A6-LM

December 8, 2021

1 Project 4 Group 7 Handling Conditional Discrimination Algorithm

[14]:
```python
# Import required packages
import numpy as np
import pandas as pd

import time
import cv2
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression

import tensorflow as tf
from tensorflow.keras.callbacks import ModelCheckpoint, ReduceLROnPlateau
from tensorflow.keras.layers import Input, Dense, BatchNormalization, Flatten,␣
↪MaxPooling2D, Activation, GlobalMaxPool2D, GlobalAvgPool2D, Concatenate,␣
↪Multiply, Dropout, Subtract
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import Activation, Dropout, Flatten, Dense
from tensorflow.keras.preprocessing.image import ImageDataGenerator,␣
↪array_to_img, img_to_array, load_img
from tensorflow.keras.optimizers import SGD, Adam, RMSprop, Nadam
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split

from functools import partial
from pprint import pprint
from hyperopt import fmin, hp, space_eval, tpe, STATUS_OK, Trials
from hyperopt.pyll import scope, stochastic
from plotly import express as px
from plotly import graph_objects as go
from plotly import offline as pyo
from sklearn.datasets import load_boston
#from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor
from sklearn.ensemble import GradientBoostingClassifier, RandomForestClassifier
```

```
from sklearn.metrics import make_scorer, mean_squared_error, log_loss
from sklearn.model_selection import cross_val_score, KFold
from sklearn.utils import check_random_state
pyo.init_notebook_mode()
```

[2]:
```
print(f"This notebook uses TensorFlow Version {tf.__version__}")
print("And Python Version:")
!python --version
print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
```

```
This notebook uses TensorFlow Version 2.5.0
And Python Version:
Python 3.8.8
Num GPUs Available:  1
```

1.0.1 After importing the data, we can remove unnceccary columns such as dates and focus on the person's more easily quantifiable features

[3]:
```
#Import the data and filter out unneccessary columns and rows that aren't of␣
↪interest (race not A-A or Cau)
df = pd.read_csv('../data/compas-scores-two-years.csv')
df = df.filter(items=['sex','age_cat','race','juv_fel_count','decile_score',
                     ␣
↪'juv_misd_count','juv_other_count','priors_count','c_charge_degree','two_year_recid'])
df = df[(df.race=='African-American') | (df.race=='Caucasian')]
df
```

[3]:

```
         sex       age_cat              race  juv_fel_count  decile_score  \
1       Male       25 - 45  African-American              0             3
2       Male  Less than 25  African-American              0             4
3       Male  Less than 25  African-American              0             8
6       Male       25 - 45         Caucasian              0             6
8     Female       25 - 45         Caucasian              0             1
…        …          …                …             …             …
7207    Male       25 - 45  African-American              0             2
7208    Male  Less than 25  African-American              0             9
7209    Male  Less than 25  African-American              0             7
7210    Male  Less than 25  African-American              0             3
7212  Female       25 - 45  African-American              0             2

      juv_misd_count  juv_other_count  priors_count c_charge_degree  \
1                  0                0             0               F
2                  0                1             4               F
3                  1                0             1               F
6                  0                0            14               F
8                  0                0             0               M
…               …                …            …              …
```

```
7207             0              0           0            M
7208             0              0           0            F
7209             0              0           0            F
7210             0              0           0            F
7212             0              0           3            M

      two_year_recid
1                1
2                1
3                0
6                1
8                0
…              …
7207             1
7208             0
7209             0
7210             0
7212             0

[6150 rows x 10 columns]
```

[4]:
```python
print(df.race.value_counts())
df.isnull().sum().sum()
```

```
African-American    3696
Caucasian           2454
Name: race, dtype: int64
```

[4]: 0

[5]:
```python
df.nunique()
```

[5]:
```
sex                2
age_cat            3
race               2
juv_fel_count     10
decile_score      10
juv_misd_count    10
juv_other_count    9
priors_count      37
c_charge_degree    2
two_year_recid     2
dtype: int64
```

1.0.2 Dummy variable creation

The previous dataframe with categorical data is not acceptable when optimizing hyperparameter with fmin later on, so we create dummy variables for the age categories, gender, race, and charge degree next.

[6]:
```
df_dummy = df.copy()
df_dummy['sex'] = (df['sex'].values == 'Female').astype(int)
df_dummy['race'] = (df['race'].values == 'African-American').astype(int)
df_dummy = pd.concat([df_dummy, pd.get_dummies(df.age_cat, drop_first=True)],␣
↪axis=1)
df_dummy = df_dummy.drop('age_cat', axis=1)
df_dummy = df_dummy.rename(columns={"Greater than 45": "gt45", "Less than 25":␣
↪"lt25"})
df_dummy['c_charge_degree'] = (df['c_charge_degree'].values == 'F').astype(int)
df_dummy
```

[6]:
```
      sex  race  juv_fel_count  decile_score  juv_misd_count  juv_other_count  \
1       0     1              0             3               0                0
2       0     1              0             4               0                1
3       0     1              0             8               1                0
6       0     0              0             6               0                0
8       1     0              0             1               0                0
…     …     …              …             …               …                …
7207    0     1              0             2               0                0
7208    0     1              0             9               0                0
7209    0     1              0             7               0                0
7210    0     1              0             3               0                0
7212    1     1              0             2               0                0

      priors_count  c_charge_degree  two_year_recid  gt45  lt25
1                0                1               1     0     0
2                4                1               1     0     1
3                1                1               0     0     1
6               14                1               1     0     0
8                0                0               0     0     0
…              …                …               …     …     …
7207             0                0               1     0     0
7208             0                1               0     0     1
7209             0                1               0     0     1
7210             0                1               0     0     1
7212             3                0               0     0     0

[6150 rows x 11 columns]
```

[50]:
```
#Our X, s, e, and y parameters for the fairness algorithims plus all the␣
↪features for the initial model
FEATURES =␣
↪['sex','gt45','lt25','juv_fel_count','decile_score','juv_misd_count','juv_other_count','pri
RACE = "race"
DEGREE = "c_charge_degree"
```

```
TWO_YEAR_RECID = "two_year_recid"
ALL_FEATURES =␣
↪['sex','gt45','lt25','juv_fel_count','decile_score','juv_misd_count','juv_other_count',
                'priors_count','race','c_charge_degree']
```

1.1 Choose one boosting and one averaging algorithm to optimize parameters

By diversifying the learning algorithm, number of estimators, learning rate, and max depth(for Gradient Boosting), we can make sure we choose a set of parameters that net us the best performance.

[19]:

```
# Define constant strings that we will use as keys in the "search space"␣
↪dictionary below.
# This helps reduce typos when spelling out the same string repeatedly
GRADIENT_BOOSTING_CLASSIFIER = "gradient_boosting_classifier"
KWARGS = "kwargs"
LEARNING_RATE = "learning_rate"
#LINEAR_REGRESSION = "linear_regression"
MAX_DEPTH = "max_depth"
MODEL = "model"
MODEL_CHOICE = "model_choice"
NORMALIZE = "normalize"
N_ESTIMATORS = "n_estimators"
RANDOM_FOREST_CLASSIFIER = "random_forest_classifier"
RANDOM_STATE = "random_state"

# Declare the search space for the random forest classifier model.
random_forest_classifier = {
    MODEL: RANDOM_FOREST_CLASSIFIER,
    # The model parameters are a separate dictionary so that we can feed the␣
↪parameters to the model
    # via dictionary unpacking which can be seen in the sample_to_model function
    KWARGS: {
        N_ESTIMATORS: scope.int(
            hp.quniform(f"{RANDOM_FOREST_CLASSIFIER}__{N_ESTIMATORS}", 30, 80,␣
↪1)
        ),
        MAX_DEPTH: scope.int(
            hp.quniform(f"{RANDOM_FOREST_CLASSIFIER}__{MAX_DEPTH}", 3, 10, 1)
        ),
        RANDOM_STATE: 0,
    },
}

# Declare the search space for the gradient boosting classifier model,␣
↪following the same structure
# as the random forest classifier search space.
```

```
gradient_boosting_classifier = {
    MODEL: GRADIENT_BOOSTING_CLASSIFIER,
    KWARGS: {
        LEARNING_RATE: scope.float(
            hp.uniform(
                f"{GRADIENT_BOOSTING_CLASSIFIER}__{LEARNING_RATE}",
                0.01,
                0.15,
            )
        ),  # lower learning rate
        N_ESTIMATORS: scope.int(
            hp.quniform(f"{GRADIENT_BOOSTING_CLASSIFIER}__{N_ESTIMATORS}", 30,␣
 ↪80, 1)
        ),
        MAX_DEPTH: scope.int(
            hp.quniform(f"{GRADIENT_BOOSTING_CLASSIFIER}__{MAX_DEPTH}", 3, 10,␣
 ↪1)
        ),
        RANDOM_STATE: 0,
    },
}

# Combine both model search spaces with a top level "choice" between the two␣
 ↪models to get the final
# search space.
space = {
    MODEL_CHOICE: hp.choice(
        MODEL_CHOICE,
        [
            random_forest_classifier,
            gradient_boosting_classifier,
        ],
    )
}

# Define a few additional variables to represent strings. Note that this code␣
 ↪expects that we have
# access to all variables that we previously defined in the "search space" code␣
 ↪snippet.
LOSS = "loss"
STATUS = "status"

# Mapping from string name to model class deinition object that we'll use to␣
 ↪create an initialized
# version of a model from a sample generated from the search space by hyperopt.
MODELS = {
```

```
    GRADIENT_BOOSTING_CLASSIFIER: GradientBoostingClassifier,
    RANDOM_FOREST_CLASSIFIER: RandomForestClassifier,
}

# Helper function that converts from a sample generated by hyperopt to an␣
↪initialized model. Note
# that because we split the model type and model keyword-arguments into␣
↪separate key-value pairs in
# the search space declaration we are able to use dictionary unpacking to␣
↪create an initialized
# version of the model.
def sample_to_model(sample):
    kwargs = sample[MODEL_CHOICE][KWARGS]
    return MODELS[sample[MODEL_CHOICE][MODEL]](**kwargs)

# Create a scoring function that we'll use in our objective
cross_ent_scorer = make_scorer(log_loss)

# Define the objective function for hyperopt. We'll fix the `dataset`,␣
↪`features`, and `target`
# arguments with `functools.partial` to create that version of this function␣
↪that we will supply as
# an argument to `fmin`
def objective(sample, dataset_df, features, target):
    model = sample_to_model(sample)
    rng = check_random_state(0)
    # Handle randomization by shuffling when creating folds. In reality, we␣
↪probably want a better
    # strategy for managing randomization than the fixed `RandomState` instance␣
↪generated above.
    cv = KFold(n_splits=10, random_state=rng, shuffle=True)

    # Calculate average cross entropy log loss for each fold. Since `n_splits`␣
↪is 10, `bce` will is an
    # array of size 10 with each element representing the average cross entropy␣
↪log loss for a fold.
    bce = cross_val_score(
        model,
        dataset_df.loc[:, features],
        dataset_df.loc[:, target],
        scoring=cross_ent_scorer,
        cv=cv,
    )

    # Return average of cross entropy log loss across all folds.
    return {LOSS: np.mean(bce), STATUS: STATUS_OK}
```

