In [ ]:

```
import random
random.seed(27)

import sys
import warnings

import numpy as np
import pandas as pd
import tensorflow as tf
import json
import time
from tqdm import tqdm

import matplotlib.pyplot as plt
import seaborn as sns

from folktables import ACSDataSource, ACSEmployment, ACSIncome, ACSPublicCove
from superquail.data.acs_helper import ACSData

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer, make_column_selector as select


from sklearn.model_selection import RandomizedSearchCV, PredefinedSplit, Grid
from sklearn.preprocessing import MinMaxScaler, StandardScaler, OneHotEncoder


from aif360.datasets import BinaryLabelDataset, StandardDataset
from aif360.algorithms.preprocessing import DisparateImpactRemover
from aif360.algorithms.inprocessing import PrejudiceRemover
from aif360.algorithms.postprocessing import CalibratedEqOddsPostprocessing,
from aif360.metrics import BinaryLabelDatasetMetric, ClassificationMetric

from aif360.explainers import MetricTextExplainer, Explainer

import BlackBoxAuditing
%matplotlib inline
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/framework/dtypes.py:5
26: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprec
ated; in a future version of numpy, it will be understood as (type, (1,)) / '(
1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/usr/local/lib/python3.7/dist-packages/tensorflow/python/framework/dtypes.py:5
27: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprec
ated; in a future version of numpy, it will be understood as (type, (1,)) / '(
1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/usr/local/lib/python3.7/dist-packages/tensorflow/python/framework/dtypes.py:5
28: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprec
ated; in a future version of numpy, it will be understood as (type, (1,)) / '(
1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/usr/local/lib/python3.7/dist-packages/tensorflow/python/framework/dtypes.py:5
29: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprec
ated; in a future version of numpy, it will be understood as (type, (1,)) / '(
1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/usr/local/lib/python3.7/dist-packages/tensorflow/python/framework/dtypes.py:5
30: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprec
ated; in a future version of numpy, it will be understood as (type, (1,)) / '(
1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/usr/local/lib/python3.7/dist-packages/tensorflow/python/framework/dtypes.py:5
35: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprec
ated; in a future version of numpy, it will be understood as (type, (1,)) / '(
1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
WARNING:root:No module named 'numba.decorators': LFR will be unavailable. To i
nstall, run:
pip install 'aif360[LFR]'
```

Problem 2

Load and split data

Load Folktables dataset and set the protected attribute, drop the other protected attribute race

We have included code to read in the folktables dataset. The Folktables dataset is taken from US Census Data and is built to solve a few simple prediction tasks. The sample we pull is data from 2018 in California. The column names are described in the table below. Note that certain categorical variables have been mapped to integer values, which we will keep as is for the following analyses.

For more information on the this dataset, please see the following paper: https://eaamo2021.eaamo.org/accepted/acceptednonarchival/EAMO21_paper_16.pdf

Column Name	Feature	Description/Notes
PINCP	Total person's income	(Target) 1 if >= $50k, 0 if less
SEX	Sex	(Sensitive Attribute) Male=1, Female=2
RAC1P	Race	Dropped from this analysis to focus on one sensitive attribute
AGEP	Age	Ranges from 0-99
COW	Class of Worker	Ranges 1-9, see paper for description
SCHL	Education Level	Ranges 1-24, see paper for description
MAR	Marital Status	Ranges 1-5, see paper for description
OCCP	Occupation	Codes taken from Public Use Microdata Sample (PUMS) from the US Census, see paper
POBP	Place of Birth	Codes taken from Public Use Microdata Sample (PUMS) from the US Census, see paper
RELP	Relationship	Relationship of individual to person who responded to the Census taker. Ranges 0-17, see paper for description
WKHP	Hours worked per week	Ranges from 0-99, averaged over previous year

In [ ]:

```
np.random.seed(27)
protected_attr = 'SEX' #set sex as the protected attribute
target = 'PINCP' #personal income as the target (1=(>50k))

#read in the folktables dataset
##change sample size back to 70 K later!!
full_df, features_df, target_df, groups_df = ACSData().return_acs_data_scenar
full_df = full_df.drop(columns='RAC1P') #drop race -- another protected attri

print(full_df.shape)
full_df.head()
```

```
(50000, 10)
```

Out[ ]:

	AGEP	COW	SCHL	MAR	OCCP	POBP	RELP	WKHP	SEX	PINCP
0	53.0	2.0	21.0	3.0	5400.0	233.0	15.0	30.0	1.0	0.0
1	51.0	2.0	21.0	1.0	350.0	217.0	0.0	40.0	2.0	1.0
2	45.0	6.0	21.0	1.0	4252.0	6.0	0.0	30.0	1.0	0.0
3	62.0	1.0	19.0	1.0	5140.0	48.0	0.0	40.0	2.0	0.0
4	63.0	6.0	19.0	1.0	4920.0	17.0	0.0	10.0	1.0	0.0

