ADS Project 4: Machine Learning Fairness

Spring 2023

In [ ]:
```python
# Load modules
!pip install prince
import os, sys
import numpy as np
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.utils import shuffle
from sklearn.metrics import log_loss
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import A2_algorithm_function as ut
import A2_loss_function as lf
from A7_algorithm_function import *
import warnings
from c_svm import SVM
import matplotlib.pyplot as plt
from prince import CA
```

- The cleaned COMPAS dataset is provided in `../output/compas-scores-two-years_cleaned.csv`.

Section 1: Load Data

In [2]:
```python
df =  pd.read_csv('../output/compas-scores-two-years_cleaned.csv')
df.head(3)
```

Out[2]:

	sex	age_cat	race	priors_count	c_charge_degree	two_year_recid	length_of_stay
0	Male	25 - 45	African-American	-0.733607	F	1	-0.167773
1	Male	< 25	African-American	0.055928	F	1	-0.340654
2	Male	25 - 45	Caucasian	2.029767	F	1	-0.244609

In [3]:
```python
# change categorical data into numerical
le = LabelEncoder()
df['sex'] = le.fit_transform(df['sex'])
df['age_cat'] = le.fit_transform(df['age_cat'])
df['race'] = le.fit_transform(df['race'])
df['c_charge_degree'] = le.fit_transform(df['c_charge_degree'])
```

Encode categorical variables with numerical variables:

- `sex` : 1 for male and 0 for female
- `age_cat` : 2 for > 45, 0 for 25 - 45 and 1 for < 25
- `race` : 1 for caucasian and 0 for african-american
- `c_charge_degree` : 0 for F and 1 for M

In [4]:
```python
#
df['sex'].value_counts(), df['age_cat'].value_counts(), df['race'].value_counts(), df['c_charge_degree'].value_counts()
```

Out[4]:
```
(1    4751
 0    1164
 Name: sex, dtype: int64,
 0    3378
 1    1281
 2    1256
 Name: age_cat, dtype: int64,
 0    3537
 1    2378
 Name: race, dtype: int64,
 0    3904
 1    2011
 Name: c_charge_degree, dtype: int64)
```

In [5]:
```python
features = df[['sex', 'age_cat', 'c_charge_degree', 'length_of_stay',"priors_count"]]
sensitive = df['race']
target = df['two_year_recid']
X_train, X_test, y_train, y_test, race_train, race_test = \
    train_test_split(features, target, sensitive, test_size=0.3, random_state=6, shuffle = True)
```

- **Protected**: Caucasians (i.e., `race == 1`)
- **Not protected**: African-Americans (i.e., `race == 0`)

In [6]:
```python
df.head()
```

Out[6]:

	sex	age_cat	race	priors_count	c_charge_degree	two_year_recid	length_of_stay
0	1	0	0	-0.733607	0	1	-0.167773
1	1	1	0	0.055928	0	1	-0.340654
2	1	0	1	2.029767	0	1	-0.244609
3	0	0	1	-0.733607	1	0	-0.321445
4	1	1	1	-0.536224	0	1	-0.359864

The p-rule function is commonly used in evaluate fairness in machine learning model, by checking whether the model's positive predictions are distributed similarly across different sensitive groups. The higher the p-rule, the better the fairness.

In [7]:
```python
# Function to compute p-rule
def p_rule(sensitive_var, y_pred):
    protected = np.where(sensitive_var == 1)[0]
    not_protected = np.where(sensitive_var == 0)[0]
    protected_pred = np.where(y_pred[protected] == 1)
    not_protected_pred = np.where(y_pred[not_protected] == 1)
    protected_percent = protected_pred[0].shape[0]/protected.shape[0]
    not_protected_percent = not_protected_pred[0].shape[0]/not_protected.shape[0]
    ratio = min(protected_percent/not_protected_percent, not_protected_percent/protected_percent)

    return ratio, protected_percent, not_protected_percent
```

In [8]:
```python
def calibration(y_true, y_pred, sensitive_features):
    y_true = np.array(y_true)
    y_pred = np.array(y_pred)

    c_index = np.where(sensitive_features == 1)[0]
    a_index = np.where(sensitive_features == 0)[0]

    y_pred_c = y_pred[c_index]
    y_true_c = y_true[c_index]
    acc_c = sum(y_pred_c == y_true_c)/len(y_pred_c)

    y_pred_a = y_pred[a_index]
    y_true_a = y_true[a_index]
    acc_a = sum(y_pred_a == y_true_a)/len(y_pred_a)

    calibration = abs(acc_c - acc_a) * 100
    return(calibration)
```

The "80% rule" (or the p%-rule) is a guideline established by the U.S. Equal Employment Opportunity Commission (EEOC) to help identify potential discrimination in hiring, promotion, or other employment decisions. It's a way to measure fairness and equal opportunity in these processes, particularly concerning sensitive attributes such as race, gender, age, or disability.

Section 2: Logistic Regression

2.1 Baseline Model

First, we train a baseline model without constaint, and then evaluate it's accuaracy and fairness.

In [9]:
```python
clf = LogisticRegression(random_state= 6).fit(X_train, y_train)
coeff = clf.coef_
intercept = clf.intercept_
optimal_loss = log_loss(y_train, clf.predict_proba(X_train))
print(f'The optimal loss of logistic model is: {optimal_loss}')
```
```
The optimal loss of logistic model is: 0.6407097826469522
```

- Accuracy & Fairness check:

In [10]:
```python
results_lr = {"Classifier": ["LR", "LR"],
              "Set": ["Train", "Test"],
              "Accuracy (%)": [clf.score(X_train, y_train)*100, clf.score(X_test, y_test)*100],
              "P-rule (%)": [p_rule(race_train, clf.predict(X_train))[0]*100, p_rule(race_test, clf.predict(X_test))[0]*100],
              "Protected (%)": [p_rule(race_train, clf.predict(X_train))[1]*100, p_rule(race_test, clf.predict(X_test))[1]*100],
              "Not protected (%)": [p_rule(race_train, clf.predict(X_train))[2]*100, p_rule(race_test, clf.predict(X_test))[2]*100]}
pd.DataFrame(results_lr)
```

Out[10]:

	Classifier	Set	Accuracy (%)	P-rule (%)	Protected (%)	Not protected (%)
0	LR	Train	63.743961	55.108121	21.962896	39.854192
1	LR	Test	62.028169	59.382529	24.186704	40.730337

Interpretation:

The p-rule, a fairness metric, indicates that there is some bias in the model (lower than 80%). This suggests that the classifier's performance could be improved in terms of both accuracy and fairness, particularly by addressing the disparity in positive outcomes between the protected and non-protected groups.

2.2 Optimizing classifier accuracy subject to fairness constraints

The fairness constraint is set to achieve a 0 covariance between the sensitive feature (race) and the distance to the decision boundary. A 0 covariance means there is no correlation between the two variables, which helps promote fairness.

1. Train the model using constraints to extract model weights (cweight).

In [11]:
```python
# Setting Constrains
#In this case, only fairness constraints are applied (apply_fairness_constraints = 1)
# While accuracy constraint and separate constraint are not applied (both set to 0).
fairness_constraint = 1
accuracy_constraint = 0
separate_constraint = 0
gamma = None
sensitive_attrs = ['race']
sensitive_attrs_to_cov_thresh = {'race': 0}
x_control = {'race': race_train}
```

In [12]:
```python
# Training model with constraints
np.random.seed(704)
cweight = ut.train_model(X_train,
                   y_train,
                   x_control,
                   lf._logistic_loss,
                   fairness_constraint,
                   accuracy_constraint,
                   separate_constraint,
                   sensitive_attrs,
                   sensitive_attrs_to_cov_thresh,
                   gamma)
```

2. Feed the model with trained weights

In [13]:
```python
# Feeding model with coefficients and weights
m = LogisticRegression()
m.coef_= cweight.reshape((1,-1))
m.intercept_ = 0
m.classes_ = np.array([0, 1])
```

- Accuracy & Fairness check:

In [14]:
```python
# Print the results
warnings.filterwarnings("ignore")
results_clr = {"Classifier": ["C-LR", "C-LR"],
               "Set": ["Train", "Test"],
               "Accuracy (%)": [m.score(X_train, y_train)*100, m.score(X_test, y_test)*100],
               "P-rule (%)": [p_rule(race_train, m.predict(X_train))[0]*100, p_rule(race_test, m.predict(X_test))[0]*100],
               "Protected (%)": [p_rule(race_train, m.predict(X_train))[1]*100, p_rule(race_test, m.predict(X_test))[1]*100],
               "Not protected (%)": [p_rule(race_train, m.predict(X_train))[2]*100, p_rule(race_test, m.predict(X_test))[2]*100]}
pd.DataFrame(results_clr)
```

Out[14]:

	Classifier	Set	Accuracy (%)	P-rule (%)	Protected (%)	Not protected (%)
0	C-LR	Train	48.405797	99.319527	94.733692	95.382746
1	C-LR	Test	49.633803	99.378233	95.190948	95.786517

Interpretation:

The accuracy is lower compared to the based-model. Fairness wise, p-rule is drastically improved nearing 100% indicating the model is fair vis-a-vis to race.

Section 3: Support Vector Machine (SVM)

3.1 Baseline Model

In [15]:
```python
from sklearn import svm
from sklearn.svm import SVC

# Train model
svm_model = SVC(kernel = 'linear', probability = True)
clf= svm_model.fit(X_train, y_train)
optimal_loss = log_loss(y_train, clf.predict_proba(X_train))
print(f'The optimal loss of SVM model is: {optimal_loss}')
```
```
The optimal loss of SVM model is: 0.6445082714142158
```

In [16]:
```python
# Display results
results_svm = {"Classifier": ["SVM", "SVM"],
               "Set": ["Train", "Test"],
               "Accuracy (%)": [clf.score(X_train, y_train)*100, clf.score(X_test, y_test)*100],
               "P-rule (%)": [p_rule(race_train, clf.predict(X_train))[0]*100, p_rule(race_test, clf.predict(X_test))[0]*100],
               "Protected (%)": [p_rule(race_train, clf.predict(X_train))[1]*100, p_rule(race_test, clf.predict(X_test))[1]*100],
               "Not protected (%)": [p_rule(race_train, clf.predict(X_train))[2]*100, p_rule(race_test, clf.predict(X_test))[2]*100]}
pd.DataFrame(results_svm)
```

Out[16]:

	Classifier	Set	Accuracy (%)	P-rule (%)	Protected (%)	Not protected (%)
0	SVM	Train	62.850242	51.049930	15.858767	31.065209
1	SVM	Test	61.352113	53.767411	17.821782	33.146067

3.2 Optimizing SVM classifier accuracy subject to fairness constraints

In [17]:
```python
# Fairness Constraints: Mechanisms for Fair Classification
svm = SVM()
x_control_train = {'race': race_train}
weights = svm.train(X_train, y_train, x_control_train, C=1, max_iter=100, lamb=1, gamma=None, apply_fairness_constraints=1, sensitive_attrs=['race'], sensitive_attrs_to_cov_thresh={'race':
pred_y_test = np.sign(np.dot(X_test, weights))
pred_y_train = np.sign(np.dot(X_train, weights))
csvm_test_acc = sum(pred_y_test == y_test)/len(y_test)
csvm_train_acc = sum(pred_y_train == y_train)/len(y_train)
```
```
Running custom model
```

In [18]:
```python
results_csvm = {"Classifier": ["C-SVM", "C-SVM"],
        "Set": ["Train", "Test"],
        "Accuracy (%)": [csvm_test_acc * 100, csvm_train_acc * 100],
        "Calibration(%)": [calibration(y_train, pred_y_train, race_train),
                           calibration(y_test, pred_y_test, race_test)],
         "P-rule (%)": [p_rule(race_train, pred_y_train)[0]*100, p_rule(race_test, pred_y_test)[0]*100],
        "Protected (%)": [p_rule(race_train, pred_y_train)[1]*100, p_rule(race_test, pred_y_test)[1]*100],
        "Not protected (%)": [p_rule(race_train, pred_y_train)[2]*100, p_rule(race_test, pred_y_test)[2]*100]}



pd.DataFrame(results_csvm)
```

Out[18]:

	Classifier	Set	Accuracy (%)	Calibration(%)	P-rule (%)	Protected (%)	Not protected (%)
0	C-SVM	Train	47.042254	14.350005	99.488510	94.733692	95.220737
1	C-SVM	Test	45.362319	11.422029	98.986143	94.908062	95.880150

Section 4: Information Theoretic Measures for Fairness-aware Feature Selection(FFS)

An another method to deal with machine learning fairness is called **Information Theoretic Measures for Fairness-aware Feature selection (FFS)**.

In short, from the joint statistics of the data, the framework proposes that two information theoretic measures can be used to quantify the **accuracy** and **discrmination** aspect for each subset of the feature space. We then compute the **Shapley coefficients** for each feature to capture its effect on the sensitive/protected group.

Below is how we choose features by using **FFS** Algorithm.

In [17]:
```python
# this code block takes ~ 20 min to run, so we directly load results from local file
y=df["two_year_recid"]
y=y.to_numpy()
y=np.reshape(y,(-1,1))

a=df["race"]
a=a.to_numpy()
a=np.reshape(a,(-1,1))

arr=["sex","age_cat","priors_count","c_charge_degree","length_of_stay"]

for i in arr:
    print("Feature:",end="")
    print(i)
    print("Marginal Accuracy Coefficient:",end="")
    print(shapley_accuracy(i,y,a))
    print("Marginal Discrimination Coefficient:",end="")
    print(shapley_discrimination(i,y,a))
```
```
Feature:sex
Marginal Accuracy Coefficient:0.003568314907946012
Marginal Discrimination Coefficient:8.16082890138538e-06
Feature:age_cat
Marginal Accuracy Coefficient:0.011273246895526084
Marginal Discrimination Coefficient:4.4881509198872635e-05
Feature:priors_count
Marginal Accuracy Coefficient:0.02427159853758174
Marginal Discrimination Coefficient:4.464995590653898e-05
Feature:c_charge_degree
Marginal Accuracy Coefficient:0.001958893676796756
Marginal Discrimination Coefficient:6.936830123648318e-06
Feature:length_of_stay
Marginal Accuracy Coefficient:0.005168319175750994
Marginal Discrimination Coefficient:1.0984742883746511e-05
```

In [19]:
```python
# display result
shapley_results = pd.DataFrame()
arr=["sex","age_cat","priors_count","c_charge_degree","length_of_stay"]

shapley_results["Feature"] = arr
shapley_results["Accuracy Coefficient"] = [0.003568314907946012, 0.011273246895526084,0.02427159853758174,0.001958893676796756,0.005168319175750994]
shapley_results["Discrimination Coefficient"] = [8.16082890138538e-06,4.4881509198872635e-05,4.464995590653898e-05,6.936830123648318e-06,1.0984742883746511e-05]
shapley_results
```

Out[19]:

	Feature	Accuracy Coefficient	Discrimination Coefficient
0	sex	0.003568	0.000008
1	age_cat	0.011273	0.000045
2	priors_count	0.024272	0.000045
3	c_charge_degree	0.001959	0.000007
4	length_of_stay	0.005168	0.000011

From the table above, we can see that **Discrimination Coefficient** of `priors_count` is highest, but **Accuracy Coefficient** is also high, so we can't ignore this feature. `length_of_stay` has a little high **Discrimination Coefficient**, and its **Accuracy Coefficient** is low, so we can ignore this feature. So finally, we can choose these four features:

- `priors_count`
- `age_cat`
- `sex`
- `c_charge_degree`

4.1 Logistic Regression using FFS

In [20]:
```python
features = df[['sex', 'age_cat', 'c_charge_degree', 'priors_count']]
sensitive = df['race']
target = df['two_year_recid']
X_train, X_test, y_train, y_test, race_train, race_test = \
    train_test_split(features, target, sensitive, test_size=0.3, random_state=6, shuffle = True)
```

In [21]:
```python
# Train model and print results
clf = LogisticRegression(random_state = 0).fit(X_train, y_train)
coeff = clf.coef_
intercept = clf.intercept_
optimal_loss = log_loss(y_train, clf.predict_proba(X_train))
print(f'The optimal loss of logistic model is: {optimal_loss}')

# Display results
results_ffs_lr = {"Classifier": ["FFS-LR", "FFS-LR"],
                  "Set": ["Train", "Test"],
                  "Accuracy (%)": [clf.score(X_train, y_train)*100, clf.score(X_test, y_test)*100],
                  "P-rule (%)": [p_rule(race_train, clf.predict(X_train))[0]*100, p_rule(race_test, clf.predict(X_test))[0]*100],
                  "Protected (%)": [p_rule(race_train, clf.predict(X_train))[1]*100, p_rule(race_test, clf.predict(X_test))[1]*100],
                  "Not protected (%)": [p_rule(race_train, clf.predict(X_train))[2]*100, p_rule(race_test, clf.predict(X_test))[2]*100]}
pd.DataFrame(results_ffs_lr)
```
```
The optimal loss of logistic model is: 0.6436511330361576
```

Out[21]:

	Classifier	Set	Accuracy (%)	P-rule (%)	Protected (%)	Not protected (%)
0	FFS-LR	Train	63.405797	58.808292	23.937762	40.704739
1	FFS-LR	Test	61.802817	65.541470	26.449788	40.355805

4.2 SVM using FFS

In [81]:
```python
# Train model
svm_model = SVC(kernel = 'linear', probability = True)
clf= svm_model.fit(X_train, y_train)
optimal_loss = log_loss(y_train, clf.predict_proba(X_train))
print(f'The optimal loss of SVM model is: {optimal_loss}')

# Display results
results_ffs_svm = {"Classifier": ["FFS-SVM", "FFS-SVM"],
               "Set": ["Train", "Test"],
               "Accuracy (%)": [clf.score(X_train, y_train)*100, clf.score(X_test, y_test)*100],
               "P-rule (%)": [p_rule(race_train, clf.predict(X_train))[0]*100, p_rule(race_test, clf.predict(X_test))[0]*100],
               "Protected (%)": [p_rule(race_train, clf.predict(X_train))[1]*100, p_rule(race_test, clf.predict(X_test))[1]*100],
               "Not protected (%)": [p_rule(race_train, clf.predict(X_train))[2]*100, p_rule(race_test, clf.predict(X_test))[2]*100]}
pd.DataFrame(results_ffs_svm)
```
```
The optimal loss of SVM model is: 0.647671669776638
```

Out[81]:

	Classifier	Set	Accuracy (%)	P-rule (%)	Protected (%)	Not protected (%)
0	FFS-SVM	Train	62.463768	50.574145	15.260323	30.174160
1	FFS-SVM	Test	61.183099	57.589169	18.387553	31.928839

Section 5: Evaluation

In this session, we compare all models from paper A2 and A7 using both accuracy and P-rule score as a measure of fairnes.

In [82]:
```python
results = [results_lr, results_clr, results_svm, results_csvm, results_ffs_lr, results_ffs_svm]
results_df = [pd.DataFrame(r) for r in results]

results_combined = pd.concat(results_df, axis=0)
results_combined = results_combined[results_combined["Set"] == "Test"]
results_combined = results_combined.drop(columns=["Set", "Calibration(%)"])

results_combined
```

Out[82]:

	Classifier	Accuracy (%)	P-rule (%)	Protected (%)	Not protected (%)
1	LR	62.028169	59.382529	24.186704	40.730337
1	C-LR	49.633803	99.378233	95.190948	95.786517
1	SVM	61.352113	53.767411	17.821782	33.146067
1	C-SVM	45.362319	98.986143	94.908062	95.880150
1	FFS-LR	61.802817	65.541470	26.449788	40.355805
1	FFS-SVM	61.183099	57.589169	18.387553	31.928839

If we take both accuracy and fairness into account, we would recommend FFS-LR with 61.8% accuracy as the second highest of all models, and with p-rule score 65.54% that's reasonably well (third highest of all models).

The reason we don't choose C-LR or C-SVM is because despite their high P-rule value, their accuracy is too low for a binary classifier. The reason we don't choose traditional LR or SVM is because despite their relative high accuracy, they do not take fairness into account.

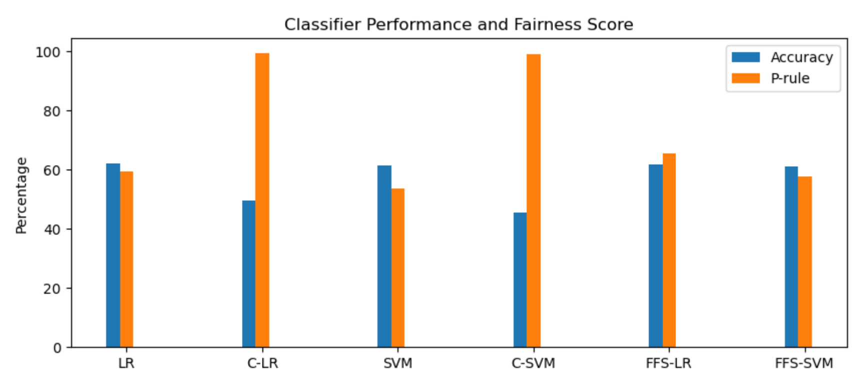
In [84]:
```python
fig, ax = plt.subplots(figsize = (10,4))
x = range(len(results_combined.index))

width = 0.1
ax.bar(x, results_combined['Accuracy (%)'], width, label='Accuracy')
ax.bar([i + width for i in x], results_combined['P-rule (%)'], width, label='P-rule')

ax.set_xticks([i + width for i in x])
ax.set_xticklabels(results_combined['Classifier'])
ax.legend()

plt.ylabel("Percentage")
plt.title("Classifier Performance and Fairness Score")

plt.show()
```


Classifier Performance and Fairness Score
Accuracy
P-rule
Percentage
0
20
40
60
80
100
LR
C-LR
SVM
C-SVM
FFS-LR
FFS-SVM