[88]:
```
#Do not run this cell again, it takes forever and is a regression model which␣
↪we don't need
# Since we defined our objective function to be generic in terms of the␣
↪dataset, we need to use
# `partial` from the `functools` module to "fix" the `dataset_df`, `features`,␣
↪and `target`
# arguments to the values that we want for this example so that we have an␣
↪objective function that
# takes in only one argument as assumed by the `hyperopt` interface.
#compas_objective = partial(
#    objective, dataset_df=df_dummy, features=FEATURES, target=TWO_YEAR_RECID
#)
# `hyperopt` tracks the results of each iteration in this `Trials` object.␣
↪We’ll be collecting the
# data that we will use for visualization from this object.
#trials = Trials()
#rng = check_random_state(0)  # reproducibility!
# `fmin` searches for hyperparameters that "minimize" our object, mean squared␣
↪error and returns the
# "best" set of hyperparameters.
#best = fmin(compas_objective, space, tpe.suggest, 1000, trials=trials,␣
↪rstate=rng)
```

```
100%|                                    | 1000/1000
[1:06:14<00:00,  3.97s/trial, best loss: 0.2076017026609608]
```

[15]:
```
trialsReg = trials
pprint([t for t in trialsReg][:5])
```

```
[{'book_time': datetime.datetime(2021, 12, 8, 15, 48, 38, 951000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
           'idxs': {'gradient_boosting_regressor__learning_rate': [],
                    'gradient_boosting_regressor__max_depth': [],
                    'gradient_boosting_regressor__n_estimators': [],
                    'model_choice': [0],
                    'random_forest_regressor__max_depth': [0],
                    'random_forest_regressor__n_estimators': [0]},
           'tid': 0,
           'vals': {'gradient_boosting_regressor__learning_rate': [],
                    'gradient_boosting_regressor__max_depth': [],
                    'gradient_boosting_regressor__n_estimators': [],
                    'model_choice': [0],
                    'random_forest_regressor__max_depth': [5.0],
                    'random_forest_regressor__n_estimators': [90.0]},
           'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 15, 48, 41, 667000),
```

```
  'result': {'loss': 0.20818754127918968, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 0,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 15, 48, 41, 674000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
           'idxs': {'gradient_boosting_regressor__learning_rate': [1],
                    'gradient_boosting_regressor__max_depth': [1],
                    'gradient_boosting_regressor__n_estimators': [1],
                    'model_choice': [1],
                    'random_forest_regressor__max_depth': [],
                    'random_forest_regressor__n_estimators': []},
           'tid': 1,
           'vals': {'gradient_boosting_regressor__learning_rate':
[0.03819110609989756],
                    'gradient_boosting_regressor__max_depth': [8.0],
                    'gradient_boosting_regressor__n_estimators': [137.0],
                    'model_choice': [1],
                    'random_forest_regressor__max_depth': [],
                    'random_forest_regressor__n_estimators': []},
           'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 15, 48, 47, 330000),
  'result': {'loss': 0.21938301350280082, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 1,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 15, 48, 47, 340000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
           'idxs': {'gradient_boosting_regressor__learning_rate': [2],
                    'gradient_boosting_regressor__max_depth': [2],
                    'gradient_boosting_regressor__n_estimators': [2],
                    'model_choice': [2],
                    'random_forest_regressor__max_depth': [],
                    'random_forest_regressor__n_estimators': []},
           'tid': 2,
           'vals': {'gradient_boosting_regressor__learning_rate':
[0.08587985607913044],
                    'gradient_boosting_regressor__max_depth': [12.0],
                    'gradient_boosting_regressor__n_estimators': [95.0],
                    'model_choice': [1],
                    'random_forest_regressor__max_depth': [],
                    'random_forest_regressor__n_estimators': []},
           'workdir': None},
```

```
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 15, 48, 52, 673000),
  'result': {'loss': 0.2453977611590717, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 2,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 15, 48, 52, 679000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
           'idxs': {'gradient_boosting_regressor__learning_rate': [],
                    'gradient_boosting_regressor__max_depth': [],
                    'gradient_boosting_regressor__n_estimators': [],
                    'model_choice': [3],
                    'random_forest_regressor__max_depth': [3],
                    'random_forest_regressor__n_estimators': [3]},
           'tid': 3,
           'vals': {'gradient_boosting_regressor__learning_rate': [],
                    'gradient_boosting_regressor__max_depth': [],
                    'gradient_boosting_regressor__n_estimators': [],
                    'model_choice': [0],
                    'random_forest_regressor__max_depth': [2.0],
                    'random_forest_regressor__n_estimators': [93.0]},
           'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 15, 48, 54, 767000),
  'result': {'loss': 0.21586693773448123, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 3,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 15, 48, 54, 774000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
           'idxs': {'gradient_boosting_regressor__learning_rate': [4],
                    'gradient_boosting_regressor__max_depth': [4],
                    'gradient_boosting_regressor__n_estimators': [4],
                    'model_choice': [4],
                    'random_forest_regressor__max_depth': [],
                    'random_forest_regressor__n_estimators': []},
           'tid': 4,
           'vals': {'gradient_boosting_regressor__learning_rate':
[0.0638511443414372],
                    'gradient_boosting_regressor__max_depth': [5.0],
                    'gradient_boosting_regressor__n_estimators': [72.0],
                    'model_choice': [1],
                    'random_forest_regressor__max_depth': [],
                    'random_forest_regressor__n_estimators': []},
```

```
          'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 15, 48, 56, 780000),
  'result': {'loss': 0.20907878867489157, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 4,
  'version': 0}]
```

[10]:
```
# This is a simple helper function that allows us to fill in `np.nan` when a␣
 ↪particular
# hyperparameter is not relevant to a particular trial.
def unpack(x):
    if x:
        return x[0]
    return np.nan


# We'll first turn each trial into a series and then stack those series␣
 ↪together as a dataframe.
trialsReg_df = pd.DataFrame([pd.Series(t["misc"]["vals"]).apply(unpack) for t␣
 ↪in trialsReg])
# Then we'll add other relevant bits of information to the correct rows and␣
 ↪perform a couple of
# mappings for convenience
trialsReg_df["loss"] = [t["result"]["loss"] for t in trialsReg]
trialsReg_df["trial_number"] = trialsReg_df.index
trialsReg_df[MODEL_CHOICE] = trialsReg_df[MODEL_CHOICE].apply(
    lambda x: RANDOM_FOREST_REGRESSOR if x == 0 else GRADIENT_BOOSTING_REGRESSOR
)
trialsReg_df
```

[10]:
```
     gradient_boosting_regressor__learning_rate  \
0                                           NaN
1                                      0.038191
2                                      0.085880
3                                           NaN
4                                      0.063851
..                                          …
995                                         NaN
996                                         NaN
997                                    0.064233
998                                         NaN
999                                         NaN

     gradient_boosting_regressor__max_depth  \
0                                       NaN
```

```
1                                        8.0
2                                       12.0
3                                        NaN
4                                        5.0
..                                       …
995                                      NaN
996                                      NaN
997                                      6.0
998                                      NaN
999                                      NaN

     gradient_boosting_regressor__n_estimators                model_choice  \
0                                          NaN     random_forest_regressor
1                                        137.0  gradient_boosting_regressor
2                                         95.0  gradient_boosting_regressor
3                                          NaN     random_forest_regressor
4                                         72.0  gradient_boosting_regressor
..                                         …                          …
995                                        NaN     random_forest_regressor
996                                        NaN     random_forest_regressor
997                                       63.0  gradient_boosting_regressor
998                                        NaN     random_forest_regressor
999                                        NaN     random_forest_regressor

     random_forest_regressor__max_depth  \
0                                   5.0
1                                   NaN
2                                   NaN
3                                   2.0
4                                   NaN
..                                  …
995                                 6.0
996                                 6.0
997                                 NaN
998                                 7.0
999                                 5.0

     random_forest_regressor__n_estimators      loss  trial_number
0                                     90.0  0.208188             0
1                                      NaN  0.219383             1
2                                      NaN  0.245398             2
3                                     93.0  0.215867             3
4                                      NaN  0.209079             4
..                                     …        …            …
995                                  125.0  0.207602           995
996                                  124.0  0.207622           996
997                                    NaN  0.210222           997
```

```
998                                          131.0   0.208061          998
999                                          136.0   0.208064          999

[1000 rows x 8 columns]
```

[104]:
```
#import dill
#dill.dump_session('notebook_env.db')
```

[9]:
```
#import dill
#dill.load_session('notebook_env.db')
```

[11]:
```
def add_hover_data(fig, df, model_choice):
    # Filter to only columns that are relevant to the current model choice.␣
 ↪Note that this relies on
    # the convention of including the model name in the hyperparameter name␣
 ↪when we declare the
    # search space.
    cols = [col for col in trialsReg_df.columns if model_choice in col]
    fig.update_traces(
        # This specifies the data that we want to plot for the current model␣
 ↪choice.
        customdata=trialsReg_df.loc[
            trialsReg_df[MODEL_CHOICE] == model_choice, cols + [MODEL_CHOICE]
        ],
        hovertemplate="<br>".join(
            [
                f"{col.split('__')[1]}: %{{customdata[{i}]}}"
                for i, col in enumerate(cols)
            ]
        )
        + "<extra></extra>",
        # We only apply the hover data for the current model choice.
        selector={"name": model_choice},
    )
    return fig

# px is an alias for "express" that's created by following the convention of␣
 ↪importing "express" by
# running `from plotly import express as px`
fig = px.scatter(
    trialsReg_df,
    x="trial_number",
    y="loss",
    color=MODEL_CHOICE,
)
# We call the `add_hover_data` function once for each model type so that we can␣
 ↪add different sets
```

```
# of hyperparameters as hover data for each model type.
fig = add_hover_data(fig, trialsReg_df, RANDOM_FOREST_REGRESSOR)
fig = add_hover_data(fig, trialsReg_df, GRADIENT_BOOSTING_REGRESSOR)
fig.show()
```

[26]:

```
# Since max_depth == 6 outperforms other settings, we'll filter to only look at␣
↪that slice. This
# creates a boolean array that we will use to filter down to relevant rows in␣
↪the `trialsReg_df`
# dataframe.
max_depth_filter = (trialsReg_df[MODEL_CHOICE] == GRADIENT_BOOSTING_REGRESSOR)␣
↪& (
    trialsReg_df["gradient_boosting_regressor__max_depth"] == 6
)

# plotly express does not support contour plots so we will use `graph_objects`␣
↪instead. `go.Contour
# automatically interpolates "z" values for our loss.
fig = go.Figure(
    data=go.Contour(
        z=trialsReg_df.loc[max_depth_filter, "loss"],
        x=trialsReg_df.loc[max_depth_filter,␣
↪"gradient_boosting_regressor__learning_rate"],
        y=trialsReg_df.loc[max_depth_filter,␣
↪"gradient_boosting_regressor__n_estimators"],
        contours=dict(
            showlabels=True,  # show labels on contours
            labelfont=dict(
                size=12,
                color="white",
            ),  # label font properties
        ),
        colorbar=dict(
            title="loss",
            titleside="right",
        ),
        hovertemplate="loss: %{z}<br>learning_rate: %{x}<br>n_estimators:␣
↪%{y}<extra></extra>",
    )
)

fig.update_layout(
    xaxis_title="learning_rate",
    yaxis_title="n_estimators",
    title={
        "text": "learning_rate vs. n_estimators | max_depth == 6",
```

```
        "xanchor": "center",
        "yanchor": "top",
        "x": 0.5,
    },
)

fig.show()
```

[28]:
```
# sample from the prepped df to split the data into training/validation set and␣
↪testing set (0.85 and 0.15, repectively)
train_df, test_df = train_test_split(df_dummy, test_size=0.15)
# samples from the train_df to create a validation dataframe ~10% the size of␣
↪the original dataset
train_df, val_df = train_test_split(train_df, test_size=0.12)
```

[20]:
```
# Since we defined our objective function to be generic in terms of the␣
↪dataset, we need to use
# `partial` from the `functools` module to "fix" the `train_df`, `features`,␣
↪and `target`
# arguments to the values that we want for this example so that we have an␣
↪objective function that
# takes in only one argument as assumed by the `hyperopt` interface.
compas_objective = partial(
    objective, dataset_df=train_df, features=FEATURES, target=TWO_YEAR_RECID
)
# `hyperopt` tracks the results of each iteration in this `Trials` object.␣
↪We'll be collecting the
# data that we will use for visualization from this object.
trials = Trials()
rng = check_random_state(0)  # reproducibility!
# `fmin` searches for hyperparameters that "minimize" our object, cross entropy␣
↪log loss and returns the
# "best" set of hyperparameters.
best = fmin(compas_objective, space, tpe.suggest, 1000, trials=trials,␣
↪rstate=rng)
```

```
100%|                                   | 1000/1000
[32:54<00:00,  1.97s/trial, best loss: 11.024427992526189]
```

[21]:
```
pprint([t for t in trials][:5])
```

```
[{'book_time': datetime.datetime(2021, 12, 8, 17, 37, 18, 443000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
           'idxs': {'gradient_boosting_classifier__learning_rate': [],
                    'gradient_boosting_classifier__max_depth': [],
                    'gradient_boosting_classifier__n_estimators': [],
                    'model_choice': [0],
```

```
                  'random_forest_classifier__max_depth': [0],
                  'random_forest_classifier__n_estimators': [0]},
         'tid': 0,
         'vals': {'gradient_boosting_classifier__learning_rate': [],
                  'gradient_boosting_classifier__max_depth': [],
                  'gradient_boosting_classifier__n_estimators': [],
                  'model_choice': [0],
                  'random_forest_classifier__max_depth': [5.0],
                  'random_forest_classifier__n_estimators': [50.0]},
         'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 17, 37, 19, 780000),
  'result': {'loss': 11.232224337269372, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 0,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 17, 37, 19, 787000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
         'idxs': {'gradient_boosting_classifier__learning_rate': [1],
                  'gradient_boosting_classifier__max_depth': [1],
                  'gradient_boosting_classifier__n_estimators': [1],
                  'model_choice': [1],
                  'random_forest_classifier__max_depth': [],
                  'random_forest_classifier__n_estimators': []},
         'tid': 1,
         'vals': {'gradient_boosting_classifier__learning_rate':
[0.03819110609989756],
                  'gradient_boosting_classifier__max_depth': [7.0],
                  'gradient_boosting_classifier__n_estimators': [73.0],
                  'model_choice': [1],
                  'random_forest_classifier__max_depth': [],
                  'random_forest_classifier__n_estimators': []},
         'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 17, 37, 25, 944000),
  'result': {'loss': 11.344549591808974, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 1,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 17, 37, 25, 951000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
         'idxs': {'gradient_boosting_classifier__learning_rate': [2],
                  'gradient_boosting_classifier__max_depth': [2],
                  'gradient_boosting_classifier__n_estimators': [2],
```

```
                  'model_choice': [2],
                  'random_forest_classifier__max_depth': [],
                  'random_forest_classifier__n_estimators': []},
         'tid': 2,
         'vals': {'gradient_boosting_classifier__learning_rate':
[0.08587985607913044],
                  'gradient_boosting_classifier__max_depth': [10.0],
                  'gradient_boosting_classifier__n_estimators': [52.0],
                  'model_choice': [1],
                  'random_forest_classifier__max_depth': [],
                  'random_forest_classifier__n_estimators': []},
         'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 17, 37, 37, 353000),
  'result': {'loss': 11.74329149737122, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 2,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 17, 37, 37, 360000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
         'idxs': {'gradient_boosting_classifier__learning_rate': [],
                  'gradient_boosting_classifier__max_depth': [],
                  'gradient_boosting_classifier__n_estimators': [],
                  'model_choice': [3],
                  'random_forest_classifier__max_depth': [3],
                  'random_forest_classifier__n_estimators': [3]},
         'tid': 3,
         'vals': {'gradient_boosting_classifier__learning_rate': [],
                  'gradient_boosting_classifier__max_depth': [],
                  'gradient_boosting_classifier__n_estimators': [],
                  'model_choice': [0],
                  'random_forest_classifier__max_depth': [3.0],
                  'random_forest_classifier__n_estimators': [52.0]},
         'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 17, 37, 38, 808000),
  'result': {'loss': 11.400702012835154, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 3,
  'version': 0},
 {'book_time': datetime.datetime(2021, 12, 8, 17, 37, 38, 814000),
  'exp_key': None,
  'misc': {'cmd': ('domain_attachment', 'FMinIter_Domain'),
         'idxs': {'gradient_boosting_classifier__learning_rate': [4],
                  'gradient_boosting_classifier__max_depth': [4],
```

```
                    'gradient_boosting_classifier__n_estimators': [4],
                    'model_choice': [4],
                    'random_forest_classifier__max_depth': [],
                    'random_forest_classifier__n_estimators': []},
          'tid': 4,
          'vals': {'gradient_boosting_classifier__learning_rate':
[0.0638511443414372],
                    'gradient_boosting_classifier__max_depth': [5.0],
                    'gradient_boosting_classifier__n_estimators': [41.0],
                    'model_choice': [1],
                    'random_forest_classifier__max_depth': [],
                    'random_forest_classifier__n_estimators': []},
          'workdir': None},
  'owner': None,
  'refresh_time': datetime.datetime(2021, 12, 8, 17, 37, 40, 880000),
  'result': {'loss': 11.220994295117999, 'status': 'ok'},
  'spec': None,
  'state': 2,
  'tid': 4,
  'version': 0}]
```

[22]:

```python
# This is a simple helper function that allows us to fill in `np.nan` when a␣
↪particular
# hyperparameter is not relevant to a particular trial.
def unpack(x):
    if x:
        return x[0]
    return np.nan


# We'll first turn each trial into a series and then stack those series␣
↪together as a dataframe.
trials_df = pd.DataFrame([pd.Series(t["misc"]["vals"]).apply(unpack) for t in␣
↪trials])
# Then we'll add other relevant bits of information to the correct rows and␣
↪perform a couple of
# mappings for convenience
trials_df["loss"] = [t["result"]["loss"] for t in trials]
trials_df["trial_number"] = trials_df.index
trials_df[MODEL_CHOICE] = trials_df[MODEL_CHOICE].apply(
    lambda x: RANDOM_FOREST_CLASSIFIER if x == 0 else␣
↪GRADIENT_BOOSTING_CLASSIFIER
)
trials_df
```

[22]:

```
   gradient_boosting_classifier__learning_rate  \
0                                          NaN
```

```
1                                      0.038191
2                                      0.085880
3                                           NaN
4                                      0.063851
..                                          …
995                                         NaN
996                                         NaN
997                                         NaN
998                                         NaN
999                                         NaN

     gradient_boosting_classifier__max_depth  \
0                                        NaN
1                                        7.0
2                                       10.0
3                                        NaN
4                                        5.0
..                                       …
995                                      NaN
996                                      NaN
997                                      NaN
998                                      NaN
999                                      NaN

     gradient_boosting_classifier__n_estimators                  model_choice  \
0                                           NaN      random_forest_classifier
1                                          73.0  gradient_boosting_classifier
2                                          52.0  gradient_boosting_classifier
3                                           NaN      random_forest_classifier
4                                          41.0  gradient_boosting_classifier
..                                          …                            …
995                                         NaN      random_forest_classifier
996                                         NaN      random_forest_classifier
997                                         NaN      random_forest_classifier
998                                         NaN      random_forest_classifier
999                                         NaN      random_forest_classifier

     random_forest_classifier__max_depth  \
0                                    5.0
1                                    NaN
2                                    NaN
3                                    3.0
4                                    NaN
..                                   …
995                                  7.0
996                                  5.0
997                                  6.0
```

```
998                                   6.0
999                                   5.0

     random_forest_classifier__n_estimators       loss  trial_number
0                                      50.0  11.232224             0
1                                       NaN  11.344550             1
2                                       NaN  11.743291             2
3                                      52.0  11.400702             3
4                                       NaN  11.220994             4
..                                        …          …           …
995                                    30.0  11.215378           995
996                                    51.0  11.220992           996
997                                    45.0  11.080588           997
998                                    59.0  11.052508           998
999                                    52.0  11.220991           999

[1000 rows x 8 columns]
```

[23]:

```
def add_hover_data(fig, df, model_choice):
    # Filter to only columns that are relevant to the current model choice.␣
 ↪Note that this relies on
    # the convention of including the model name in the hyperparameter name␣
 ↪when we declare the
    # search space.
    cols = [col for col in trials_df.columns if model_choice in col]
    fig.update_traces(
        # This specifies the data that we want to plot for the current model␣
 ↪choice.
        customdata=trials_df.loc[
            trials_df[MODEL_CHOICE] == model_choice, cols + [MODEL_CHOICE]
        ],
        hovertemplate="<br>".join(
            [
                f"{col.split('__')[1]}: %{{customdata[{i}]}}"
                for i, col in enumerate(cols)
            ]
        )
        + "<extra></extra>",
        # We only apply the hover data for the current model choice.
        selector={"name": model_choice},
    )
    return fig

# px is an alias for "express" that's created by following the convention of␣
 ↪importing "express" by
# running `from plotly import express as px`
fig = px.scatter(
```

```
    trials_df,
    x="trial_number",
    y="loss",
    color=MODEL_CHOICE,
)
# We call the `add_hover_data` function once for each model type so that we can␣
↪add different sets
# of hyperparameters as hover data for each model type.
fig = add_hover_data(fig, trials_df, RANDOM_FOREST_CLASSIFIER)
fig = add_hover_data(fig, trials_df, GRADIENT_BOOSTING_CLASSIFIER)
fig.show()
```

[27]:

```
# Since max_depth == 6 outperforms other settings, we'll filter to only look at␣
↪that slice. This
# creates a boolean array that we will use to filter down to relevant rows in␣
↪the `trials_df`
# dataframe.
max_depth_filter = (trials_df[MODEL_CHOICE] == GRADIENT_BOOSTING_CLASSIFIER) & (
    trials_df["gradient_boosting_classifier__max_depth"] == 6
)

# plotly express does not support contour plots so we will use `graph_objects`␣
↪instead. `go.Contour
# automatically interpolates "z" values for our loss.
fig = go.Figure(
    data=go.Contour(
        z=trials_df.loc[max_depth_filter, "loss"],
        x=trials_df.loc[max_depth_filter,␣
↪"gradient_boosting_classifier__learning_rate"],
        y=trials_df.loc[max_depth_filter,␣
↪"gradient_boosting_classifier__n_estimators"],
        contours=dict(
            showlabels=True,  # show labels on contours
            labelfont=dict(
                size=12,
                color="white",
            ),  # label font properties
        ),
        colorbar=dict(
            title="loss",
            titleside="right",
        ),
        hovertemplate="loss: %{z}<br>learning_rate: %{x}<br>n_estimators:␣
↪%{y}<extra></extra>",
    )
)
```

```
fig.update_layout(
    xaxis_title="learning_rate",
    yaxis_title="n_estimators",
    title={
        "text": "learning_rate vs. n_estimators | max_depth == 6",
        "xanchor": "center",
        "yanchor": "top",
        "x": 0.5,
    },
)

fig.show()
```

1.2 Optimized model parameters:

We end up using the Gradient Boosting Classifier with 71 estimators, a max depth of 6, and a learning rate of 0.02973046

With these optimized model parameters we can now implement the Local Massaging and Local Preferential Sampling algorithms

2 Model Training:

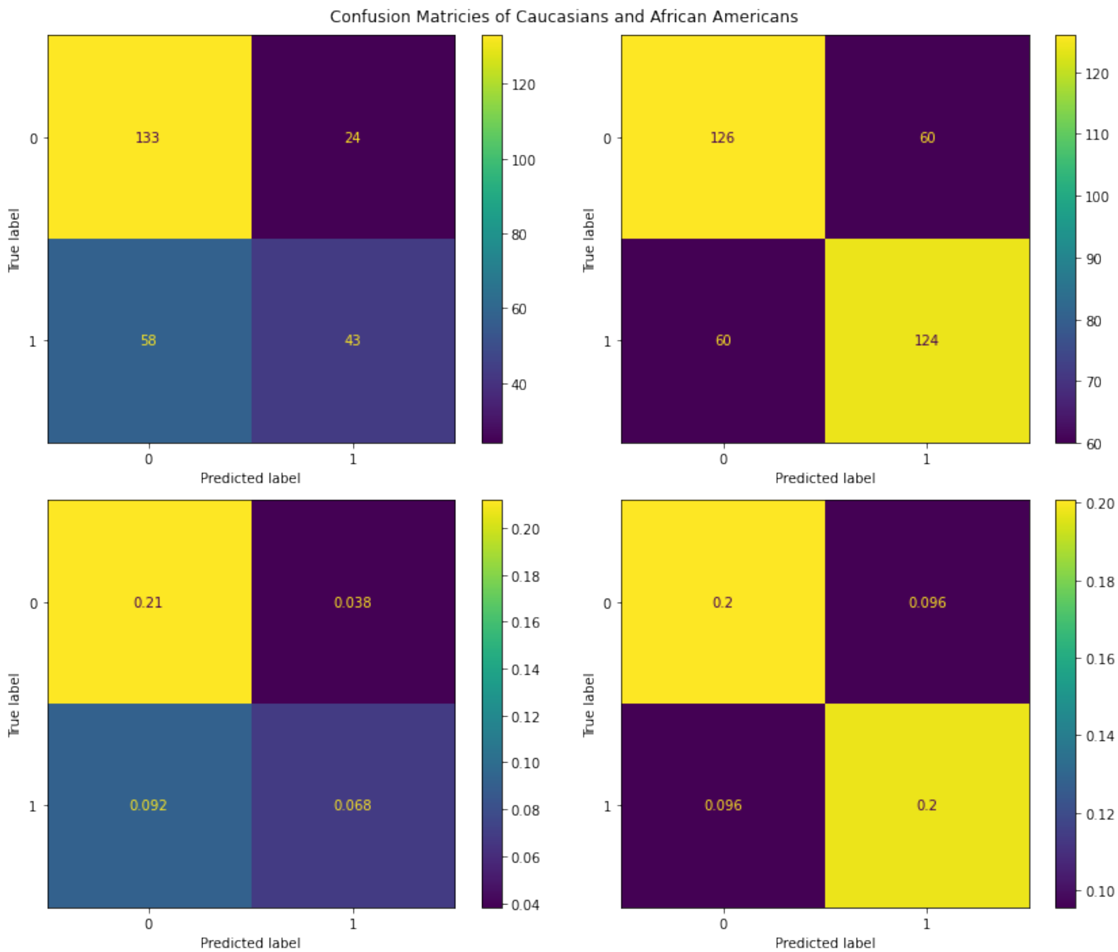
[440]:
```
from sklearn.datasets import make_classification
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
 ↪precision_score, recall_score, accuracy_score
from sklearn.svm import SVC

X_train = train_df[ALL_FEATURES]
L_train = train_df[FEATURES]
s_train = train_df[RACE]
e_train = train_df[DEGREE]
y_train = train_df[TWO_YEAR_RECID]

X_val = val_df[ALL_FEATURES]
L_val = val_df[FEATURES]
s_val = val_df[RACE]
e_val = val_df[DEGREE]
y_val = val_df[TWO_YEAR_RECID]

X_test = test_df[ALL_FEATURES]
L_test = test_df[FEATURES]
s_test = test_df[RACE]
e_test = test_df[DEGREE]
y_test = test_df[TWO_YEAR_RECID]
```

```
summary_stats = list()
```

[441]:
```
GBC = GradientBoostingClassifier(n_estimators=71, learning_rate=0.02973046,␣
 ↪max_depth=6, random_state=0)
classifier = GBC.fit(X_train, y_train)
classifier.score(X_val, y_val)
```

[441]: 0.678343949044586

[442]:
```
fig, axs = plt.subplots(2, 2, figsize=(12,10))
fig.suptitle('Confusion Matricies of Caucasians and African Americans')

CaucVal = X_val.race==0
CVpredictions = classifier.predict(X_val[CaucVal])
CVcm = confusion_matrix(y_val[CaucVal], CVpredictions, labels=classifier.
 ↪classes_)
CVdisp = ConfusionMatrixDisplay(confusion_matrix=CVcm,
                              display_labels=classifier.classes_)
CVdisp.plot(ax=axs[0,0])

cmTot = np.sum(CVcm[:,:]) + np.sum(AAVcm[:,:])
CVcmF = CVcm/cmTot
CVdispF = ConfusionMatrixDisplay(confusion_matrix=CVcmF,
                              display_labels=classifier.classes_)
CVdispF.plot(ax=axs[1,0])

AAVal = X_val.race==1
AAVpredictions = classifier.predict(X_val[AAVal])
AAVcm = confusion_matrix(y_val[AAVal], AAVpredictions, labels=classifier.
 ↪classes_)
AAVdisp = ConfusionMatrixDisplay(confusion_matrix=AAVcm,
                              display_labels=classifier.classes_)
AAVdisp.plot(ax=axs[0,1])

AAVcmF = AAVcm/cmTot
AAVdispF = ConfusionMatrixDisplay(confusion_matrix=AAVcmF,
                              display_labels=classifier.classes_)
AAVdispF.plot(ax=axs[1,1])

fig.tight_layout()
plt.show()
```



[443]:
```
def train_model(model, prediction_function, X_train, y_train, X_test, y_test):
    model.fit(X_train, y_train)
    stats = list()

    y_train_pred = prediction_function(model, X_train)
    Ps = precision_score(y_train, y_train_pred)
    Rs = recall_score(y_train, y_train_pred)
    As = accuracy_score(y_train, y_train_pred)
    print('train precision: ' + str(Ps))
    print('train recall: ' + str(Rs))
    print('train accuracy: ' + str(As))
    stats.extend([Ps,Rs,As])

    y_test_pred = prediction_function(model, X_test)
    Ps = precision_score(y_test, y_test_pred)
    Rs = recall_score(y_test, y_test_pred)
    As = accuracy_score(y_test, y_test_pred)
```

```
    print('test precision: ' + str(Ps))
    print('test recall: ' + str(Rs))
    print('test accuracy: ' + str(As))
    stats.extend([Ps,Rs,As])

    return model, stats

def get_predicted_outcome(model, data):
    return np.argmax(model.predict_proba(data), axis=1).astype(np.float32)
```

[444]:
```
GBCmodel, stats = train_model(GBC, get_predicted_outcome, X_train, y_train,␣
 ↪X_val, y_val)
summary_stats.extend(stats)
```

```
train precision: 0.7232905982905983
train recall: 0.6309412861136999
train accuracy: 0.7151554685801261
test precision: 0.6653386454183267
test recall: 0.5859649122807018
test accuracy: 0.678343949044586
```

3 Inferences from fitting a gradient boosting classifier trained on the base training set to the validation set

The cross validation statistics improving when using all parameters to predict recidivism and the imbalanced confusion matricies suggest the model might not be fair, which is something we will check next

3.1 Evaluating the 3 fairness definitions - Parity, Calibration, and Equality of Odds - we get the following results:

3.1.1 Parity:

The algorithm should satisfy P(G=1|D=0)=P(G=1|D=1) to achieve fairness definition 1. This suggests that the probability of a positive recividism guess should be the same regardless of demographic (race in our case).

However, it's apparent that this is far from true (difference of 0.2376).

[445]:
```
C = sum(CVcmF[:,1])/np.sum(CVcmF)
AA = sum(AAVcmF[:,1])/np.sum(AAVcmF)
print('P(G=1|race=caucasian)=', C)
print('P(G=1|race=african american)=', AA)
print('P(G=1|race=african american)!=P(G=1|race=caucasian)')
print('Parity:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=1|race=caucasian)= 0.2596899224806202
P(G=1|race=african american)= 0.4972972972972974
```

```
P(G=1|race=african american)!=P(G=1|race=caucasian)
Parity: 0.2376073748166772
```

3.1.2 Calibration:

The algorithm should satisfy P(G=T|D=0)=P(G=T|D=1) to achieve fairness definition 2. This suggests that the probability of an accurate recividism guess should be the same regardless of demographic (race in our case). This is the difference between Accuracies.

In this case, the algorithim almost satisfies calibration (difference of only 0.0065).

[446]:
```
C = (CVcmF[0,0]+CVcmF[1,1])/np.sum(CVcmF)
AA = (AAVcmF[0,0]+AAVcmF[1,1])/np.sum(AAVcmF)
print('P(G=T|race=caucasian)=', C)
print('P(G=T|race=african american)=', AA)
print('P(G=T|race=african american)~=P(G=T|race=caucasian)')
print('Calibration:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=T|race=caucasian)= 0.6821705426356589
P(G=T|race=african american)= 0.6756756756756758
P(G=T|race=african american)~=P(G=T|race=caucasian)
Calibration: 0.006494866959983137
```

3.1.3 Equality of Odds:

The algorithm should satisfy P(G=T|D=0,T=1)=P(G=T|D=1,T=1) to achieve fairness definition 3. This suggests that the probability of an accurate positive recividism guess should be the same regardless of demographic (race in our case). This is the difference between Recalls.

In this case, the algorithim is even further off than definition 1 (difference of 0.2482)

[447]:
```
C = (CVcmF[1,1])/sum(CVcmF[1,:])
AA = (AAVcmF[1,1])/sum(AAVcmF[1,:])
print('P(G=T|race=caucasian,recidivism=true)=', C)
print('P(G=T|race=african american,recidivism=true)=', AA)
print('P(G=T|race=african american,recidivism=true)!
 ↪=P(G=T|race=caucasian,recidivism=true)')
print('Equality of Odds:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=T|race=caucasian,recidivism=true)= 0.42574257425742573
P(G=T|race=african american,recidivism=true)= 0.6739130434782608
P(G=T|race=african
american,recidivism=true)!=P(G=T|race=caucasian,recidivism=true)
Equality of Odds: 0.24817046922083502
```

4 Local Massaging (Handling Conditional Discrimination Alg1)

[448]:
```
#Helper functions

#full_df is the dataframe with all columns to be partitioned
#e is the column/list of values of the different crime degrees
def PARTITION(full_df, e):
    ret_dfs = list()
    uniques = np.unique(e)

    for u in uniques:
        ret_dfs.append(full_df[full_df[DEGREE]==u])

    return ret_dfs

#full_dfi is the dataframe with all columns, but partitioned to one crime degree
#si is the current sensitive parameter value
def DELTA(full_df, full_dfi, si):

    raceSub = full_dfi[RACE]==si
    Gi = sum(raceSub)

    num = sum(full_dfi[raceSub][TWO_YEAR_RECID]==1)/len(full_df)
    denom = len(full_dfi[raceSub])/len(full_df)
    P1 = num/denom

    raceSub = full_dfi[RACE]!=si
    num = sum(full_dfi[raceSub][TWO_YEAR_RECID]==1)/len(full_df)
    denom = len(full_dfi[raceSub])/len(full_df)
    Ps = 0.5*(P1 + num/denom)

    return np.floor(Gi*abs(P1-Ps)).astype(np.int64)
```

[449]:
```
#Local Massaging algorithm
LM_parts = list()
for part in PARTITION(train_df, train_df[DEGREE]):
    #train the model
    X_part = part.drop(TWO_YEAR_RECID, axis=1)
    y_part = part[TWO_YEAR_RECID]
    model = GBC.fit(X_part, y_part)

    part1 = part[part[RACE]==1]
    part1.reset_index(drop=True, inplace=True)
    delta1 = DELTA(train_df, part, 1)
    X_part1 = part1.drop(TWO_YEAR_RECID, axis=1)
    y_part1 = part1[TWO_YEAR_RECID]
    rank = pd.DataFrame(model.decision_function(X_part1), columns = ['rank'])
```

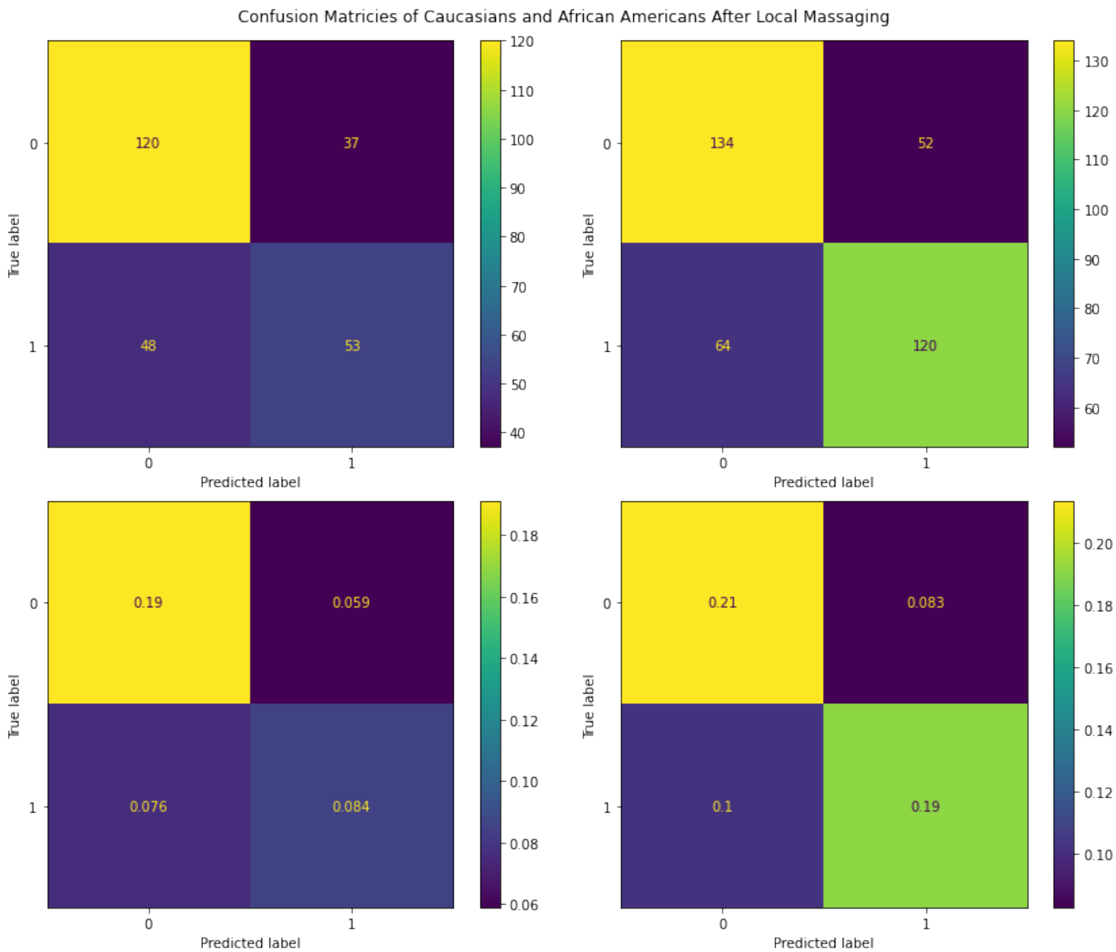
```
    comb1 = pd.concat([part1, rank], axis=1)

    part0 = part[part[RACE]==0]
    part0.reset_index(drop=True, inplace=True)
    delta0 = DELTA(train_df, part, 0)
    X_part0 = part0.drop(TWO_YEAR_RECID, axis=1)
    y_part0 = part0[TWO_YEAR_RECID]
    rank = pd.DataFrame(model.decision_function(X_part0), columns = ['rank'])
    comb0 = pd.concat([part0, rank], axis=1)

    #relabel closest delta datapoints from + to - based on rank for AA␣
↪datapoints
    comb1 = comb1.sort_values(['rank'])
    comb1.reset_index(drop=True, inplace=True)

    t = sum(comb1['rank']>0)
    l = len(comb1)

    F1 = np.full(l-t, False)
    T = np.full(delta1, True)
    F2 = np.full(t-delta1, False)
    flip = np.concatenate([F1, T, F2])
    comb1.loc[flip, TWO_YEAR_RECID] = 0
    LM_parts.append(comb1)

    #relabel closest delta datapoints from - to + based on rank for C datapoints
    comb0 = comb0.sort_values(['rank'])
    comb0.reset_index(drop=True, inplace=True)

    t = sum(comb0['rank']<0)
    l = len(comb0)

    F1 = np.full(t-delta0, False)
    T = np.full(delta0, True)
    F2 = np.full(l-t, False)

    flip = np.concatenate([F1, T, F2])
    comb0.loc[flip, TWO_YEAR_RECID] = 1
    LM_parts.append(comb0)

loc_mass = pd.concat(LM_parts, axis=0)
```

[450]:

```
X_train = loc_mass[ALL_FEATURES]
y_train = loc_mass[TWO_YEAR_RECID]
classifier = GBC.fit(X_train, y_train)
classifier.score(X_val, y_val)
```

[450]: 0.6799363057324841

[451]:
```
fig, axs = plt.subplots(2, 2, figsize=(12,10))
fig.suptitle('Confusion Matricies of Caucasians and African Americans After␣
↪Local Massaging')

CaucVal = X_val.race==0
CVpredictions = classifier.predict(X_val[CaucVal])
CVcm = confusion_matrix(y_val[CaucVal], CVpredictions, labels=classifier.
↪classes_)
CVdisp = ConfusionMatrixDisplay(confusion_matrix=CVcm,
                              display_labels=classifier.classes_)
CVdisp.plot(ax=axs[0,0])

cmTot = np.sum(CVcm[:,:]) + np.sum(AAVcm[:,:])
CVcmF = CVcm/cmTot
CVdispF = ConfusionMatrixDisplay(confusion_matrix=CVcmF,
                              display_labels=classifier.classes_)
CVdispF.plot(ax=axs[1,0])

AAVal = X_val.race==1
AAVpredictions = classifier.predict(X_val[AAVal])
AAVcm = confusion_matrix(y_val[AAVal], AAVpredictions, labels=classifier.
↪classes_)
AAVdisp = ConfusionMatrixDisplay(confusion_matrix=AAVcm,
                              display_labels=classifier.classes_)
AAVdisp.plot(ax=axs[0,1])

AAVcmF = AAVcm/cmTot
AAVdispF = ConfusionMatrixDisplay(confusion_matrix=AAVcmF,
                              display_labels=classifier.classes_)
AAVdispF.plot(ax=axs[1,1])

fig.tight_layout()
plt.show()
```




```
[452]: GBCmodel, stats = train_model(GBC, get_predicted_outcome, X_train, y_train,
        X_val, y_val)
       summary_stats.extend(stats)
```

```
train precision: 0.7386243386243386
train recall: 0.6572504708097928
train accuracy: 0.7342900630571864
test precision: 0.6603053435114504
test recall: 0.6070175438596491
test accuracy: 0.6799363057324841
```

5 Inferences from fitting a gradient boosting classifier trained on a locally massaged training set to the validation set

5.1 Evaluating the 3 fairness definitions - Parity, Calibration, and Equality of Odds - we get the following results:

5.1.1 Parity:

The algorithm should satisfy P(G=1|D=0)=P(G=1|D=1) to achieve fairness definition 1. This suggests that the probability of a positive recividism guess should be the same regardless of demographic (race in our case).

While there was a massive improvement, the parity is still too high (difference of 0.11603 vs original 0.2376).

[453]:
```
C = sum(CVcmF[:,1])/np.sum(CVcmF)
AA = sum(AAVcmF[:,1])/np.sum(AAVcmF)
print('P(G=1|race=caucasian)=', C)
print('P(G=1|race=african american)=', AA)
print('P(G=1|race=african american)!=P(G=1|race=caucasian)')
print('Parity:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=1|race=caucasian)= 0.3488372093023256
P(G=1|race=african american)= 0.4648648648648649
P(G=1|race=african american)!=P(G=1|race=caucasian)
Parity: 0.1160276555625393
```

5.1.2 Calibration:

The algorithm should satisfy P(G=T|D=0)=P(G=T|D=1) to achieve fairness definition 2. This suggests that the probability of an accurate recividism guess should be the same regardless of demographic (race in our case). This is the difference between Accuracies.

In this case, the algorithim made the calibration worse, making it substantially worse than before (0.0159 vs original 0.0065).

[454]:
```
C = (CVcmF[0,0]+CVcmF[1,1])/np.sum(CVcmF)
AA = (AAVcmF[0,0]+AAVcmF[1,1])/np.sum(AAVcmF)
print('P(G=T|race=caucasian)=', C)
print('P(G=T|race=african american)=', AA)
print('P(G=T|race=african american)~=P(G=T|race=caucasian)')
print('Calibration:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=T|race=caucasian)= 0.6705426356589148
P(G=T|race=african american)= 0.6864864864864866
P(G=T|race=african american)~=P(G=T|race=caucasian)
Calibration: 0.01594385082757177
```

5.1.3 Equality of Odds:

The algorithm should satisfy P(G=T|D=0,T=1)=P(G=T|D=1,T=1) to achieve fairness definition 3. This suggests that the probability of an accurate positive recividism guess should be the same regardless of demographic (race in our case). This is similar to Recall.

In this case, the algorithim is the furthest of the three equality definitions, but is a great improvement compared to before the local massaging (difference of 0.1274 vs original 0.2482)

[455]:
```
C = (CVcmF[1,1])/sum(CVcmF[1,:])
AA = (AAVcmF[1,1])/sum(AAVcmF[1,:])
print('P(G=T|race=caucasian,recidivism=true)=', C)
print('P(G=T|race=african american,recidivism=true)=', AA)
print('P(G=T|race=african american,recidivism=true)!
 ↪=P(G=T|race=caucasian,recidivism=true)')
print('Equality of Odds:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=T|race=caucasian,recidivism=true)= 0.5247524752475248
P(G=T|race=african american,recidivism=true)= 0.6521739130434782
P(G=T|race=african
american,recidivism=true)!=P(G=T|race=caucasian,recidivism=true)
Equality of Odds: 0.12742143779595339
```

5.2 Overall, the local massaging algorithm improved the parity and equality of odds statistics, improved training accuracy, and had no loss to accuracy on the validation set, but resulted in a worse calibration.

6 Local Preferential Sampling (Handling Conditional Discrimination Alg2)

[456]:
```
#Local Massaging algorithm
LPS_parts = list()
for part in PARTITION(train_df, train_df[DEGREE]):
    #train the model
    X_part = part.drop(TWO_YEAR_RECID, axis=1)
    y_part = part[TWO_YEAR_RECID]
    model = GBC.fit(X_part, y_part)

    part1 = part[part[RACE]==1]
    part1.reset_index(drop=True, inplace=True)
    delta1 = DELTA(train_df, part, 1)//2
    X_part1 = part1.drop(TWO_YEAR_RECID, axis=1)
    y_part1 = part1[TWO_YEAR_RECID]
    rank = pd.DataFrame(model.decision_function(X_part1), columns = ['rank'])
    comb1 = pd.concat([part1, rank], axis=1)

    part0 = part[part[RACE]==0]
```

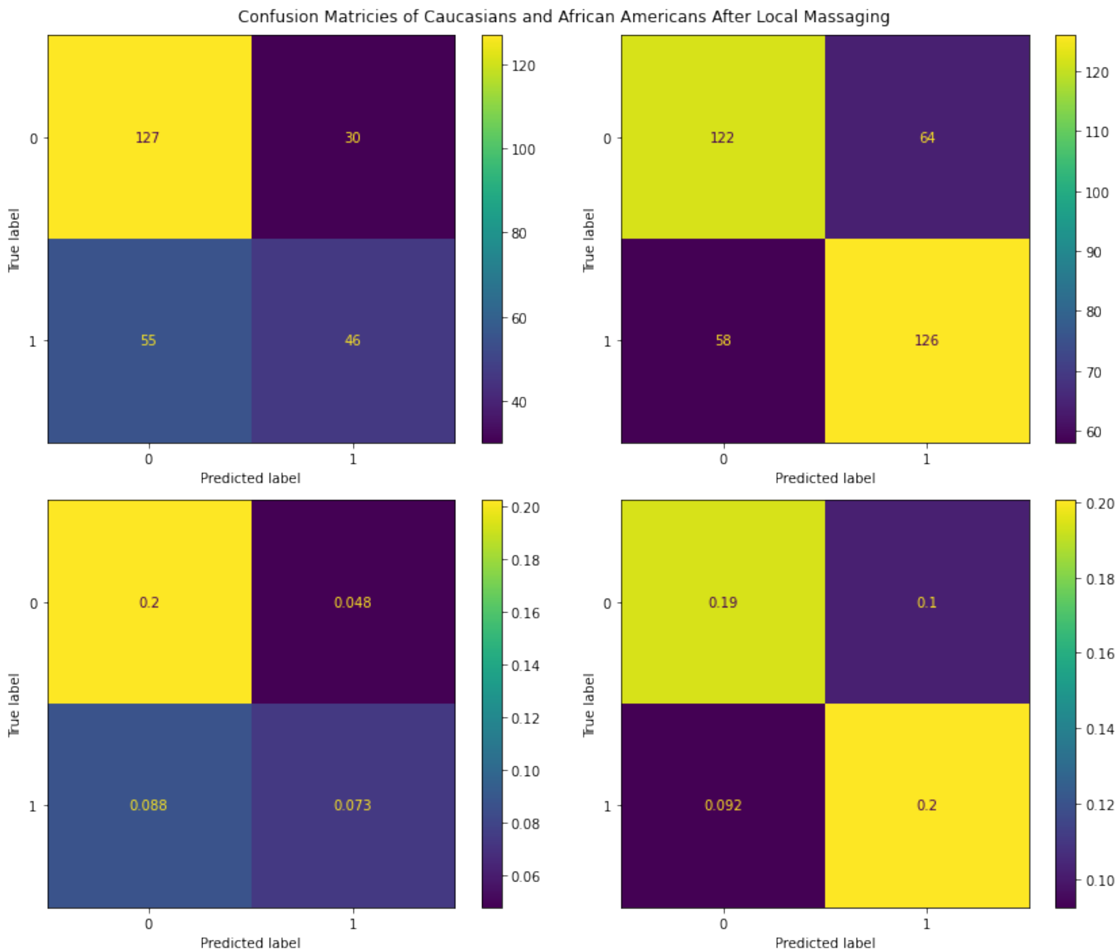
```
    part0.reset_index(drop=True, inplace=True)
    delta0 = DELTA(train_df, part, 0)//2
    X_part0 = part0.drop(TWO_YEAR_RECID, axis=1)
    y_part0 = part0[TWO_YEAR_RECID]
    rank = pd.DataFrame(model.decision_function(X_part0), columns = ['rank'])
    comb0 = pd.concat([part0, rank], axis=1)

    #delete closest 0.5*delta datapoints from + and duplicate the same number␣
↪of  -
    #datapoints based on rank for AA datapoints
    comb1 = comb1.sort_values(['rank'])
    comb1.reset_index(drop=True, inplace=True)

    t = sum(comb1['rank']>0)
    l = len(comb1)

    F1 = np.full(l-t, False)
    T = np.full(delta1, True)
    F2 = np.full(t-delta1, False)
    delete = np.invert(np.concatenate([F1, T, F2]))
    F3 = np.full(l-t-delta1, False)
    F4 = np.full(t, False)
    duplicate = np.concatenate([F3, T, F4])
    dupes = comb1[duplicate]
    comb1 = comb1[delete]
    comb1 = pd.concat([comb1,dupes], axis=0)
    LPS_parts.append(comb1)

    #delete closest 0.5*delta datapoints from - and duplicate the same number␣
↪of +
    #datapoints based on rank for C datapoints
    comb0 = comb0.sort_values(['rank'])
    comb0.reset_index(drop=True, inplace=True)

    t = sum(comb0['rank']<0)
    l = len(comb0)

    F1 = np.full(t-delta0, False)
    T = np.full(delta0, True)
    F2 = np.full(l-t, False)
    delete = np.invert(np.concatenate([F1, T, F2]))
    F3 = np.full(t, False)
    F4 = np.full(l-t-delta0, False)
    duplicate = np.concatenate([F3, T, F4])
    dupes = comb0[duplicate]
    comb0 = comb0[delete]
    comb0 = pd.concat([comb0,dupes], axis=0)
```

```
    LPS_parts.append(comb0)

    t = sum(comb0['rank']>0)
    l = len(comb0)

loc_mass = pd.concat(LPS_parts, axis=0)
```

[457]:
```
X_train = loc_mass[ALL_FEATURES]
y_train = loc_mass[TWO_YEAR_RECID]
classifier = GBC.fit(X_train, y_train)
classifier.score(X_val, y_val)
```

[457]: 0.6703821656050956

[458]:
```
fig, axs = plt.subplots(2, 2, figsize=(12,10))
fig.suptitle('Confusion Matricies of Caucasians and African Americans After␣
 ↪Local Massaging')

CaucVal = X_val.race==0
CVpredictions = classifier.predict(X_val[CaucVal])
CVcm = confusion_matrix(y_val[CaucVal], CVpredictions, labels=classifier.
 ↪classes_)
CVdisp = ConfusionMatrixDisplay(confusion_matrix=CVcm,
                              display_labels=classifier.classes_)
CVdisp.plot(ax=axs[0,0])

cmTot = np.sum(CVcm[:,:]) + np.sum(AAVcm[:,:])
CVcmF = CVcm/cmTot
CVdispF = ConfusionMatrixDisplay(confusion_matrix=CVcmF,
                              display_labels=classifier.classes_)
CVdispF.plot(ax=axs[1,0])

AAVal = X_val.race==1
AAVpredictions = classifier.predict(X_val[AAVal])
AAVcm = confusion_matrix(y_val[AAVal], AAVpredictions, labels=classifier.
 ↪classes_)
AAVdisp = ConfusionMatrixDisplay(confusion_matrix=AAVcm,
                              display_labels=classifier.classes_)
AAVdisp.plot(ax=axs[0,1])

AAVcmF = AAVcm/cmTot
AAVdispF = ConfusionMatrixDisplay(confusion_matrix=AAVcmF,
                              display_labels=classifier.classes_)
AAVdispF.plot(ax=axs[1,1])

fig.tight_layout()
plt.show()
```




```
[459]: GBCmodel,stats = train_model(GBC, get_predicted_outcome, X_train, y_train,
        X_val, y_val)
       summary_stats.extend(stats)
```

```
train precision: 0.7275091003640146
train recall: 0.6491879350348028
train accuracy: 0.7216786257882148
test precision: 0.6466165413533834
test recall: 0.6035087719298246
test accuracy: 0.6703821656050956
```

7 Inferences from fitting a gradient boosting classifier trained on a local preferential sampling training set to the validation set

7.1 Evaluating the 3 fairness definitions - Parity, Calibration, and Equality of Odds - we get the following results:

7.1.1 Parity:

The algorithm should satisfy P(G=1|D=0)=P(G=1|D=1) to achieve fairness definition 1. This suggests that the probability of a positive recividism guess should be the same regardless of demographic (race in our case).

The LPS algorithm landed in the middle of the pack in terms of parity (difference of 0.2189 vs LM 0.1160 vs original 0.2376).

[460]:
```
C = sum(CVcmF[:,1])/np.sum(CVcmF)
AA = sum(AAVcmF[:,1])/np.sum(AAVcmF)
print('P(G=1|race=caucasian)=', C)
print('P(G=1|race=african american)=', AA)
print('P(G=1|race=african american)!=P(G=1|race=caucasian)')
print('Parity:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=1|race=caucasian)= 0.29457364341085274
P(G=1|race=african american)= 0.5135135135135136
P(G=1|race=african american)!=P(G=1|race=caucasian)
Parity: 0.21893987010266086
```

7.1.2 Calibration:

The algorithm should satisfy P(G=T|D=0)=P(G=T|D=1) to achieve fairness definition 2. This suggests that the probability of an accurate recividism guess should be the same regardless of demographic (race in our case). This is the difference between Accuracies.

In this case, the algorithim absolutely satisfies calibration with the tightest difference yet (difference of 0.0024 vs LM 0.0159 vs original 0.0065).

[461]:
```
C = (CVcmF[0,0]+CVcmF[1,1])/np.sum(CVcmF)
AA = (AAVcmF[0,0]+AAVcmF[1,1])/np.sum(AAVcmF)
print('P(G=T|race=caucasian)=', C)
print('P(G=T|race=african american)=', AA)
print('P(G=T|race=african american)~=P(G=T|race=caucasian)')
print('Calibration:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

```
P(G=T|race=caucasian)= 0.6705426356589148
P(G=T|race=african american)= 0.6702702702702703
P(G=T|race=african american)~=P(G=T|race=caucasian)
Calibration: 0.0002723653886445021
```

7.1.3 Equality of Odds:

The algorithm should satisfy P(G=T|D=0,T=1)=P(G=T|D=1,T=1) to achieve fairness definition 3. This suggests that the probability of an accurate positive recividism guess should be the same regardless of demographic (race in our case). This is similar to Recall.

In this case, the equality of odds landed in the middle of the pack just like parity (difference of 0.2293 vs LM 0.1274 vs original 0.2482)

[462]:
```
C = (CVcmF[1,1])/sum(CVcmF[1,:])
AA = (AAVcmF[1,1])/sum(AAVcmF[1,:])
print('P(G=T|race=caucasian,recidivism=true)=', C)
print('P(G=T|race=african american,recidivism=true)=', AA)
print('P(G=T|race=african american,recidivism=true)!
 ↪=P(G=T|race=caucasian,recidivism=true)')
print('Equality of Odds:', abs(AA-C))
summary_stats.append(abs(AA-C))
```

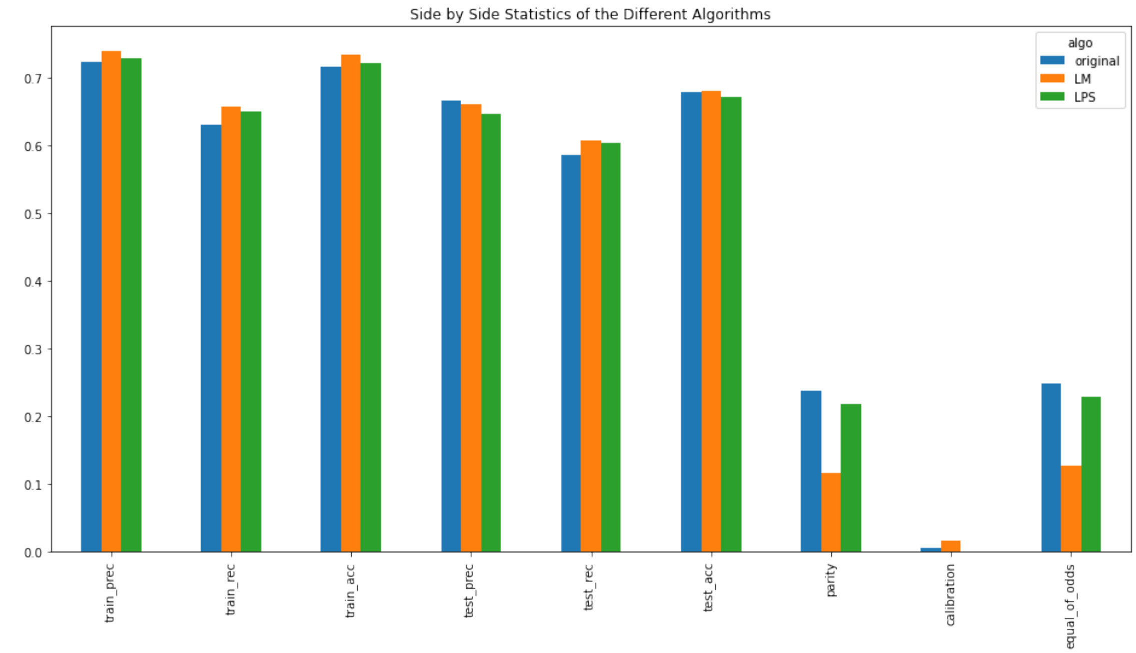
```
P(G=T|race=caucasian,recidivism=true)= 0.45544554455445546
P(G=T|race=african american,recidivism=true)= 0.6847826086956522
P(G=T|race=african
american,recidivism=true)!=P(G=T|race=caucasian,recidivism=true)
Equality of Odds: 0.22933706414119676
```

7.2 Overall, the local preferential sampling algorithm improved the calibration statistic, improved training accuracy, and had no loss to accuracy on the validation set, making it a net positive.

8 Conclusion

Depending on the constraints and what the priorities are between the three equality definitions, it would appear as though the local preferential sampling and local massaging techniques come at a gain in fairness in exchange for a slight sacrifice to complexity.

[463]:
```
from matplotlib.pyplot import figure
labels = ['train_prec', 'train_rec', 'train_acc', 'test_prec', 'test_rec',␣
 ↪'test_acc', 'parity', 'calibration', 'equal_of_odds']
conc_df = pd.DataFrame(np.array(summary_stats).reshape(3,9), columns=labels)
algo = pd.DataFrame(['original', 'LM', 'LPS'], columns = ['algo'])
conc_df = pd.concat([conc_df, algo], axis=1)
conc_df = conc_df.set_index('algo').T#.rename_axis('Variable')

conc_df.plot(kind='bar', figsize=(16,8), title='Side by Side Statistics of the␣
 ↪Different Algorithms')
plt.show()
```


Side by Side Statistics of the Different Algorithms
algo
original
LM
LPS
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
train_prec
train_rec
train_acc
test_prec
test_rec
test_acc
parity
calibration
equal_of_odds