In [ ]:

```
# convert this dataframe into an aif360 dataset
dataset_orig = BinaryLabelDataset(
    favorable_label=1,
    unfavorable_label=0,
    df=full_df,
    label_names=[target],
    protected_attribute_names=[protected_attr])


privileged_groups = [{protected_attr: 1}]
unprivileged_groups = [{protected_attr: 2}]
```

Create the train test val split

In [ ]:

```
#split data into train_orig, containing 80% and test_orig
train_orig, test_orig = dataset_orig.split([0.8], shuffle=True , seed= 27)
#create train_new and val_new, train_new has 70% of data, val_new has 10% of
train_new, val_new = train_orig.split([.875],shuffle=True)


# Convert to dataframes
train_orig_df, _ = train_orig.convert_to_dataframe()
train_new_df,_ =train_new.convert_to_dataframe()
val_new_df, _ = val_new.convert_to_dataframe()
test_orig_df, _ = test_orig.convert_to_dataframe()


#inspect shapes
print("Train set: ", train_new_df.shape)
print("Val set: ", val_new_df.shape)
print("Test set: ", test_orig_df.shape)



#examine baseline disparate impact and mean difference
metric_orig_panel19_train = BinaryLabelDatasetMetric(
        train_orig,
        unprivileged_groups=unprivileged_groups,
        privileged_groups=privileged_groups)
explainer_orig_panel19_train = MetricTextExplainer(metric_orig_panel19_train)

print(explainer_orig_panel19_train.disparate_impact(),'\n',explainer_orig_pan

print('In our combined training and validation datasets, women receive a labe
```

```
Train set:  (35000, 10)
Val set:  (5000, 10)
Test set:  (10000, 10)
Disparate impact (probability of favorable outcome for unprivileged instances
/ probability of favorable outcome for privileged instances): 0.74825700591220
93
 Mean difference (mean label value on unprivileged instances - mean label valu
e on privileged instances): -0.1171091586712878
In our combined training and validation datasets, women receive a label of 1,
75%  as often as men
```

Problem 2, Part (a)

Train a baseline Random Forest (RF) model and report metrics

Train a random forest model - Baseline

In [ ]:

```
#create train and test vectors used for
x_train, x_test = train_orig_df.drop(target, axis=1), test_orig_df.drop(targe

y_train, y_test= train_orig_df.PINCP,  test_orig_df.PINCP

y_train.value_counts()
```

Out[ ]:

```
0.0    23602
1.0    16398
Name: PINCP, dtype: int64
```

In [ ]:

```
#preprocess data using min max scalar and one hot encode variables
unmitigated_predictor = Pipeline(
    steps=[
            #feature engineering component
        ("preprocessor", ColumnTransformer(transformers=[
                                    # we use selector to indentify
                                    # Normalize numerical features
                                     ("num", MinMaxScaler(), select
                                    # Encoding (transforming) categ
                                    ("cat", OneHotEncoder(handle_un
                                  ]
                                )
        ),
        # model component
        ("classifier",RandomForestClassifier(max_depth = 1, n_estimators=1),
        ),
    ]
)
#fit predictor object on the training data
unmitigated_predictor.fit(x_train, y_train)
```

Out[ ]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num', MinMaxScaler(),
                                                  <sklearn.compose._column_tra
nsformer.make_column_selector object at 0x7f8560aabf10>),
                                                 ('cat',
                                                  OneHotEncoder(handle_unknown
='ignore'),
                                                  <sklearn.compose._column_tra
nsformer.make_column_selector object at 0x7f8534244210>)])),
                ('classifier',
                 RandomForestClassifier(max_depth=1, n_estimators=1))])
```

Problem 2A:

Train a baseline Randomforest, with max_depth = 1 and num_estimators = 1 and report performance on the five metrics of interest on the test set.

In [ ]:
```
#create new dataframe with predictions as the target column
test_pred_df = test_orig_df.copy()
test_pred_df[target] = unmitigated_predictor.predict(x_test)

#initiate a metric list to be used when examining metrics of interest
metric_list = ['accuracy','privileged_groups_accuracy', 'unprivileged_groups_

#create AIF360 objects as input to a ClassificationMetric
preds_aif360 = StandardDataset(test_pred_df, label_name=target, protected_att
               privileged_classes=[[1]], favorable_classes=[1])
orig_aif360 = StandardDataset(test_orig_df, label_name=target, protected_attr
               privileged_classes=[[1]], favorable_classes=[1])

#store model performance in Classification metric Object
metrics_final = ClassificationMetric(orig_aif360, preds_aif360, unprivileged_
```

Calculate Metrics

In [ ]:

```
def calculate_metric(metric_list, ClassificationMetrObj, verbose):
  """
  function used to examine the 5 metrics of interest for ClassificationMetrOb
  """

  for metric in metric_list:
      message = metric +' is '
      if metric == 'accuracy':
        statement = round(ClassificationMetrObj.accuracy(),5)
      elif metric == 'privileged_groups_accuracy':
        statement = round(ClassificationMetrObj.accuracy(privileged=True),5)
      elif metric == 'unprivileged_groups_accuracy':
        statement = round(ClassificationMetrObj.accuracy(privileged=False),5)
      elif metric == 'disparate_impact':
        statement = round(ClassificationMetrObj.disparate_impact(),5)
      else:
        statement = round(ClassificationMetrObj.false_positive_rate_differenc
      if verbose == True:
        print(message + str(statement))
      return(statement)
```

In [ ]:

```
#print statements to show model performance
calculate_metric(metric_list[0:],metrics_final, True)
calculate_metric(metric_list[1:],metrics_final, True)
calculate_metric(metric_list[2:],metrics_final, True)
calculate_metric(metric_list[3:],metrics_final, True)
calculate_metric(metric_list[4:],metrics_final, True)
```

```
accuracy is 0.6146
privileged_groups_accuracy is 0.60663
unprivileged_groups_accuracy is 0.62371
disparate_impact is 0.82383
false_positive_difference_rate is -0.14745
```

Out[ ]:

```
-0.14745
```

Problem 2, Part (b)

Hyperparameter tuning of baseline RF model

Define a program to conduct tune the Random Forest

Optimize the Accuracy. You should try the following hyperparameters:

max_depth=[1, 5, 10]

n_estimators=[1, 5, 10, 15, 20]

In [ ]:

```
#YOUR CODE HERE

def tune_base_rf():
  """
```

```
    function that sequentially:
        creates a train/val/test datasplit
        specifies a hyperparameters grid to iterate over using RandomSearchCV
        fits a model to each training dataset using a base model,
        validates optimal hyperparameters on the validation dataset
        captures test set performance for both models
        stores the results to a dictionary
        repeats this process 9 more times times
        outputs the dictionary of results
    """

    #initialize seed values used in data splitting

    seed_list = [27,100,65,12345,59,210398,4231,45,1,98753]

    #create gridSearchCV inputs
    max_depth_list = [1,5,10]
    n_estimators_list = [1,5,10,15,20]
    param_grid = [{'classifier__max_depth':max_depth_list,
                   'classifier__n_estimators':n_estimators_list
                   }]
    #dictionary that will be our final output
    run_dict = {}
    for i in range(len(seed_list)):

      #create an index for each run in our dictionary, that corresponds to a ne
      run_dict[i] = {}


      #create splits for train,validation and test datasets
      train_orig, test_orig = dataset_orig.split([0.8], shuffle=True , seed= se
      train_new, val_new = train_orig.split([.875],shuffle=True, seed = seed_li

      #create dataframe objects
      train_orig_df, _ = train_orig.convert_to_dataframe()
      train_new_df,_ =train_new.convert_to_dataframe()
      val_new_df, _ = val_new.convert_to_dataframe()
      test_orig_df, _ = test_orig.convert_to_dataframe()

      #create vectors for base and tuned models

      x_base_train, x_base_test = train_orig_df.drop(target, axis=1), test_orig
      y_base_train, y_base_test= train_orig_df.PINCP,  test_orig_df.PINCP


      x_val_train, x_val_test = train_new_df.drop(target, axis=1), val_new_df.d
      y_val_train, y_val_test = train_new_df.PINCP, val_new_df.PINCP

      #create splits for hyperparameter tuning
      split_index = [-1 if x in x_val_train.index else 0 for x in x_base_train.
      pds = PredefinedSplit(test_fold = split_index)



      #create pipeline object
      unmitigated_predictor = Pipeline(
          steps=[
```

```
            #feature engineering component
          ("preprocessor", ColumnTransformer(transformers=[
                                                  # we use selector to indent
                                                  # Normalize numerical featu
                                                  ("num", MinMaxScaler(), sel
                                                  # Encoding (transforming) c
                                                  ("cat", OneHotEncoder(handl
                                                ]
                                              )
          ),
          # model component
          ("classifier",RandomForestClassifier(max_depth = 1, n_estimators=
          ),
      ])

  #fit our base model on the training data, without using validation datase

  unmitigated_predictor.fit(x_base_train, y_base_train)



  #create RandomizedSearhCV finding the optimized weights for this split on
  clf = RandomizedSearchCV(unmitigated_predictor,
                       n_iter=10,
                       cv = pds,
                       scoring = 'accuracy',
                       param_distributions = param_grid)

  #fit the model with various hyperparameters on the training and validatio
  clf.fit(x_base_train,y_base_train)

  #capture the best accuracy and parameters of our tuned model
  run_dict[i]['max_validation_score'] = clf.best_score_
  run_dict[i]['params'] =clf.best_params_



  ##create dataframe objects that will be
  base_pred_df = test_orig_df.copy()
  base_pred_df[target] = unmitigated_predictor.predict(x_base_test)
  tuned_pred_df = test_orig_df.copy()
  tuned_pred_df[target] = clf.predict(x_base_test)


  ##create AIF360 datasets
  base_aif360 = StandardDataset(base_pred_df, label_name=target, protected_
              privileged_classes=[[1]], favorable_classes=[1])
  preds_aif360 = StandardDataset(tuned_pred_df, label_name=target, protecte
              privileged_classes=[[1]], favorable_classes=[1])
  orig_aif360 = StandardDataset(test_orig_df, label_name=target, protected_
              privileged_classes=[[1]], favorable_classes=[1])

  #create the classification metric object to store
  metrics_tuned = ClassificationMetric(orig_aif360, preds_aif360, unprivile
  metrics_base = ClassificationMetric(orig_aif360, base_aif360, unprivilege

  #store the classificatoin metric objects in our dictionary
```

```
        run_dict[i]['base_metric'] = metrics_base
        run_dict[i]['tuned_metric'] = metrics_tuned

    return(run_dict)
```

Compare the initial model to the fine-tuned model for 10 train/val/test splits for Random Forest

In [ ]:

```
def compute_metric_lists(dict, metric_list, repair):
  """
  Args:
    dict -- a dictionary containing ClassificationMetric Objects that we will
    metric_list -- a list of the metrics we want to evaluate
    repair -- a boolean that indicates if the metrics we are interested in ar
    which has a different input structure than the other problems

  returns: a dictionary of the metrics of interest for problems 2b-2e

  """
  if repair == False:
    initial_metric_dict, tuned_metric_dict = {}, {}
    for metric in metric_list:
      initial_metric_dict[metric] = []
      tuned_metric_dict[metric] = []

    """
    used for the tuning vs non tuning metric evaluation (2b/2)

    """
    for k,v in dict.items():
       if 'base_metric' in v.keys():
        for metric in metric_list:
          initial_metric_dict[metric].append(calculate_metric([metric],v['bas
          tuned_metric_dict[metric].append(calculate_metric([metric],v['tuned
       else:

         """
         used for the ROC metric evaluation (2e)

         """
        for metric in metric_list:
          tuned_metric_dict[metric].append(calculate_metric([metric],v['metri
    if initial_metric_dict:
      return(initial_metric_dict,tuned_metric_dict)
    else:
      return(tuned_metric_dict)

  """
  used for the Repair prediction metric evaluation (2c/2d)

  """
  else:
    repair_metric_dict = {}
    for metric in metric_list:
      repair_metric_dict[metric] = []
    for i in range(len(dict)):
      for metric in metric_list:
        repair_metric_dict[metric].append(calculate_metric([metric],dict[i],v

    return(repair_metric_dict)
```

In [ ]:

```
output_dict = tune_base_rf()
```

In [ ]:

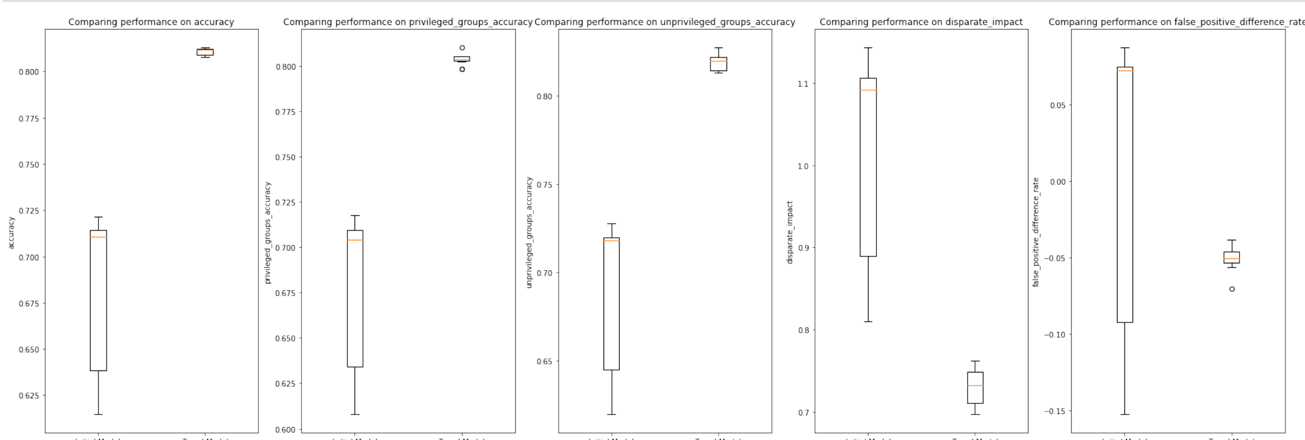
```
initial_metrics, tuned_metrics = compute_metric_lists(output_dict, metric_lis
```

In [ ]:

```
# for boxplots
def plot_init_v_tuned_box(init_metrics, tuned_metrics, metric_name):
  '''Creates a bar graph comparing init_metrics to tuned_metrics'''

  # Make some x values
  x_init = list(range(len(init_metrics)))
  x_tuned = [x + 0.35 for x in x_init]

  # Plot the metrics
  plt.boxplot([init_metrics, tuned_metrics], labels=['Initial Model', 'Tuned 
  plt.title('comparing untuned and tuned Random Forest ' + metric_name)
  # Create labels, etc.
  plt.ylabel(metric_name)
  plt.legend()
  #plt.show()
```

In [ ]:

```
#create 5 graphs
ig, axs = plt.subplots(1,5, figsize=(30,10))

for i in range(len(metric_list)):
  metric = metric_list[i]
  ax = axs[i]
  pcm = ax.boxplot([initial_metrics[metric], tuned_metrics[metric]], labels =
  ax.title.set_text('Comparing performance on ' + metric)
  ax.set_ylabel(metric)

plt.show()
```



Problem 2, Part (c)

Disparate Impact Pre-Processing intervention

In [ ]:
```
#tuned_metrics
#uncomment the above to analyze which parameters did the best out of our 5 me

#best performance on test set data was run 4, which had parameters of max_dep
output_dict[4]
```

Out[ ]:
```
{'base_metric': <aif360.metrics.classification_metric.ClassificationMetric at
0x7f8532cff850>,
 'max_validation_score': 0.821,
 'params': {'classifier__max_depth': 10, 'classifier__n_estimators': 20},
 'tuned_metric': <aif360.metrics.classification_metric.ClassificationMetric at
0x7f8534242ed0>}
```

In [ ]:
```
#create 10 data points to plot performance over repair level
repair_list = np.linspace(0,1,10)
```

In [ ]:
```
def repair_tuned_rf(repair_list):
  #initialize seed values used in data splitting
  ClassificationMetric_list = []
  seed_list = [27,100,65,12345,59,210398,4231,45,1,98753]
  for i in range(len(repair_list)):
    repair = DisparateImpactRemover(repair_list[i],sensitive_attribute='SEX')
    train_orig, test_orig = dataset_orig.split([0.8], shuffle=True , seed= se


  #apply preprocessing to our data
    repair_train, repair_test = repair.fit_transform(train_orig), repair.fit_

  #create dataframe objects
    repair_train_orig_df, _ = repair_train.convert_to_dataframe()
    repair_test_orig_df, _ = repair_test.convert_to_dataframe()

  #create vectors for base and tuned models

    x_base_train, x_base_test = repair_train_orig_df.drop(target, axis=1), re
    y_base_train, y_base_test= repair_train_orig_df.PINCP,  repair_test_orig_


    #replicate our best predictor
    tuned_predictor = Pipeline(
          steps=[
                #feature engineering component
              ("preprocessor", ColumnTransformer(transformers=[
                                                  # we use selector to inde
                                                  # Normalize numerical fea
                                                  ("num", MinMaxScaler(), s
                                                  # Encoding (transforming)
                                                  ("cat", OneHotEncoder(han
                                                ]
                                              )
              ),
              # model component
              #using optimal hyperparameters after RandomSearch CV, determine
              ("classifier",RandomForestClassifier(max_depth = 10, n_estimato
```

```
            ),
        ])

    #fit tuned model
    tuned_predictor.fit(x_base_train, y_base_train)

    #predict tuned model onto dataframe

    tuned_pred_df = test_orig_df.copy()
    tuned_pred_df[target] = tuned_predictor.predict(x_base_test)

    #create AIF360 objects
    preds_aif360 = StandardDataset(tuned_pred_df, label_name=target, protecte
                privileged_classes=[[1]], favorable_classes=[1])
    orig_aif360 = StandardDataset(test_orig_df, label_name=target, protected_
                privileged_classes=[[1]], favorable_classes=[1])

    #store results
    ClassificationMetric_list.append(ClassificationMetric(orig_aif360, preds_

  return(ClassificationMetric_list)
```

In [ ]:

```
#run the func
repair_metric_list = repair_tuned_rf(repair_list)
```

In [ ]:

```
#compute 5 metrics of interest
repair_metrics = compute_metric_lists(repair_metric_list,metric_list, True)
```

In [ ]:

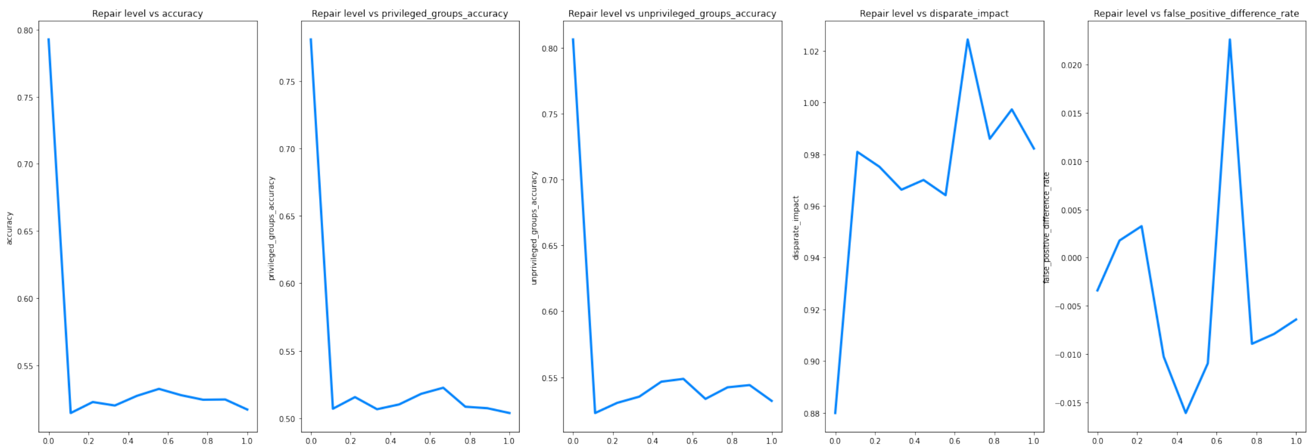
```
#create a new key for the repair level itself
repair_metrics['repair_level'] = repair_list
#repair_metrics
```

In [ ]:

```
def plot_repair_levels(repair_levels, metric_vals, metric_name, x_label='Repa
  '''Creates a line plot showing how the metric changed for different values 

  # Plot the metrics
  plt.plot(repair_levels, metric_vals, color='#0384fc', linewidth=3, label=me

  # Create labels, etc.
  plt.xlabel(x_label)
  plt.ylabel(metric_name)
  plt.legend()
  plt.show()
```

In [ ]:

```
#plot metrics according to repair level
fig, axs = plt.subplots(1,5, figsize=(30,10))

for i in range(len(metric_list)):
  metric = metric_list[i]
  ax = axs[i]
  pcm = ax.plot(repair_list, repair_metrics[metric], color='#0384fc', linewid
  ax.title.set_text('Repair level vs ' + metric)
  ax.set_ylabel(metric)

plt.show()
```



Apply pre-processing techniques to the dataset, then re-train the models with the optimal hyperparameters from part b

In [ ]:

```
def prejudice_remover(eta_list):

  #initialize seed values used in data splitting

  ClassificationMetric_list = []
  seed_list = [27,100,65,12345,59,210398,4231,45,1,98753][0:9]

  #for 9 iterations,

  for i in range(len(eta_list)):

    #split data into train/test
    train_orig, test_orig = dataset_orig.split([0.8], shuffle=True , seed= se

    #create PrejudiceRemover Object with value of eta
    PrejudiceRemoverObj = PrejudiceRemover(eta_list[i])


    #create dataframe objects
    train_orig_df, _ = train_orig.convert_to_dataframe()
    test_orig_df, _ = test_orig.convert_to_dataframe()

    #create a preprocess object
    preprocessing = ColumnTransformer(
    [("scaler", MinMaxScaler(), [0, 1])],
```

```
    remainder="passthrough")

    #create binarylabeldataset objects for train/test

    BinaryTrainDataset = BinaryLabelDataset(favorable_label=1,
      unfavorable_label=0,
      df=train_orig_df,
      label_names=[target],
      protected_attribute_names=[protected_attr])

    BinaryTestDataSet = BinaryLabelDataset(favorable_label=1,
      unfavorable_label=0,
      df=test_orig_df,
      label_names=[target],
      protected_attribute_names=[protected_attr])


    #preprocess train/test datasets
    BinaryTrainDataset.features = preprocessing.fit_transform(BinaryTrainData
    BinaryTestDataSet.features = preprocessing.transform(BinaryTestDataSet.fe

    #fit the data onto the training data

    fit = PrejudiceRemoverObj.fit(BinaryTrainDataset)

    #store predictions into a dataframe
    unprejudiced_df = test_orig_df.copy()
    unprejudiced_df[target] = fit.predict(BinaryTestDataSet).labels

    #create aif360 objects
    preds_aif360 = StandardDataset(unprejudiced_df, label_name=target, protec
                privileged_classes=[[1]], favorable_classes=[1])
    orig_aif360 = StandardDataset(test_orig_df, label_name=target, protected_
                privileged_classes=[[1]], favorable_classes=[1])

    #store metrics
    ClassificationMetric_list.append(ClassificationMetric(orig_aif360, preds_

  return(ClassificationMetric_list)
```

Problem 2, Part (d)

Prejudice Remover In-Processing intervention

Fit new models using the Prejudice Remover technique

In [ ]:

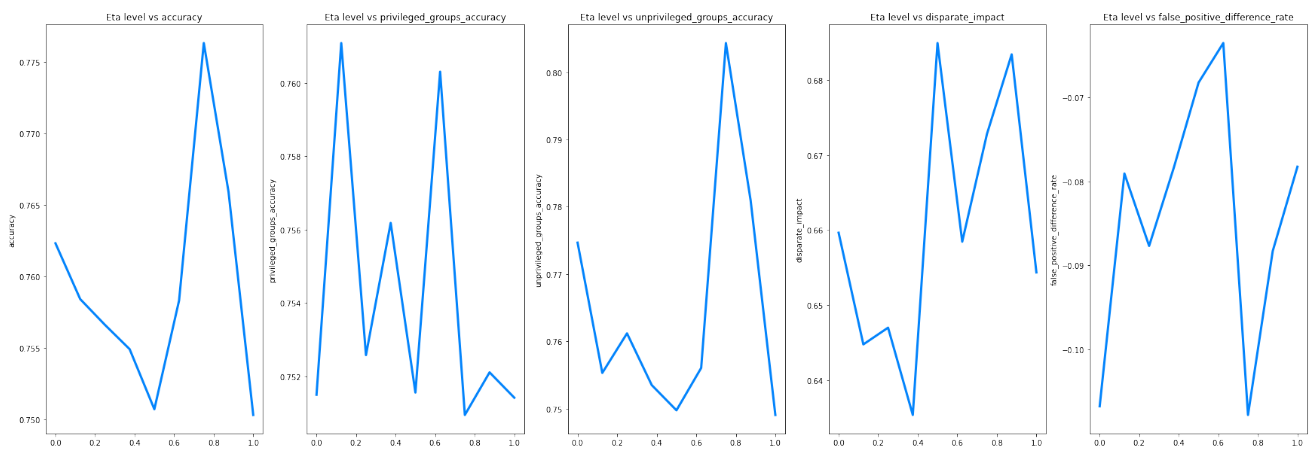
```
#create eta list to remove prejudice, run func
eta_list = np.linspace(0,1,9)

unprejudiced_models = prejudice_remover(eta_list)
```

In [ ]:

```
#compute metrics
unprejudiced_metrics = compute_metric_lists(unprejudiced_models, metric_list,
```

In [ ]:

```
#plot performance across eta levels
fig, axs = plt.subplots(1,5, figsize=(30,10))

for i in range(len(metric_list)):
  metric = metric_list[i]
  ax = axs[i]
  pcm = ax.plot(eta_list, unprejudiced_metrics[metric], color='#0384fc', line
  ax.title.set_text('Eta level vs ' + metric)
  ax.set_ylabel(metric)
```



Problem 2, Part (e)

Reject Option Post-Processing intervention

Using the same random forest models as before, apply the post-processing technique to your results and compare

In [ ]:

```
def ROC_rf():
  ###steps:
      ##split data into train/val/test
      #train data using optimally tuned random forest
      #pass trained model into ROC classifer, validating on validation datase
      #test new model after post-processing on test dataset

  #initialize seed values used in data splitting

  seed_list = [27,100,65,12345,59,210398,4231,45,1,98753]

  #create gridSearchCV inputs

  final_dict = {}
  for i in range(len(seed_list)):
    final_dict[i] = {}
```

```
#create splits for train,validation and test datasets
train_orig, test_orig = dataset_orig.split([0.8], shuffle=True , seed= se
train_new, val_new = train_orig.split([.875],shuffle=True, seed = seed_li

#create dataframe objects
train_orig_df, _ = train_orig.convert_to_dataframe()
train_new_df,_ =train_new.convert_to_dataframe()
val_new_df, _ = val_new.convert_to_dataframe()
test_orig_df, _ = test_orig.convert_to_dataframe()

#create vectors for base and tuned models

x_base_train, x_base_test = train_orig_df.drop(target, axis=1), test_orig
y_base_train, y_base_test= train_orig_df.PINCP,  test_orig_df.PINCP


x_val_train, x_val_test = train_new_df.drop(target, axis=1), val_new_df.d
y_val_train, y_val_test = train_new_df.PINCP, val_new_df.PINCP

#create splits for hyperparameter tuning
split_index = [-1 if x in x_val_train.index else 0 for x in x_base_train.
pds = PredefinedSplit(test_fold = split_index)
params_list= []

for k in sorted(output_dict[i]['params'].keys()):
  params_list.append(output_dict[i]['params'][k])


#create pipeline object
tuned_predictor = Pipeline(
    steps=[
          #feature engineering component
        ("preprocessor", ColumnTransformer(transformers=[
                                                     # we use selector to indent
                                                     # Normalize numerical featu
                                                     ("num", MinMaxScaler(), sel
                                                     # Encoding (transforming) c
                                                     ("cat", OneHotEncoder(handl
                                                   ]
                                                 )
        ),
        # model component
        ("classifier",RandomForestClassifier(max_depth = params_list[0], 
        ),
    ])

#fit optimized rf on training data
tuned_predictor.fit(x_base_train, y_base_train)
pos_ind = np.where(tuned_predictor.classes_ == train_orig.favorable_label

#predict on validation data
valid_pred_BLD = val_new.copy()


valid_pred_BLD.scores = tuned_predictor.predict_proba(x_val_test)[:,pos_i
fav_inds = valid_pred_BLD.scores > .5
```

```
        valid_pred_BLD.labels[fav_inds], valid_pred_BLD.labels[~fav_inds] = val_n


        #validate optimal ROC parameters on validation dataset
        ROC = RejectOptionClassification(unprivileged_groups=unprivileged_groups,
                                         privileged_groups=privileged_groups,
                                         low_class_thresh = 0.01,
                                         high_class_thresh =.99,
                                         num_class_thresh = 10,
                                         num_ROC_margin=10
                                         )

        ROC.fit(val_new,valid_pred_BLD)

        #store decision boundaries and ROC margin
        best_class_threshold = ROC.classification_threshold
        best_margin = ROC.ROC_margin

        final_dict[i]['class_threshold'] = best_class_threshold
        final_dict[i]['margin'] = best_margin

        #predict on test datasets

        dataset_orig_test_pred = test_orig.copy()
        dataset_orig_test_pred.scores = tuned_predictor.predict_proba(x_base_test

        #transfrom scores into labels using calcualted decision boundary
        fav_inds = dataset_orig_test_pred.scores > best_class_threshold
        dataset_orig_test_pred.labels[fav_inds] = dataset_orig_test_pred.favorabl
        dataset_orig_test_pred.labels[~fav_inds] = dataset_orig_test_pred.unfavor

        #predict data on test set
        ROC_Test = ROC.predict(dataset_orig_test_pred)

        orig_aif360 = StandardDataset(test_orig_df, label_name=target, protected_
                    privileged_classes=[[1]], favorable_classes=[1])

        #store results
        final_dict[i]['metric_list']=ClassificationMetric(test_orig, ROC_Test, un
    return(final_dict)
```

In [ ]:

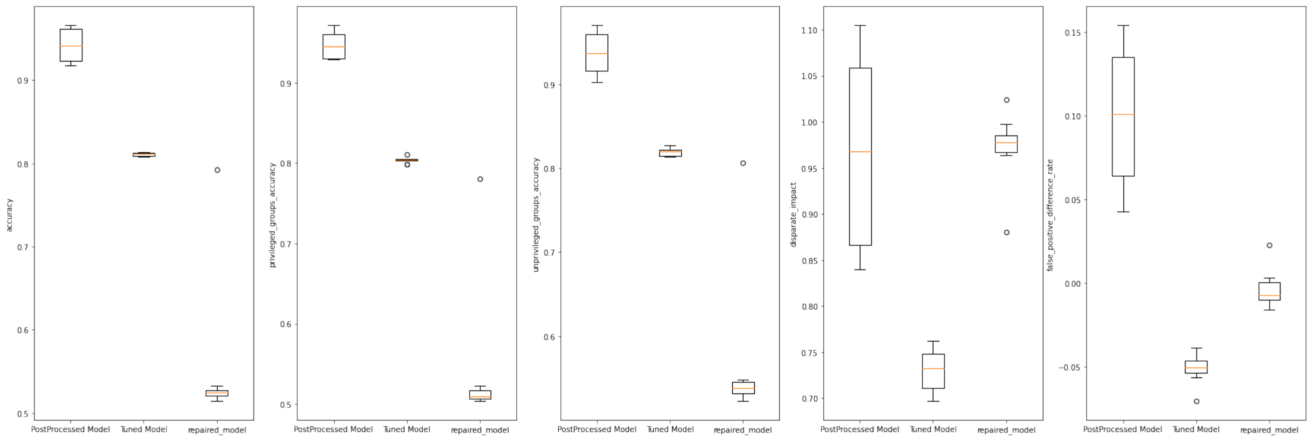
```
ROC_list = ROC_rf()
```

In [ ]:

```
ROC_metric_list = ['accuracy', 'privileged_groups_accuracy', 'unprivileged_gr
 'class_threshold', 'margin',]
post_processed_metrics = compute_metric_lists(ROC_list, ROC_metric_list, Fals
```

In [ ]:

```
#plot performance across 5 metrics for ROC, tuned and base random forests
fig, axs = plt.subplots(1,5, figsize=(30,10))

for i in range(len(metric_list)):
  metric = metric_list[i]
  ax = axs[i]
  pcm = ax.boxplot([post_processed_metrics[metric],tuned_metrics[metric],repa
                   labels = ['PostProcessed Model', 'Tuned Model', 'repaired_r
  #ax.title.set_text('Eta level vs ' + metric)
  ax.set_ylabel(metric)
```



In [ ]: