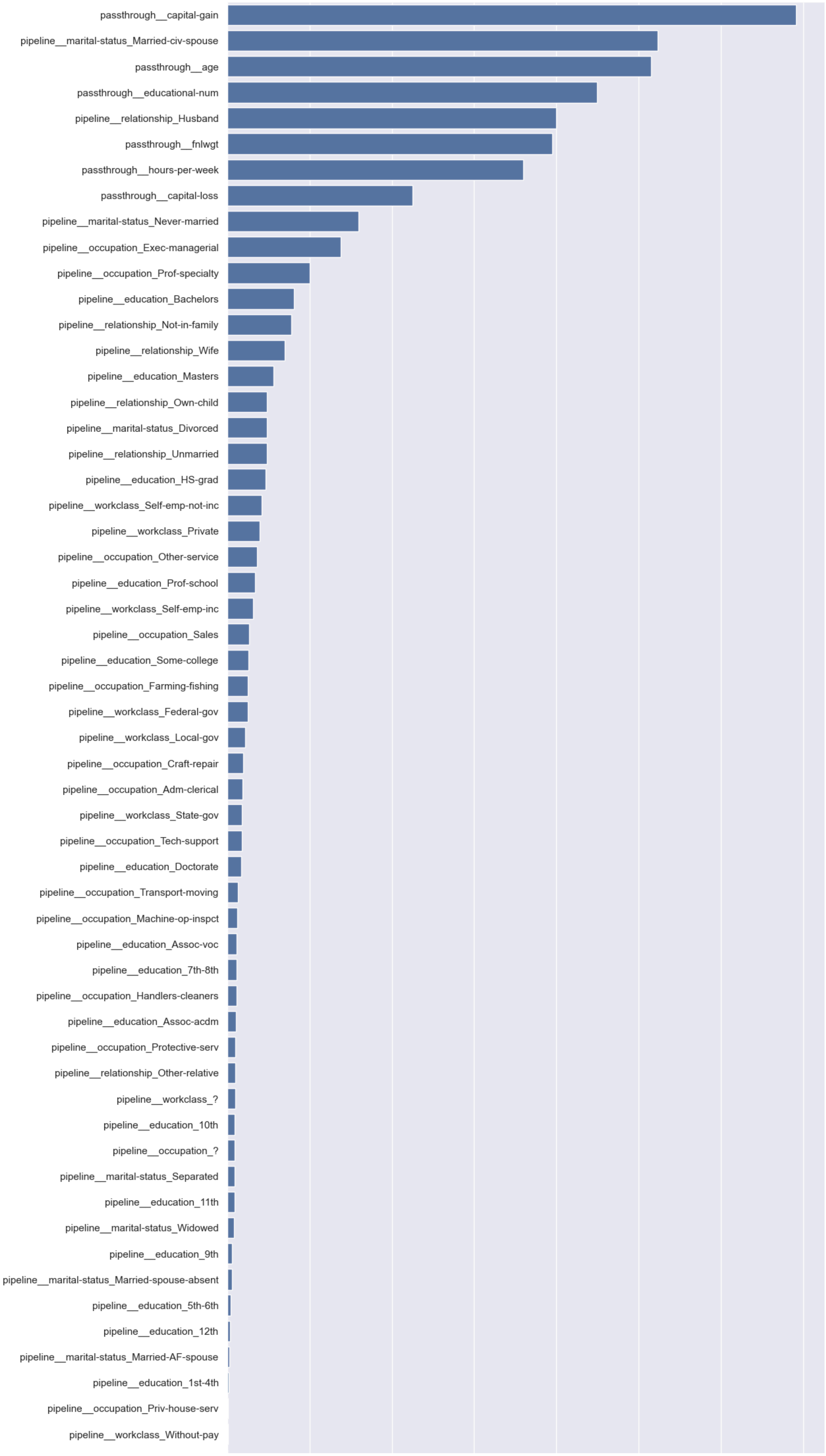
Out[25]:

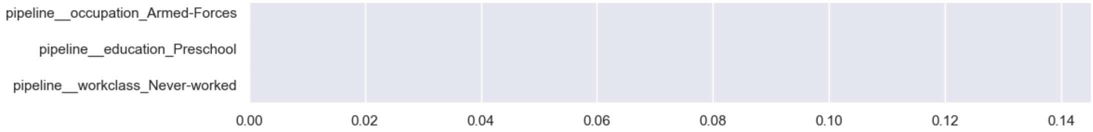
	PPRD	PPGRD	FDRD	FPRD	FORD	FNRD	adfr
model							
Random Forest (Training)	0.175265	0.353936	0.389925	0.107931	0.255968	0.852545	0.644072
Random Forest (Testing)	0.143736	0.288830	0.837058	0.188731	0.351694	1.211745	0.566949
Random Forest (Training (New))	0.176575	0.356581	0.337220	0.094040	0.253960	0.847751	0.655645
Random Forest (Testing (New))	0.150043	0.301504	0.987371	0.232391	0.352168	1.215761	0.532047

Q4.4: There is relatively minimal changes in accuracy and fairness metrics for each dataset. The accuracy upon the removal of `race`, `gender`, `native-country` increased slightly on the training set from 0.9064318932990143 to 0.9185410512153032, and decreased slightly on the testing set from 0.8624172524397734 to 0.860301644714393. In terms of fairness metrics, there are no obvious changes in the values of `PPRD`, `PPGRD`, `FORD`, and `FNRD`, and the values of `FDRD` and `FPRD` have been further from the good value "1" for the training set been closer to the good value "1" for the testing set. The `adfr` is a bit further from the good value "0" for the training set, but is somehow closer to the good value "0" for the testing set, which is a very slight improvement.

In [26]:
```
# Step 5
feature_importances_new = clf_new.feature_importances_

# Sort the feature importances from greatest to least using the sorted indices
sorted_indices_new = feature_importances_new.argsort()[::-1]
sorted_feature_names_new = ct_new.get_feature_names_out()[sorted_indices_new]
sorted_importances_new = feature_importances_new[sorted_indices_new]

# # Create a bar plot of the feature importances
sns.set(rc={'figure.figsize':(11.7,30)})
sns.barplot(x=sorted_importances_new, y=sorted_feature_names_new)
```

Out[26]:
```
<Axes: >
```


passthrough__capital-gain
pipeline__marital-status_Married-civ-spouse
passthrough__age
passthrough__educational-num
pipeline__relationship_Husband
passthrough__fnlwgt
passthrough__hours-per-week
passthrough__capital-loss
pipeline__marital-status_Never-married
pipeline__occupation_Exec-managerial
pipeline__occupation_Prof-specialty
pipeline__education_Bachelors
pipeline__relationship_Not-in-family
pipeline__relationship_Wife
pipeline__education_Masters
pipeline__relationship_Own-child
pipeline__marital-status_Divorced
pipeline__relationship_Unmarried
pipeline__education_HS-grad
pipeline__workclass_Self-emp-not-inc
pipeline__workclass_Private
pipeline__occupation_Other-service
pipeline__education_Prof-school
pipeline__workclass_Self-emp-inc
pipeline__occupation_Sales
pipeline__education_Some-college
pipeline__occupation_Farming-fishing
pipeline__workclass_Federal-gov
pipeline__workclass_Local-gov
pipeline__occupation_Craft-repair
pipeline__occupation_Adm-clerical
pipeline__workclass_State-gov
pipeline__occupation_Tech-support
pipeline__education_Doctorate
pipeline__occupation_Transport-moving
pipeline__occupation_Machine-op-inspct
pipeline__education_Assoc-voc
pipeline__education_7th-8th
pipeline__occupation_Handlers-cleaners
pipeline__education_Assoc-acdm
pipeline__occupation_Protective-serv
pipeline__relationship_Other-relative
pipeline__workclass_?
pipeline__education_10th
pipeline__occupation_?
pipeline__marital-status_Separated
pipeline__education_11th
pipeline__marital-status_Widowed
pipeline__education_9th
pipeline__marital-status_Married-spouse-absent
pipeline__education_5th-6th
pipeline__education_12th
pipeline__marital-status_Married-AF-spouse
pipeline__education_1st-4th
pipeline__occupation_Priv-house-serv
pipeline__workclass_Without-pay



```
In [27]: sorted_feature_names_new
```

```
Out[27]: array(['passthrough__capital-gain',
                'pipeline__marital-status_Married-civ-spouse', 'passthrough__age',
                'passthrough__educational-num', 'pipeline__relationship_Husband',
                'passthrough__fnlwgt', 'passthrough__hours-per-week',
                'passthrough__capital-loss',
                'pipeline__marital-status_Never-married',
                'pipeline__occupation_Exec-managerial',
                'pipeline__occupation_Prof-specialty',
                'pipeline__education_Bachelors',
                'pipeline__relationship_Not-in-family',
                'pipeline__relationship_Wife', 'pipeline__education_Masters',
                'pipeline__relationship_Own-child',
                'pipeline__marital-status_Divorced',
                'pipeline__relationship_Unmarried', 'pipeline__education_HS-grad',
                'pipeline__workclass_Self-emp-not-inc',
                'pipeline__workclass_Private',
                'pipeline__occupation_Other-service',
                'pipeline__education_Prof-school',
                'pipeline__workclass_Self-emp-inc', 'pipeline__occupation_Sales',
                'pipeline__education_Some-college',
                'pipeline__occupation_Farming-fishing',
                'pipeline__workclass_Federal-gov', 'pipeline__workclass_Local-gov',
                'pipeline__occupation_Craft-repair',
                'pipeline__occupation_Adm-clerical',
                'pipeline__workclass_State-gov',
                'pipeline__occupation_Tech-support',
                'pipeline__education_Doctorate',
                'pipeline__occupation_Transport-moving',
                'pipeline__occupation_Machine-op-inspct',
                'pipeline__education_Assoc-voc', 'pipeline__education_7th-8th',
                'pipeline__occupation_Handlers-cleaners',
                'pipeline__education_Assoc-acdm',
                'pipeline__occupation_Protective-serv',
                'pipeline__relationship_Other-relative', 'pipeline__workclass_?',
                'pipeline__education_10th', 'pipeline__occupation_?',
                'pipeline__marital-status_Separated', 'pipeline__education_11th',
                'pipeline__marital-status_Widowed', 'pipeline__education_9th',
                'pipeline__marital-status_Married-spouse-absent',
                'pipeline__education_5th-6th', 'pipeline__education_12th',
                'pipeline__marital-status_Married-AF-spouse',
                'pipeline__education_1st-4th',
                'pipeline__occupation_Priv-house-serv',
                'pipeline__workclass_Without-pay',
                'pipeline__occupation_Armed-Forces',
                'pipeline__education_Preschool',
                'pipeline__workclass_Never-worked'], dtype=object)
```

Q4.5: The top most important features for the classifier with scores greater than approximately 0.01 are `passthrough__capital-gain` , `pipeline__marital-status_Married-civ-spouse` , `passthrough__age` , `passthrough__educational-num` , `pipeline__relationship_Husband` , `passthrough__fnlwgt` , `passthrough__hours-per-week` , `passthrough__capital-loss` , `pipeline__marital-status_Never-married`, `pipeline__occupation_Exec-managerial`, `pipeline__occupation_Prof-specialty`, `pipeline__education_Bachelors`, `pipeline__relationship_Not-in-family`, `pipeline__relationship_Wife`, `pipeline__education_Masters`, `pipeline__relationship_Own-child`, `pipeline__marital-status_Divorced`, `pipeline__relationship_Unmarried` and `pipeline__education_HS-grad`. The only top most feature that was featured in the original model that did not appear in the above list was `pipeline__gender_Male`, which would have been excluded from the new model from the start.

Debiasing techniques: undersampling

As you should have seen when exploring the dataset, the groups of males and females who make more or less than \$50k are of very different sizes. This alone may have a significant impact on the way the classifier is trained, by teaching it that some groups are much more likely to make more than \$50k than others.

Let's try to fix this problem by creating a more balanced training set.

Question 5

1. Run the cell below to create a new training set by selecting a subset of samples from the original one, in which the groups of males and females who make more or less than \$50k are of equal size. To use the maximum number of training samples possible, the size of each group should be equal to the size of the smallest of these groups in the original dataset. **What is the size of each group, and of the final training set?**
2. Separate features from target, and transform the cleaned dataset using one-hot encoding. **Remeber to re-transform the test set accordingly!**
3. Re-train the random forest classifier.
4. Compare accuracy and fairness of this new classifier to the previous ones. Do we see any improvement? How do you explain the changes you see (or lack thereof)? Pay particular attention to the difference in results on the training and test set: can you explain these results?
5. Create a new plot of the feature importance according to this classifier. Do you see any changes from the previous ones?

In [28]:

```
# Check the distribution of gender and income
gender_distribution = train_df['gender'].value_counts()
income_distribution = train_df['income'].value_counts()

# Create balanced subsets
balanced_subsets = []
smallest = train_df.shape[0]

# Finding size of smallest subset by gender and income
for gender_category in gender_distribution.index:
    for income_category in income_distribution.index:
        if train_df[(train_df['gender'] == gender_category) & (train_df['income'
            smallest = train_df[(train_df['gender'] == gender_category) & (train

# Sampling subsets
for gender_category in gender_distribution.index:
    for income_category in income_distribution.index:
        subset = train_df[(train_df['gender'] == gender_category) & (train_df['i
        subset = subset.sample(smallest, random_state=0)  # Sample to match the
        balanced_subsets.append(subset)

# Merge the balanced subsets to create the final balanced dataset
balanced_df = pd.concat(balanced_subsets)
print(balanced_df.shape, train_df[(train_df["gender"] == "Female") & (train_df["
```

```
(4996, 15) (1249, 15)
```

Q5.1: The size of the balanced training dataset is 4996, with $\frac{4996}{4}=1249$ samples in each combination group of `income` and `gender`, which matches the size of the smallest of these groups (Female with income >50K) in the original training dataset that only has 1249 samples.

In [29]:

```
# STEP 1
# Run this cell create training and test sets
# train_df_bal, test_df_bal = train_test_split(balanced_df, test_size=0.3, rando

X_train_bal, y_train_bal = (
    balanced_df.drop(columns=["income"]),
    balanced_df["income"],
)
X_test_bal, y_test_bal = (
    test_df.drop(columns=["income"]),
    test_df["income"],
)
```

In [30]:

```
# Your answer here (you may add more cells) # Need to refit column transformer d

# STEP 2
# Run this cell to do the necessary dataset preprocessing (encoding of categoric
# Note that, since we are using a tree based classifier, we don't need to scale
# numerical features.
categorical_feats = ["workclass",
                     "education",
                     "marital-status",
                     "occupation",
                     "relationship",
                     "race",
                     "gender",
                     "native-country",
                     ]  # Apply one-hot encoding
passthrough_feats = ["age",
                     "fnlwgt",
                     "educational-num",
                     "capital-gain",
                     "capital-loss",
                     "hours-per-week"
                     ]  # Numerical - no need to scale
target = "income"

ct_bal = make_column_transformer(
    (
        make_pipeline(OneHotEncoder(handle_unknown="ignore",drop="if_binary")),
        categorical_feats,
    ),  # OHE on categorical features
    ("passthrough", passthrough_feats)  # no transformations on numerical featur
)

X_train_transformed_bal = ct_bal.fit_transform(X_train_bal).toarray()
X_test_transformed_bal = ct_bal.transform(X_test_bal).toarray()

column_names_bal = list(
    ct_bal.named_transformers_["pipeline"].get_feature_names_out(
        categorical_feats
    )
) + passthrough_feats
```

In [31]:

```
# column_names_bal
X_test_transformed_bal
```

Out[31]:

```
array([[ 0.,  0.,  0., ...,  0.,  0., 40.],
       [ 0.,  0.,  0., ...,  0.,  0., 30.],
       [ 0.,  1.,  0., ...,  0.,  0., 40.],
       ...,
       [ 0.,  0.,  0., ...,  0.,  0., 40.],
       [ 0.,  0.,  0., ...,  0.,  0., 40.],
       [ 0.,  0.,  0., ...,  0.,  0., 40.]])
```

In [32]:

```
# STEP 3
# Run this cell to train a random forest classifer. The hyperparameters have bee

clf_bal = RandomForestClassifier(random_state=0, max_depth = 19, n_estimators =
```

In [33]:

```
# Step 4.1
print("Training accuracy: " + str(clf.score(X_train_transformed, y_train)))
print("Testing accuracy: " + str(clf.score(X_test_transformed, y_test)))
print("Training accuracy (Balanced): " + str(clf_bal.score(X_train_transformed_b
print("Testing accuracy (Balanced): " + str(clf_bal.score(X_test_transformed_bal
```

```
Training accuracy: 0.9064318932990143
Testing accuracy: 0.8624172524397734
Training accuracy (Balanced): 0.960568454763811
Testing accuracy (Balanced): 0.8035897085920972
```

In [34]:

```
# Step 4.2
# Splitting datasets by gender

X_train_transformed_bal = pd.DataFrame(X_train_transformed_bal, columns=column_n
X_test_transformed_bal = pd.DataFrame(X_test_transformed_bal, columns=column_nam

X_train_transformed_bal_m_df = pd.DataFrame(X_train_transformed_bal[X_train_tran
X_train_transformed_bal_f_df = pd.DataFrame(X_train_transformed_bal[X_train_tran
X_test_transformed_bal_m_df = pd.DataFrame(X_test_transformed_bal[X_test_transfo
X_test_transformed_bal_f_df = pd.DataFrame(X_test_transformed_bal[X_test_transfo

y_train_bal_m = balanced_df[balanced_df["gender"] == "Male"]["income"]
y_train_bal_f = balanced_df[balanced_df["gender"] == "Female"]["income"]
y_test_bal_m = test_df[test_df["gender"] == "Male"]["income"]
y_test_bal_f = test_df[test_df["gender"] == "Female"]["income"]
# display(X_train_transformed_bal_m_df.head())

# fairness_metrics("Random Forest", clf_bal, X_train_transformed_bal_m_df, y_tra
# fairness_metrics("Random Forest", clf_bal, X_test_transformed_bal_m_df, y_test
fairness_metrics("Random Forest", clf_bal.predict(X_train_transformed_bal_m_df),
fairness_metrics("Random Forest", clf_bal.predict(X_test_transformed_bal_m_df),
fairness_mets_df = pd.DataFrame(fairness_mets)
fairness_mets_df = fairness_mets_df.set_index(["model"])
fairness_mets_df
```

Out[34]:

	PPRD	PPGRD	FDRD	FPRD	FORD	FNRD	adfr
model							
Random Forest (Training)	0.175265	0.353936	0.389925	0.107931	0.255968	0.852545	0.644072
Random Forest (Testing)	0.143736	0.288830	0.837058	0.188731	0.351694	1.211745	0.566949
Random Forest (Training (New))	0.176575	0.356581	0.337220	0.094040	0.253960	0.847751	0.655645
Random Forest (Testing (New))	0.150043	0.301504	0.987371	0.232391	0.352168	1.215761	0.532047
Random Forest (Training (Balanced))	0.949963	0.949963	0.378593	0.359649	0.709013	0.750000	0.317137
Random Forest (Testing (Balanced))	0.252283	0.506949	1.408318	0.557327	0.217873	0.843031	0.505143

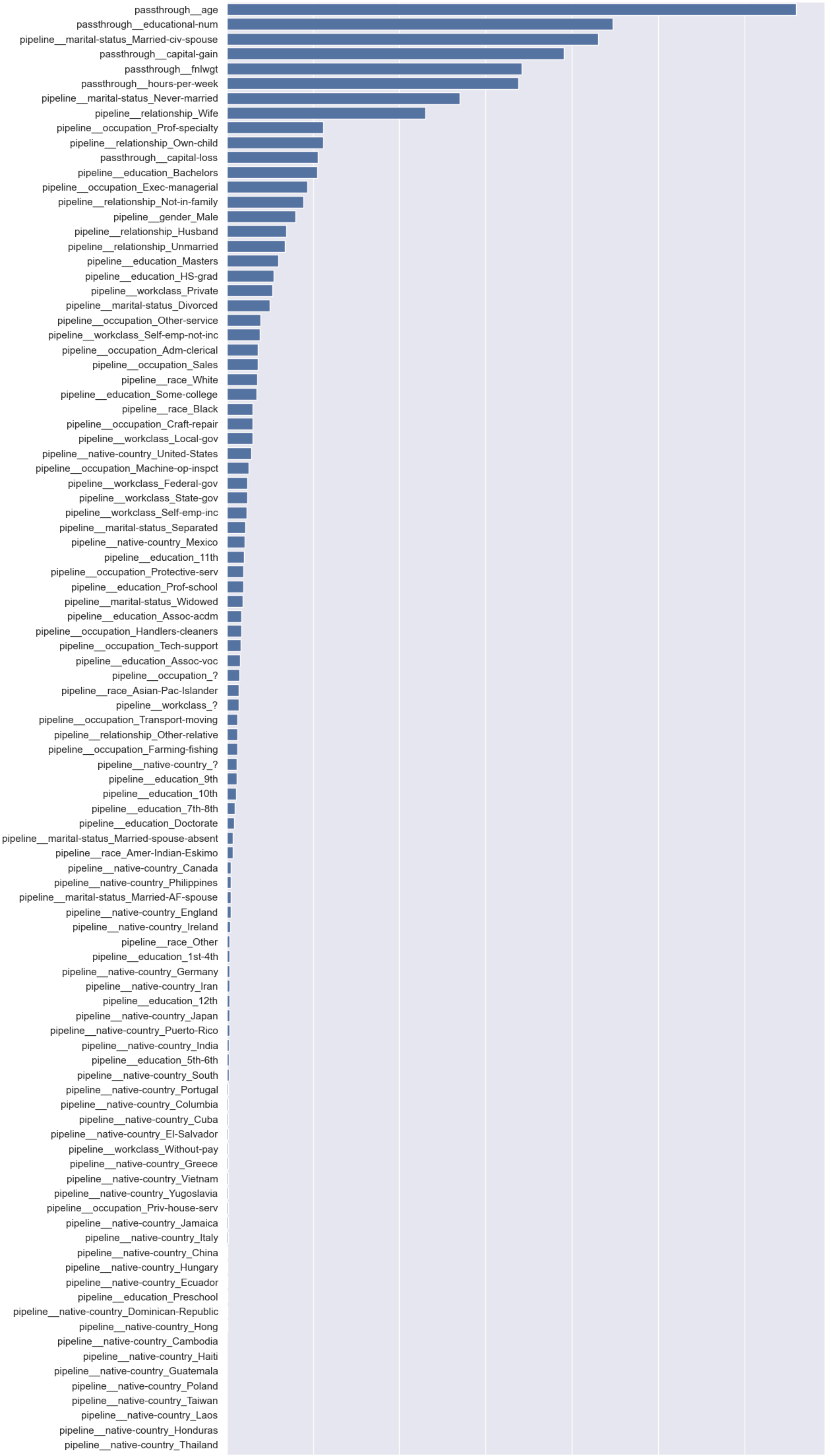
~~**Q5.4:** There are some significant changes in the accuracy and fairness metrics for each dataset after undersampling. The accuracy upon undersampling increased on the training set from 0.9064318932990143 to 0.960568454763811, and decreased slightly on the testing set from 0.8624172524397734 to 0.8035897085920972. There is a substantial increase in values for most the fairness metrics in the undersampled dataset compared to the original, with the exception of `FDRD` , `FNRD` and `adfr` . `PPRD` and `PPGRD` become very close in value to the reference value of 1, while `adfr` becomes relatively closer in value to the reference value of 0. `FDRD` is decreased for the training set and increased for the testing set, while `FNRD` is decreased for both the training and testing sets.~~

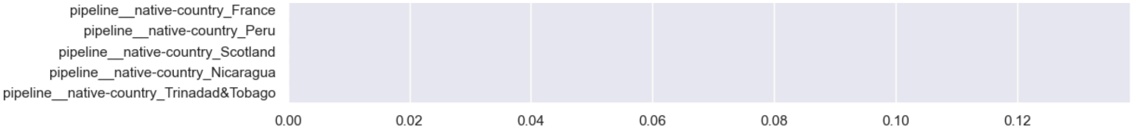
Refined answer:

Q5.4: There are some significant changes in the accuracy and fairness metrics for each dataset after undersampling. The accuracy upon undersampling increased on the training set from 0.9064318932990143 to 0.960568454763811, and decreased slightly on the testing set from 0.8624172524397734 to 0.8035897085920972. The increase in training accuracy and decrease in testing accuracy indicates the model is slightly **overfitted to the data** because we have a larger gap between the training score and the testing score. There is a substantial increase in values for most of the fairness metrics in the undersampled dataset compared to the original, with the exception of `FDRD`, `FNRD`, and `adfr`. `PPRD` and `PPGRD` become very close in value to the reference value of 1, while `adfr` becomes relatively closer in value to the reference value of 0. `FDRD` is decreased for the training set and increased for the testing set, while `FNRD` is decreased for both the training and testing sets.

In [35]:
```
# Step 5
feature_importances_bal = clf_bal.feature_importances_

# Sort the feature importances from greatest to least using the sorted indices
sorted_indices_bal = feature_importances_bal.argsort()[::-1]
sorted_feature_names_bal = ct_bal.get_feature_names_out()[sorted_indices_bal]
sorted_importances_bal = feature_importances_bal[sorted_indices_bal]

# # Create a bar plot of the feature importances
sns.set(rc={'figure.figsize':(11.7,30)})
sns.barplot(x=sorted_importances_bal, y=sorted_feature_names_bal)
```

Out[35]:
```
<Axes: >
```


passthrough__age
passthrough__educational-num
pipeline__marital-status_Married-civ-spouse
passthrough__capital-gain
passthrough__fnlwgt
passthrough__hours-per-week
pipeline__marital-status_Never-married
pipeline__relationship_Wife
pipeline__occupation_Prof-specialty
pipeline__relationship_Own-child
passthrough__capital-loss
pipeline__education_Bachelors
pipeline__occupation_Exec-managerial
pipeline__relationship_Not-in-family
pipeline__gender_Male
pipeline__relationship_Husband
pipeline__relationship_Unmarried
pipeline__education_Masters
pipeline__education_HS-grad
pipeline__workclass_Private
pipeline__marital-status_Divorced
pipeline__occupation_Other-service
pipeline__workclass_Self-emp-not-inc
pipeline__occupation_Adm-clerical
pipeline__occupation_Sales
pipeline__race_White
pipeline__education_Some-college
pipeline__race_Black
pipeline__occupation_Craft-repair
pipeline__workclass_Local-gov
pipeline__native-country_United-States
pipeline__occupation_Machine-op-inspct
pipeline__workclass_Federal-gov
pipeline__workclass_State-gov
pipeline__workclass_Self-emp-inc
pipeline__marital-status_Separated
pipeline__native-country_Mexico
pipeline__education_11th
pipeline__occupation_Protective-serv
pipeline__education_Prof-school
pipeline__marital-status_Widowed
pipeline__education_Assoc-acdm
pipeline__occupation_Handlers-cleaners
pipeline__occupation_Tech-support
pipeline__education_Assoc-voc
pipeline__occupation_?
pipeline__race_Asian-Pac-Islander
pipeline__workclass_?
pipeline__occupation_Transport-moving
pipeline__relationship_Other-relative
pipeline__occupation_Farming-fishing
pipeline__native-country_?
pipeline__education_9th
pipeline__education_10th
pipeline__education_7th-8th
pipeline__education_Doctorate
pipeline__marital-status_Married-spouse-absent
pipeline__race_Amer-Indian-Eskimo
pipeline__native-country_Canada
pipeline__native-country_Philippines
pipeline__marital-status_Married-AF-spouse
pipeline__native-country_England
pipeline__native-country_Ireland
pipeline__race_Other
pipeline__education_1st-4th
pipeline__native-country_Germany
pipeline__native-country_Iran
pipeline__education_12th
pipeline__native-country_Japan
pipeline__native-country_Puerto-Rico
pipeline__native-country_India
pipeline__education_5th-6th
pipeline__native-country_South
pipeline__native-country_Portugal
pipeline__native-country_Columbia
pipeline__native-country_Cuba
pipeline__native-country_El-Salvador
pipeline__workclass_Without-pay
pipeline__native-country_Greece
pipeline__native-country_Vietnam
pipeline__native-country_Yugoslavia
pipeline__occupation_Priv-house-serv
pipeline__native-country_Jamaica
pipeline__native-country_Italy
pipeline__native-country_China
pipeline__native-country_Hungary
pipeline__native-country_Ecuador
pipeline__education_Preschool
pipeline__native-country_Dominican-Republic
pipeline__native-country_Hong
pipeline__native-country_Cambodia
pipeline__native-country_Haiti
pipeline__native-country_Guatemala
pipeline__native-country_Poland
pipeline__native-country_Taiwan
pipeline__native-country_Laos
pipeline__native-country_Honduras
pipeline__native-country_Thailand



In [36]:

```
sorted_feature_names_bal
```

```
Out[36]: array(['passthrough__age', 'passthrough__educational-num',
                'pipeline__marital-status_Married-civ-spouse',
                'passthrough__capital-gain', 'passthrough__fnlwgt',
                'passthrough__hours-per-week',
                'pipeline__marital-status_Never-married',
                'pipeline__relationship_Wife',
                'pipeline__occupation_Prof-specialty',
                'pipeline__relationship_Own-child', 'passthrough__capital-loss',
                'pipeline__education_Bachelors',
                'pipeline__occupation_Exec-managerial',
                'pipeline__relationship_Not-in-family', 'pipeline__gender_Male',
                'pipeline__relationship_Husband',
                'pipeline__relationship_Unmarried', 'pipeline__education_Masters',
                'pipeline__education_HS-grad', 'pipeline__workclass_Private',
                'pipeline__marital-status_Divorced',
                'pipeline__occupation_Other-service',
                'pipeline__workclass_Self-emp-not-inc',
                'pipeline__occupation_Adm-clerical', 'pipeline__occupation_Sales',
                'pipeline__race_White', 'pipeline__education_Some-college',
                'pipeline__race_Black', 'pipeline__occupation_Craft-repair',
                'pipeline__workclass_Local-gov',
                'pipeline__native-country_United-States',
                'pipeline__occupation_Machine-op-inspct',
                'pipeline__workclass_Federal-gov', 'pipeline__workclass_State-gov',
                'pipeline__workclass_Self-emp-inc',
                'pipeline__marital-status_Separated',
                'pipeline__native-country_Mexico', 'pipeline__education_11th',
                'pipeline__occupation_Protective-serv',
                'pipeline__education_Prof-school',
                'pipeline__marital-status_Widowed',
                'pipeline__education_Assoc-acdm',
                'pipeline__occupation_Handlers-cleaners',
                'pipeline__occupation_Tech-support',
                'pipeline__education_Assoc-voc', 'pipeline__occupation_?',
                'pipeline__race_Asian-Pac-Islander', 'pipeline__workclass_?',
                'pipeline__occupation_Transport-moving',
                'pipeline__relationship_Other-relative',
                'pipeline__occupation_Farming-fishing',
                'pipeline__native-country_?', 'pipeline__education_9th',
                'pipeline__education_10th', 'pipeline__education_7th-8th',
                'pipeline__education_Doctorate',
                'pipeline__marital-status_Married-spouse-absent',
                'pipeline__race_Amer-Indian-Eskimo',
                'pipeline__native-country_Canada',
                'pipeline__native-country_Philippines',
                'pipeline__marital-status_Married-AF-spouse',
                'pipeline__native-country_England',
                'pipeline__native-country_Ireland', 'pipeline__race_Other',
                'pipeline__education_1st-4th', 'pipeline__native-country_Germany',
                'pipeline__native-country_Iran', 'pipeline__education_12th',
                'pipeline__native-country_Japan',
                'pipeline__native-country_Puerto-Rico',
                'pipeline__native-country_India', 'pipeline__education_5th-6th',
                'pipeline__native-country_South',
                'pipeline__native-country_Portugal',
                'pipeline__native-country_Columbia',
                'pipeline__native-country_Cuba',
                'pipeline__native-country_El-Salvador',
                'pipeline__workclass_Without-pay',
                'pipeline__native-country_Greece',
                'pipeline__native-country_Vietnam',
                'pipeline__native-country_Yugoslavia',
                'pipeline__occupation_Priv-house-serv',
                'pipeline__native-country_Jamaica',
                'pipeline__native-country_Italy', 'pipeline__native-country_China',
                'pipeline__native-country_Hungary',
                'pipeline__native-country_Ecuador',
                'pipeline__education_Preschool',
                'pipeline__native-country_Dominican-Republic',
                'pipeline__native-country_Hong',
                'pipeline__native-country_Cambodia',
                'pipeline__native-country_Haiti',
                'pipeline__native-country_Guatemala',
                'pipeline__native-country_Poland',
                'pipeline__native-country_Taiwan', 'pipeline__native-country_Laos',
                'pipeline__native-country_Honduras',
                'pipeline__native-country_Thailand',
                'pipeline__native-country_France', 'pipeline__native-country_Peru',
                'pipeline__native-country_Scotland',
                'pipeline__native-country_Nicaragua',
                'pipeline__native-country_Trinadad&Tobago'], dtype=object)
```

Q5.5: The top most important features for the classifier with scores greater than approximately 0.01 are `passthrough__age`, `pipeline__marital-status_Married-civ-spouse`, `passthrough__educational-num`, `passthrough__capital-gain`, `passthrough__fnlwgt`, `passthrough__hours-per-week`, `pipeline__relationship_Wife`, `pipeline__marital-status_Never-married`, `pipeline__occupation_Exec-managerial`, `pipeline__relationship_Husband`, `passthrough__capital-loss`, `pipeline__relationship_Own-child`, `pipeline__occupation_Prof-specialty`, `pipeline__education_Bachelors`, `pipeline__gender_Male`, `pipeline__relationship_Not-in-family`, `pipeline__education_Masters`, `pipeline__workclass_Private`, `pipeline__marital-status_Divorced`, `pipeline__occupation_Other-service`, `pipeline__relationship_Unmarried`, and `pipeline__education_HS-grad`. Compared to the original model, the features `pipeline__workclass_Private`, `pipeline__occupation_Other-service`, `pipeline__relationship_Unmarried` and `pipeline__education_HS-grad` have significantly greater importance relative to the other model features.

Debiasing techniques: oversampling (with SMOTE)

Another way to create a more balanced training set, but without sacrificing training samples, is by *oversampling*, which means artificially increasing the size of the training set with "fake" samples. This can be achieved mainly in two ways:

1. By resampling (replicating) samples from the original training set, or
2. By introducing artificial *new* samples, similar enough to those included in the original training set

The Synthetic Minority Oversampling Technique (SMOTE) seen in class falls in the second group. In this portion of the assignment, you will create a more balanced dataset using SMOTE (specifically SMOTENC, a version of SMOTE that allows working with categorical variables).

Question 6

1. Run the cell below to create a more balanced training set using SMOTE. Note that a large portion of code is replicated to guarantee that the correct data is used, and not one modified in previous cells. The actual rebalancing all happens in the last 2 lines.
2. Explore the new training set, and provide the following information: what is the size of the new training set? Is the target variable balanced? How many samples are classified as >\$50, and how many as <=\$50k? Is the target variable balanced across protected groups, or at least more balanced than before? How many males and females are classified as >\$50, and how many as <=\$50k?
3. Re-train the random forest classifier.
4. Compare accuracy and fairness of this new classifier to the previous ones. Do we see any improvement? How do you explain the changes you see (or lack thereof)? Pay particular attention to the difference in results on the training and test set: can you explain these results?
5. Create a new plot of the feature importance according to this classifier. Do you see any changes from the previous ones?

In [37]:
```
from imblearn.over_sampling import SMOTENC

X_train, y_train = (
    train_df.drop(columns=["income"]),
    train_df["income"],
)
X_test, y_test = (
    test_df.drop(columns=["income"]),
    test_df["income"],
)

oversample = SMOTENC(categorical_features=categorical_feats, random_state=0)

X_train_SMOTE, y_train_SMOTE = oversample.fit_resample(X_train, y_train)
```

In [38]:
```
# Transformation applied after oversampling

categorical_feats = ["workclass",
                     "education",
                     "marital-status",
                     "occupation",
                     "relationship",
                     "race",
                     "gender",
                     "native-country",
                     ]  # Apply one-hot encoding
passthrough_feats = ["age",
                "fnlwgt",
                 "educational-num",
                 "capital-gain",
                 "capital-loss",
                 "hours-per-week"
                 ]  # Numerical - no need to scale
target = "income"


ctSMOTE = make_column_transformer(
    (
        OneHotEncoder(handle_unknown="ignore",drop="if_binary",sparse_output=Fal
        categorical_feats,
    ),  # OHE on categorical features
    ("passthrough", passthrough_feats)  # no transformations on numerical featur
)

# X_train_transformed = ctSMOTE.fit_transform(X_train_SMOTE)
# X_test_transformed = ctSMOTE.transform(X_test)
X_train_transformed_SMOTE = ctSMOTE.fit_transform(X_train_SMOTE)
X_test_transformed_SMOTE = ctSMOTE.transform(X_test)

# Column names, if needed
column_names_SMOTE = list(
    ctSMOTE.named_transformers_["onehotencoder"].get_feature_names_out(
        categorical_feats
    )
) + passthrough_feats

# X_train_transformed and X_test_transformed can now be used to answer the quest
```

In [39]:

```
# Your answer here (you may add more cells)
train_df_SMOTE = pd.concat([X_train_SMOTE, y_train_SMOTE], axis=1)

# print(train_df_SMOTE.size) # 779520
print(train_df_SMOTE.shape) # (51968, 15)
display(y_train_SMOTE.value_counts(normalize=True).sort_index()) # Balance?
display(y_train_SMOTE.value_counts(normalize=False).sort_index()) # Number of ea
# display(train_df_SMOTE.head())
```

```
(51968, 15)
income
<=50K    0.5
>50K     0.5
Name: proportion, dtype: float64
income
<=50K    25984
>50K     25984
Name: count, dtype: int64
```

Q6.2.1, 6.2.2, 6.2.3: The size of the new training set is 51968 samples. Overall, the target variable is balanced, with 25984 samples classified as `income == "<=50K"` and 25984 samples classified as `income == ">50K"` .

In [40]:

```
genders = df["gender"].astype("string").value_counts().sort_index().index
genders_2 = train_df_SMOTE["gender"].astype("string").value_counts().sort_index(
# print(genders)
# print(genders_2)

for gen in genders_2:
    data = df[df["gender"] == gen]
    print("Distribution of income for " + gen.lower() + " overall")
    display(data["income"].value_counts(normalize=True).sort_index())

    data_2 = train_df_SMOTE[train_df_SMOTE["gender"] == gen]
    print("Distribution of income for " + gen.lower() + " in SMOTE training set"
    display(data_2["income"].value_counts(normalize=True).sort_index())

for gen in genders_2:
    data_2 = train_df_SMOTE[train_df_SMOTE["gender"] == gen]
    print("Count of income for " + gen.lower() + " in SMOTE training set")
    display(data_2["income"].value_counts(normalize=False).sort_index())
```

```
Distribution of income for female overall
income
<=50K    0.890749
>50K     0.109251
Name: proportion, dtype: float64
Distribution of income for female in SMOTE training set
income
<=50K    0.836503
>50K     0.163497
Name: proportion, dtype: float64
Distribution of income for male overall
income
<=50K    0.696233
>50K     0.303767
Name: proportion, dtype: float64
Distribution of income for male in SMOTE training set
income
<=50K    0.398497
>50K     0.601503
Name: proportion, dtype: float64
Count of income for female in SMOTE training set
income
<=50K    10074
>50K      1969
Name: count, dtype: int64
Count of income for male in SMOTE training set
income
<=50K    15910
>50K     24015
Name: count, dtype: int64
```

Q6.2.4.1, 6.2.5: The target variable `income` is only slightly more balanced across each `gender` group compared to the original dataset, and the distributions of each `income` category are not equal across each level of `gender`. For instance, the proportion of `income == "<=50K"` samples is 0.836503 among female individuals and 0.398497 among male individuals. There are 15910 males and 10074 females classified as `income == "<=50K"`, and 24015 males and 1969 females classified as `income == "<=50K"`.

In [41]:
```
races = df["race"].astype("string").value_counts().sort_index().index
races_2 = train_df_SMOTE["race"].astype("string").value_counts().sort_index().in
# print(races)
# print(races_2)

for gen in races_2:
    data = df[df["race"] == gen]
    print("Distribution of income for " + gen.lower() + " overall")
    display(data["income"].value_counts(normalize=True).sort_index())

    data_2 = train_df_SMOTE[train_df_SMOTE["race"] == gen]
    print("Distribution of income for " + gen.lower() + " in SMOTE training set"
    display(data_2["income"].value_counts(normalize=True).sort_index())
```

```
Distribution of income for amer-indian-eskimo overall
income
<=50K    0.882979
>50K     0.117021
Name: proportion, dtype: float64
Distribution of income for amer-indian-eskimo in SMOTE training set
income
<=50K    0.904908
>50K     0.095092
Name: proportion, dtype: float64
Distribution of income for asian-pac-islander overall
income
<=50K    0.730744
>50K     0.269256
Name: proportion, dtype: float64
Distribution of income for asian-pac-islander in SMOTE training set
income
<=50K    0.684073
>50K     0.315927
Name: proportion, dtype: float64
Distribution of income for black overall
income
<=50K    0.879189
>50K     0.120811
Name: proportion, dtype: float64
Distribution of income for black in SMOTE training set
income
<=50K    0.857315
>50K     0.142685
Name: proportion, dtype: float64
Distribution of income for other overall
income
<=50K    0.876847
>50K     0.123153
Name: proportion, dtype: float64
Distribution of income for other in SMOTE training set
income
<=50K    0.879195
>50K     0.120805
Name: proportion, dtype: float64
Distribution of income for white overall
income
<=50K    0.746013
>50K     0.253987
Name: proportion, dtype: float64
Distribution of income for white in SMOTE training set
income
<=50K    0.464996
>50K     0.535004
Name: proportion, dtype: float64
```

Q6.2.4.2: The target variable `income` is only slightly more balanced across each `race` group Compared to the original dataset, the target variable `income` is significantly more balanced for `race == "white"`, only slightly more balanced for `race == "asian-pac-islander"` and `race == "black"`, and slightly less balanced for `race == "amer-indian-eskimo"` and `race == "other"`. The distributions of each `income` category are not equal across each level of `race`. For instance, the proportion of `income == "<=50K"` samples is 0.904908 among amer-indian-eskimo individuals and 0.464996 among white individuals.

In [42]:

```
# Step 3
clf_SMOTE = RandomForestClassifier(random_state=0, max_depth = 19, n_estimators
```

In [43]:

```
# Step 4.1
print("Training accuracy: " + str(clf.score(X_train_transformed, y_train)))
print("Testing accuracy: " + str(clf.score(X_test_transformed, y_test)))
print("Training accuracy (SMOTE): " + str(clf_SMOTE.score(X_train_transformed_SM
print("Testing accuracy (SMOTE): " + str(clf_SMOTE.score(X_test_transformed_SMOT
```

```
Training accuracy: 0.9064318932990143
Testing accuracy: 0.8624172524397734
Training accuracy (SMOTE): 0.9203163485221675
Testing accuracy (SMOTE): 0.8413294205964649
```

In [44]:

```
# Step 4.2
# Splitting datasets by gender

X_train_transformed_SMOTE = pd.DataFrame(X_train_transformed_SMOTE, columns=colu
X_test_transformed_SMOTE = pd.DataFrame(X_test_transformed_SMOTE, columns=column

X_train_transformed_SMOTE_m_df = pd.DataFrame(X_train_transformed_SMOTE[X_train_
X_train_transformed_SMOTE_f_df = pd.DataFrame(X_train_transformed_SMOTE[X_train_
X_test_transformed_SMOTE_m_df = pd.DataFrame(X_test_transformed_SMOTE[X_test_tra
X_test_transformed_SMOTE_f_df = pd.DataFrame(X_test_transformed_SMOTE[X_test_tra

y_train_SMOTE_m = train_df_SMOTE[train_df_SMOTE["gender"] == "Male"]["income"]
y_train_SMOTE_f = train_df_SMOTE[train_df_SMOTE["gender"] == "Female"]["income"]
y_test_SMOTE_m = test_df[test_df["gender"] == "Male"]["income"]
y_test_SMOTE_f = test_df[test_df["gender"] == "Female"]["income"]
# display(X_train_transformed_bal_m_df.head())

# fairness_metrics("Random Forest", clf_SMOTE, X_train_transformed_SMOTE_m_df, y
# fairness_metrics("Random Forest", clf_SMOTE, X_test_transformed_SMOTE_m_df, y_
fairness_metrics("Random Forest", clf_SMOTE.predict(X_train_transformed_SMOTE_m_
fairness_metrics("Random Forest", clf_SMOTE.predict(X_test_transformed_SMOTE_m_d
fairness_mets_df = pd.DataFrame(fairness_mets)
fairness_mets_df = fairness_mets_df.set_index(["model"])
fairness_mets_df
```

Out[44]:

model	PPRD	PPGRD	FDRD	FPRD	FORD	FNRD	adfr
Random Forest (Training)	0.175265	0.353936	0.389925	0.107931	0.255968	0.852545	0.644072
Random Forest (Testing)	0.143736	0.288830	0.837058	0.188731	0.351694	1.211745	0.566949
Random Forest (Training (New))	0.176575	0.356581	0.337220	0.094040	0.253960	0.847751	0.655645
Random Forest (Testing (New))	0.150043	0.301504	0.987371	0.232391	0.352168	1.215761	0.532047
Random Forest (Training (Balanced))	0.949963	0.949963	0.378593	0.359649	0.709013	0.750000	0.317137
Random Forest (Testing (Balanced))	0.252283	0.506949	1.408318	0.557327	0.217873	0.843031	0.505143
Random Forest (Training (SMOTE))	0.072344	0.239834	0.779045	0.089008	0.357397	3.117290	0.929944
Random Forest (Testing (SMOTE))	0.105559	0.212114	0.681541	0.112852	0.498124	2.101040	0.748475

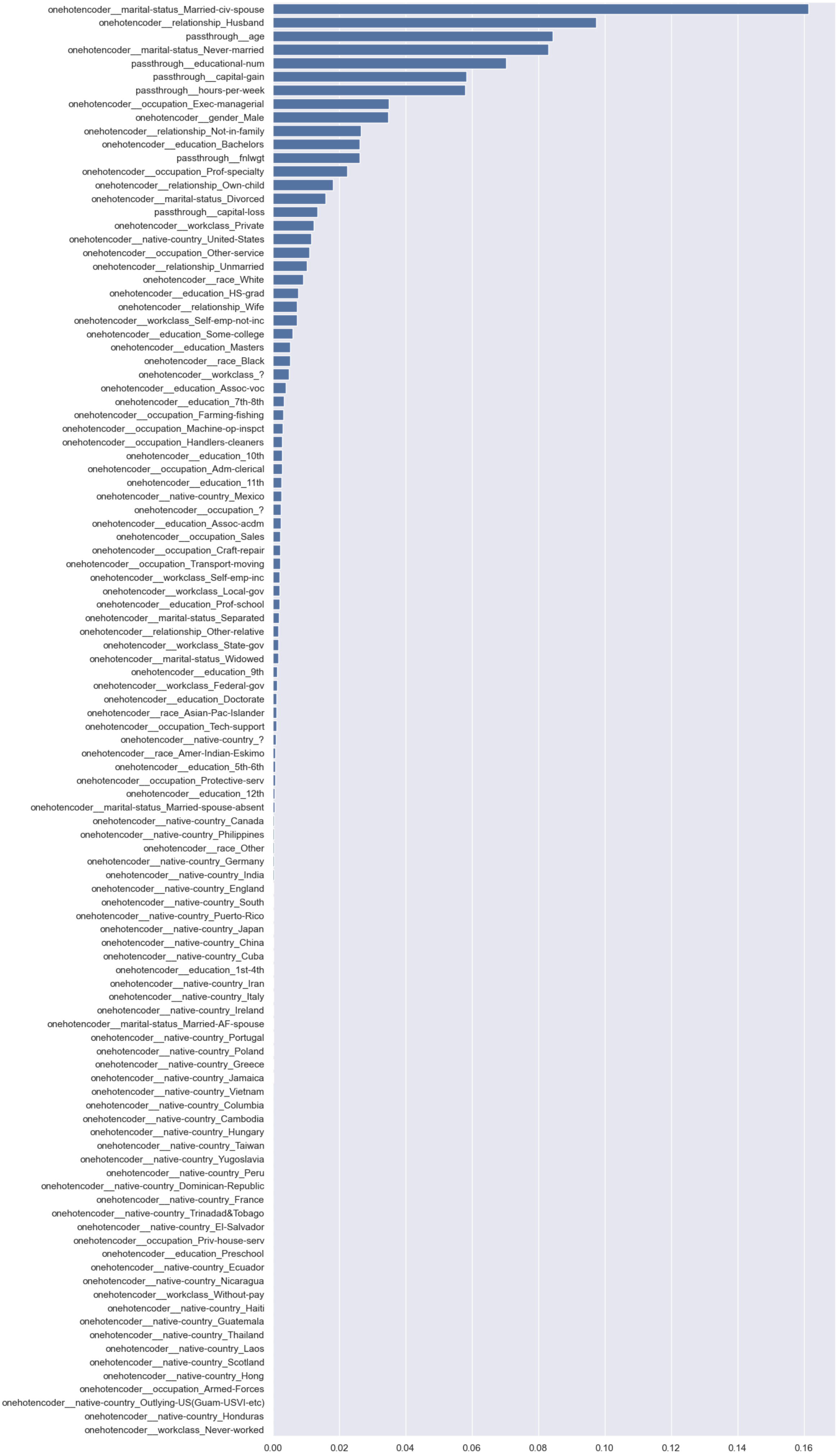
~~**Q6.4:** There are some significant changes in the accuracy and fairness metrics for each dataset after using SMOTE. The accuracy upon undersampling increased slightly on the training set from 0.9064318932990143 to 0.9203163485221675, and decreased slightly on the testing set from 0.8624172524397734 to 0.8413294205964649. `PPRD` , `PPGRD` and `FPRD` are decreased significantly for the training and testing sets, `FORD` , `FNRD` , and `adfr` are increased significantly for both the training and testing sets, and `FDRD` is increased for the training sets and decreased for the testing sets. `FNRD` becoming relatively further in value from the reference value of 1. As a consequence, `adfr` is increased significantly for both the training and testing sets.~~

Refined answer:

Q6.4: There are some significant changes in the accuracy and fairness metrics for each dataset after using SMOTE. The accuracy upon oversampling increased slightly on the training set from 0.9064318932990143 to 0.9203163485221675, and decreased slightly on the testing set from 0.8624172524397734 to 0.8413294205964649, indicating slight overfitting for the model to the training set. `PPRD` , `PPGRD` and `FPRD` decreased significantly for the training and testing sets (being a bit further from the good value "1"), `FORD` , and `FNRD` increased significantly for both the training and testing sets (`FORD` is being closer to the good value "1" while `FNRD` is being larger but much further from the good value "1"). `FDRD` is increased for the training sets (closer to 1) and decreased for the testing sets (a bit further from 1). `FNRD` becomes relatively much further in value from the reference value of 1. As a consequence, `adfr` is increased significantly for both the training and testing sets, being much further from the good value "0". The results of the model on the testing set indicate more fair metrics overall compared to the results on the training set.

In [45]:
```
# Step 5
feature_importances_SMOTE = clf_SMOTE.feature_importances_

# Sort the feature importances from greatest to least using the sorted indices
sorted_indices_SMOTE = feature_importances_SMOTE.argsort()[::-1]
sorted_feature_names_SMOTE = ctSMOTE.get_feature_names_out()[sorted_indices_SMOT
sorted_importances_SMOTE = feature_importances_SMOTE[sorted_indices_SMOTE]

# # Create a bar plot of the feature importances
sns.set(rc={'figure.figsize':(11.7,30)})
sns.barplot(x=sorted_importances_SMOTE, y=sorted_feature_names_SMOTE)
```

Out[45]:
```
<Axes: >
```


onehotencoder__marital-status_Married-civ-spouse
onehotencoder__relationship_Husband
passthrough__age
onehotencoder__marital-status_Never-married
passthrough__educational-num
passthrough__capital-gain
passthrough__hours-per-week
onehotencoder__occupation_Exec-managerial
onehotencoder__gender_Male
onehotencoder__relationship_Not-in-family
onehotencoder__education_Bachelors
passthrough__fnlwgt
onehotencoder__occupation_Prof-specialty
onehotencoder__relationship_Own-child
onehotencoder__marital-status_Divorced
passthrough__capital-loss
onehotencoder__workclass_Private
onehotencoder__native-country_United-States
onehotencoder__occupation_Other-service
onehotencoder__relationship_Unmarried
onehotencoder__race_White
onehotencoder__education_HS-grad
onehotencoder__relationship_Wife
onehotencoder__workclass_Self-emp-not-inc
onehotencoder__education_Some-college
onehotencoder__education_Masters
onehotencoder__race_Black
onehotencoder__workclass_?
onehotencoder__education_Assoc-voc
onehotencoder__education_7th-8th
onehotencoder__occupation_Farming-fishing
onehotencoder__occupation_Machine-op-inspct
onehotencoder__occupation_Handlers-cleaners
onehotencoder__education_10th
onehotencoder__occupation_Adm-clerical
onehotencoder__education_11th
onehotencoder__native-country_Mexico
onehotencoder__occupation_?
onehotencoder__education_Assoc-acdm
onehotencoder__occupation_Sales
onehotencoder__occupation_Craft-repair
onehotencoder__occupation_Transport-moving
onehotencoder__workclass_Self-emp-inc
onehotencoder__workclass_Local-gov
onehotencoder__education_Prof-school
onehotencoder__marital-status_Separated
onehotencoder__relationship_Other-relative
onehotencoder__workclass_State-gov
onehotencoder__marital-status_Widowed
onehotencoder__education_9th
onehotencoder__workclass_Federal-gov
onehotencoder__education_Doctorate
onehotencoder__race_Asian-Pac-Islander
onehotencoder__occupation_Tech-support
onehotencoder__native-country_?
onehotencoder__race_Amer-Indian-Eskimo
onehotencoder__education_5th-6th
onehotencoder__occupation_Protective-serv
onehotencoder__education_12th
onehotencoder__marital-status_Married-spouse-absent
onehotencoder__native-country_Canada
onehotencoder__native-country_Philippines
onehotencoder__race_Other
onehotencoder__native-country_Germany
onehotencoder__native-country_India
onehotencoder__native-country_England
onehotencoder__native-country_South
onehotencoder__native-country_Puerto-Rico
onehotencoder__native-country_Japan
onehotencoder__native-country_China
onehotencoder__native-country_Cuba
onehotencoder__education_1st-4th
onehotencoder__native-country_Iran
onehotencoder__native-country_Italy
onehotencoder__native-country_Ireland
onehotencoder__marital-status_Married-AF-spouse
onehotencoder__native-country_Portugal
onehotencoder__native-country_Poland
onehotencoder__native-country_Greece
onehotencoder__native-country_Jamaica
onehotencoder__native-country_Vietnam
onehotencoder__native-country_Columbia
onehotencoder__native-country_Cambodia
onehotencoder__native-country_Hungary
onehotencoder__native-country_Taiwan
onehotencoder__native-country_Yugoslavia
onehotencoder__native-country_Peru
onehotencoder__native-country_Dominican-Republic
onehotencoder__native-country_France
onehotencoder__native-country_Trinadad&Tobago
onehotencoder__native-country_El-Salvador
onehotencoder__occupation_Priv-house-serv
onehotencoder__education_Preschool
onehotencoder__native-country_Ecuador
onehotencoder__native-country_Nicaragua
onehotencoder__workclass_Without-pay
onehotencoder__native-country_Haiti
onehotencoder__native-country_Guatemala
onehotencoder__native-country_Thailand
onehotencoder__native-country_Laos
onehotencoder__native-country_Scotland
onehotencoder__native-country_Hong
onehotencoder__occupation_Armed-Forces
onehotencoder__native-country_Outlying-US(Guam-USVI-etc)
onehotencoder__native-country_Honduras
onehotencoder__workclass_Never-worked
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16

In [46]:
```
sorted_feature_names_SMOTE
```

```
Out[46]: array(['onehotencoder__marital-status_Married-civ-spouse',
                'onehotencoder__relationship_Husband', 'passthrough__age',
                'onehotencoder__marital-status_Never-married',
                'passthrough__educational-num', 'passthrough__capital-gain',
                'passthrough__hours-per-week',
                'onehotencoder__occupation_Exec-managerial',
                'onehotencoder__gender_Male',
                'onehotencoder__relationship_Not-in-family',
                'onehotencoder__education_Bachelors', 'passthrough__fnlwgt',
                'onehotencoder__occupation_Prof-specialty',
                'onehotencoder__relationship_Own-child',
                'onehotencoder__marital-status_Divorced',
                'passthrough__capital-loss', 'onehotencoder__workclass_Private',
                'onehotencoder__native-country_United-States',
                'onehotencoder__occupation_Other-service',
                'onehotencoder__relationship_Unmarried',
                'onehotencoder__race_White', 'onehotencoder__education_HS-grad',
                'onehotencoder__relationship_Wife',
                'onehotencoder__workclass_Self-emp-not-inc',
                'onehotencoder__education_Some-college',
                'onehotencoder__education_Masters', 'onehotencoder__race_Black',
                'onehotencoder__workclass_?', 'onehotencoder__education_Assoc-voc',
                'onehotencoder__education_7th-8th',
                'onehotencoder__occupation_Farming-fishing',
                'onehotencoder__occupation_Machine-op-inspct',
                'onehotencoder__occupation_Handlers-cleaners',
                'onehotencoder__education_10th',
                'onehotencoder__occupation_Adm-clerical',
                'onehotencoder__education_11th',
                'onehotencoder__native-country_Mexico',
                'onehotencoder__occupation_?',
                'onehotencoder__education_Assoc-acdm',
                'onehotencoder__occupation_Sales',
                'onehotencoder__occupation_Craft-repair',
                'onehotencoder__occupation_Transport-moving',
                'onehotencoder__workclass_Self-emp-inc',
                'onehotencoder__workclass_Local-gov',
                'onehotencoder__education_Prof-school',
                'onehotencoder__marital-status_Separated',
                'onehotencoder__relationship_Other-relative',
                'onehotencoder__workclass_State-gov',
                'onehotencoder__marital-status_Widowed',
                'onehotencoder__education_9th',
                'onehotencoder__workclass_Federal-gov',
                'onehotencoder__education_Doctorate',
                'onehotencoder__race_Asian-Pac-Islander',
                'onehotencoder__occupation_Tech-support',
                'onehotencoder__native-country_?',
                'onehotencoder__race_Amer-Indian-Eskimo',
                'onehotencoder__education_5th-6th',
                'onehotencoder__occupation_Protective-serv',
                'onehotencoder__education_12th',
                'onehotencoder__marital-status_Married-spouse-absent',
                'onehotencoder__native-country_Canada',
                'onehotencoder__native-country_Philippines',
                'onehotencoder__race_Other',
                'onehotencoder__native-country_Germany',
                'onehotencoder__native-country_India',
                'onehotencoder__native-country_England',
                'onehotencoder__native-country_South',
                'onehotencoder__native-country_Puerto-Rico',
                'onehotencoder__native-country_Japan',
                'onehotencoder__native-country_China',
                'onehotencoder__native-country_Cuba',
                'onehotencoder__education_1st-4th',
                'onehotencoder__native-country_Iran',
                'onehotencoder__native-country_Italy',
                'onehotencoder__native-country_Ireland',
                'onehotencoder__marital-status_Married-AF-spouse',
                'onehotencoder__native-country_Portugal',
                'onehotencoder__native-country_Poland',
                'onehotencoder__native-country_Greece',
                'onehotencoder__native-country_Jamaica',
                'onehotencoder__native-country_Vietnam',
                'onehotencoder__native-country_Columbia',
                'onehotencoder__native-country_Cambodia',
                'onehotencoder__native-country_Hungary',
                'onehotencoder__native-country_Taiwan',
                'onehotencoder__native-country_Yugoslavia',
                'onehotencoder__native-country_Peru',
                'onehotencoder__native-country_Dominican-Republic',
                'onehotencoder__native-country_France',
                'onehotencoder__native-country_Trinadad&Tobago',
                'onehotencoder__native-country_El-Salvador',
                'onehotencoder__occupation_Priv-house-serv',
                'onehotencoder__education_Preschool',
                'onehotencoder__native-country_Ecuador',
                'onehotencoder__native-country_Nicaragua',
                'onehotencoder__workclass_Without-pay',
                'onehotencoder__native-country_Haiti',
                'onehotencoder__native-country_Guatemala',
                'onehotencoder__native-country_Thailand',
                'onehotencoder__native-country_Laos',
                'onehotencoder__native-country_Scotland',
                'onehotencoder__native-country_Hong',
                'onehotencoder__occupation_Armed-Forces',
                'onehotencoder__native-country_Outlying-US(Guam-USVI-etc)',
                'onehotencoder__native-country_Honduras',
                'onehotencoder__workclass_Never-worked'], dtype=object)
```

Q6.5: The top most important features for the classifier with scores greater than approximately 0.01 are `onehotencoder__marital-status_Married-civ-spouse`, `onehotencoder__relationship_Husband`, `passthrough__age`, `onehotencoder__marital-status_Never-married`, `passthrough__educational-num`, `passthrough__capital-gain`, `passthrough__hours-per-week`, `onehotencoder__occupation_Exec-managerial`, `onehotencoder__gender_Male`, `onehotencoder__relationship_Not-in-family`, `onehotencoder__education_Bachelors`, `passthrough__fnlwgt`, `onehotencoder__occupation_Prof-specialty`, `onehotencoder__relationship_Own-child`, `onehotencoder__marital-status_Divorced`, `passthrough__capital-loss`, `onehotencoder__workclass_Private`, `onehotencoder__native-country_United-States`, `onehotencoder__occupation_Other-service`, `onehotencoder__relationship_Unmarried`, and `onehotencoder__race_White`. Compared to the previous models, the features `onehotencoder__native-`

`country_United-States` and `onehotencoder__race_White` have significantly greater importance relative to the other model features. `pipeline__education_Masters` has significantly less importance compared to the original model, while `pipeline__education_HS-grad` has significantly less importance compared to the undersampling model.

Equalized odd post processing

An alternative to the methods seen so far (which may produce unsatisfactory results), is applying post-processing to the predictions of the classifier, so that they optimize equalized odds (whether the TPR and FPR are on par across groups).

`aif360`, a popular open-source library dedicated to detecting and mitigating bias in machine learning models, includes `EqOddsPostprocessing`, a function to performe equalized odds post-processing. The function is slightly more intricate to use than others you have used so far (typically from `sklearn`), so we will see together how to apply it on the test (you may try and replicate this on the training set for your own practice).

In [47]:

```
# Run this cell to reset training and test sets (and clear accidental prior chan

X_train, y_train = (
    train_df.drop(columns=["income"]),
    train_df["income"],
)
X_test, y_test = (
    test_df.drop(columns=["income"]),
    test_df["income"],
)
```

In [48]:

```
# Run this cell to do the necessary dataset preprocessing (encoding of categoric
# Note that, since we are using a tree based classifier, we don't need to scale
# numerical features.

categorical_feats = ["workclass",
                     "education",
                     "marital-status",
                     "occupation",
                     "relationship",
                     "race",
                     "gender",
                     "native-country",
                     ]  # Apply one-hot encoding
passthrough_feats = ["age",
                "fnlwgt",
                "educational-num",
                "capital-gain",
                "capital-loss",
                "hours-per-week"
                ]  # Numerical - no need to scale
target = "income"
```

```
ct = make_column_transformer(
    (
        make_pipeline(OneHotEncoder(handle_unknown="ignore",drop="if_binary")),
        categorical_feats,
    ),  # OHE on categorical features
    ("passthrough", passthrough_feats)  # no transformations on numerical featur
)

X_train_transformed = ct.fit_transform(X_train).toarray()
X_test_transformed = ct.transform(X_test).toarray()
```

In [49]:

```
# Convert numpy arrays to pandas dataframes

column_names = list(
    ct.named_transformers_["pipeline"].get_feature_names_out(
        categorical_feats
    )
) + passthrough_feats

X_train_df = pd.DataFrame(X_train_transformed, columns=column_names)
X_test_df = pd.DataFrame(X_test_transformed, columns=column_names)
```

In [50]:

```
# Train RandomForestClassifier
clf = RandomForestClassifier(random_state=0, max_depth = 19, n_estimators = 100)

# Get predictions for test set
y_pred = clf.predict(X_test_df)

# So far, all this is the same as the biased classifier we started with
```

In [51]:

```
# Convert test data into a BinaryLabelDataset, necessary to work in aif360

from aif360.datasets import BinaryLabelDataset

X_test_df = X_test_df.reset_index(drop=True)
y_test = y_test.reset_index(drop=True)

y_binary = y_test.map({'>50K': 1, '<=50K': 0})  # Map categorical values to bina

test_mld = BinaryLabelDataset(df=pd.concat([X_test_df, y_binary], axis=1),
                              label_names=['income'],
                              protected_attribute_names=['gender_Male'])
```

In [52]:

```
# Create another dataset with predicted labels for comparison
test_pred_mld = test_mld.copy()

# Convert to binary label (e.g., class 2 is positive, others are negative)
y_pred_binary = np.where(y_pred == '>50K', 1, 0)

test_pred_mld.labels = y_pred_binary.reshape(-1, 1)
```

In [53]:

```
from aif360.algorithms.postprocessing import EqOddsPostprocessing

# Initialize EqOddsPostprocessing
eq_odds = EqOddsPostprocessing(unprivileged_groups=[{'gender_Male': 0}],
                               privileged_groups=[{'gender_Male': 1}], seed=0)
```

In [54]:

```
# Fit the EqOddsPostprocessing model # Changing of predictions
eq_odds = eq_odds.fit(test_mld, test_pred_mld)

# Get new fair predictions
fair_pred_mld = eq_odds.predict(test_pred_mld)

# Convert predictions back to array
fair_predictions = fair_pred_mld.labels
```

In [55]:

```
# Modified predictions
fair_predictions_cat = np.where(fair_predictions == 1, '>50K', '<=50K')
fair_predictions_cat
```

Out[55]:

```
array([['<=50K'],
       ['<=50K'],
       ['<=50K'],
       ...,
       ['<=50K'],
       ['<=50K'],
       ['<=50K']], dtype='<U5')
```

`fair_predictions_cat` now includes the post-processed predictions, after equalized odds postprocessing.

Question 7

Compute accuracy and fairness of this new predictions, and compare the results to the previous ones. Do we see any improvement? Is this technique more or less effective than the others tried before?

In [56]:

```
print("Training accuracy: " + str(clf.score(X_train_transformed, y_train)))
print("Testing accuracy: " + str(clf.score(X_test_transformed, y_test)))
# print("Training accuracy (EqOddsPostprocessing): " + str(clf.score(X_train_df,
print("Testing accuracy (EqOddsPostprocessing): " + str(clf.score(X_test_df, fai
```

```
Training accuracy: 0.9064318932990143
Testing accuracy: 0.8624172524397734
Testing accuracy (EqOddsPostprocessing): 0.9680611478878045
```

In [57]:

```
y_test_eq_odds = pd.DataFrame(fair_predictions_cat, columns = ["income"])
test_df_eq_odds = pd.concat([X_test_df, y_test_eq_odds], axis=1)
# test_df_eq_odds["gender_Male"]
# display(test_df_eq_odds)

X_test_eq_odds_m = pd.DataFrame(X_test_df[X_test_df["gender_Male"] == 1])
X_test_eq_odds_f = pd.DataFrame(X_test_df[X_test_df["gender_Male"] == 0])
# display(X_test_eq_odds_m.head())

y_test_eq_odds_m = test_df_eq_odds[test_df_eq_odds["gender_Male"] == 1]["income"
y_test_eq_odds_f = test_df_eq_odds[test_df_eq_odds["gender_Male"] == 0]["income"
# display(y_test_eq_odds_m.head())

y_test_m = test_df[test_df["gender"] == "Male"]["income"]
y_test_f = test_df[test_df["gender"] == "Female"]["income"]
# display(y_test_eq_odds_m.head())

# cm_m_eq_odds = confusion_matrix(y_test_eq_odds_m, clf.predict(X_test_eq_odds_m
# cm_f_eq_odds = confusion_matrix(y_test_eq_odds_f, clf.predict(X_test_eq_odds_f
cm_m_eq_odds = confusion_matrix(y_test_m, y_test_eq_odds_m) # clf is not model
cm_f_eq_odds = confusion_matrix(y_test_f, y_test_eq_odds_f)
print(cm_m_eq_odds)
print(cm_f_eq_odds)

# fairness_metrics("Random Forest", clf, X_test_eq_odds_m, y_test_eq_odds_m, X_t
fairness_metrics("Random Forest", y_test_eq_odds_m, y_test_m, y_test_eq_odds_f,
fairness_mets_df = pd.DataFrame(fairness_mets)
fairness_mets_df = fairness_mets_df.set_index(["model"])
fairness_mets_df
```

```
[[6353  469]
 [1381 1581]]
[[4060  289]
 [ 239  281]]
```

Out[57]:

	PPRD	PPGRD	FDRD	FPRD	FORD	FNR
model						
Random Forest (Training)	0.175265	0.353936	0.389925	0.107931	0.255968	0.85254
Random Forest (Testing)	0.143736	0.288830	0.837058	0.188731	0.351694	1.21174
Random Forest (Training (New))	0.176575	0.356581	0.337220	0.094040	0.253960	0.84775
Random Forest (Testing (New))	0.150043	0.301504	0.987371	0.232391	0.352168	1.21576
Random Forest (Training (Balanced))	0.949963	0.949963	0.378593	0.359649	0.709013	0.75000
Random Forest (Testing (Balanced))	0.252283	0.506949	1.408318	0.557327	0.217873	0.84303
Random Forest (Training (SMOTE))	0.072344	0.239834	0.779045	0.089008	0.357397	3.11729
Random Forest (Testing (SMOTE))	0.105559	0.212114	0.681541	0.112852	0.498124	2.10104
Random Forest (Testing (EqOddsPostprocessing))	0.278049	0.558724	2.216175	0.966601	0.311344	0.98579

~~There are some significant changes in the accuracy and fairness metrics for each dataset after using equalised odd post processing. The accuracy upon equalised odds post processing on the testing set is increased from 0.8624172524397734 to 0.9680611478878045. `PPRD`, `PPGRD`, `FDRD` and `FPRD` are increased for the testing set after equalising odds post processing, while `FORD`, `FNRD` and `adfr` are decreased. `PPRD`, `PPGRD`, `FPRD` and `FNRD` are closer in value to the reference value of 1, while `FDRD` and `FORD` are further in value from the reference value. Overall, `adfr` is decreased.~~

Refined answer:

There are some significant changes in the accuracy and fairness metrics for each dataset after using equalised odd post processing. The accuracy upon equalised odds post processing on the testing set is increased from 0.8624172524397734 to 0.9680611478878045. `PPRD`, `PPGRD`, `FDRD` and `FPRD` are increased for the testing set after equalising odds post processing (`PPRD`, `PPGRD`, and `FPRD` are being close to 1 but `FDRD` is being further from 1), while `FORD`, `FNRD` and `adfr` are decreased. Overall, `PPRD`, `PPGRD`, `FPRD` and `FNRD` are closer in value to the reference value of 1, while `FDRD` and `FORD` are further in value from the reference value of 1. And in particular, `FNRD` and `FPRD` are **very close to 1**, which makes sense because the FPRD and FNRD definitions are the closest related to the definition of equalized odds. Overall, `adfr` is decreased.

Final remarks

Question 8

Based on the results seen so far, provide an overall evaluation of our debiasing efforts. In particular, try answering the following questions:

1. What do you think was the most successful technique? Which one was the least successful?
2. If you found that bias still persists after attempting a debiasing strategy, what do you think is the reason? What could be done to fix this problem?

(max 400 words)

~~**Q8.1**: The technique that was most successful in debiasing this dataset was the undersampling technique, as it provided the smallest absolute value of `adfr` for training and testing sets, which acts as a measure of overall fairness of the classifications. However, equalised odds provides better testing `PPRD`, `PPGRD`, `FPRD` and `FNRD` scores closer to 1, the removal of protected characteristics provides a better testing `FDRD` score closer to 1, and SMOTE oversampling provides a better testing `FORD` score closer to 1. Oversampling with SMOTE was the least successful in debiasing the dataset, as it has managed to cause every fairness metric except `FDRD` and `FORD` to deviate further from the reference value of 1, leading to an overall increase in `adfr` for both datasets.~~

~~**Q8.2**: Bias after the debiasing strategy may be due to the features selected for greater importance on the debiased dataset (e.g. Protected characteristics) or due to the model of choice in measuring bias. The issue may be mitigated by further debiasing through iterative debiasing techniques or by selecting models with less inherent bias.~~

Refined answer:

Q8.1: The technique that was **most successful** in debiasing this dataset was the **undersampling technique**, as it provided the **smallest** `adfr` for both training and testing sets, which acts as a measure of overall fairness of the classifications.

The technique that was **least successful** in debiasing this dataset was the **oversampling method with SMOTE**, as it provided the **largest** **`adfr`** for both training and testing sets, which is even worse than the `adfr` without any debiasing method. The **oversampling method with SMOTE** has managed to cause every fairness metric except `FDRD` and `FORD` to deviate further from the reference value of 1, leading to an overall increase in `adfr` for both datasets. In addition, we think that **equalised odds technique** is also very successful as its testing `adfr` is the second smallest among all debiased models. In particular, it brings `FPRD` and `FNRD` scores super closer to the good value "1". The `adfr` on the unseen testing without any debiasing method is 0.566949. The testing `adfr` using **oversampling method with SMOTE** is 0.748475; it performs even worse on the unseen dataset than before debaising. The testing `adfr` 's for **removal of protected characteristics method**, **undersampling method** and **equalised odds technique** are 0.532047, 0.505143, and 0.519277 respectively. This only shows a very limited improvement in fairness on unseen samples after using these debiasing tecuniques; with the best testing `adfr` being 0.505143 which is only a bit smaller than 0.566949. It should be noted that given their relatively high `adfr` scores and very limited improvements in `adfr` scores on the testing set, none of the given techniques were particularly successful on unseen samples; we saw small improvements, but these improvements may not be practically significant due to the limited decrease in `adfr` scores.

Q8.2: Bias after the debiasing strategy may be due to the features selected for greater importance on the debiased dataset (e.g. Protected characteristics) or due to the model of choice in measuring bias. The issue may be mitigated by further debiasing through iterative debiasing techniques or by selecting models with less inherent bias.

Final thoughts

1. If you have completed this assignment in a group, please write a detailed description of how you divided the work and how you helped each other completing it:

We worked on the assignment separately, each taking turns to answer all parts and modifying the responses down the line.

2. Have you used ChatGPT or a similar Large Language Model (LLM) to complete this homework? Please describe how you used the tool. We will never deduct points for using LLMs for completing homework assignments, but this helps us understand how you are using the tool and advise you in case we believe you are using it incorrectly.

- Jingyuan's response: I used ChatGPT to help me with the following scenarios: 1. How to create a side-by-side bar chart categorized by another feature.
- Nicholas' response: Ideas for what biases may persist after debiasing technique.

3. Have you struggled with some parts (or all) of this homework? Do you have pending questions you would like to ask? Write them down here!

- Jingyuan's response: I am still confused about the mechanism of oversampling (with SMOTE). How does it simulate artificial new samples, similar enough to those included in the original training set? Pending question: is an imbalanced dataset always going to be biased? Which one is more important? A balanced target variable or a balanced protected feature like `gender`
- Nicholas' response: How to interpret the usage of equalized odd post processing for accuracy and fairness metrics.

In [ ]: