In [1]:

```
# Load Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.ticker as mtick
import sqlite3
import seaborn as sns
from imblearn.over_sampling import SMOTENC
from sklearn.linear_model import LinearRegression
from sklearn import tree, preprocessing
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classificatio
n_report, plot_confusion_matrix, recall_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, Ext
raTreesClassifier
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardSc
aler
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_curve, auc, f1_score, make_scorer, recall_s
core
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from matplotlib.offsetbox import OffsetImage, AnnotationBbox
from matplotlib.pyplot import figure
from bs4 import BeautifulSoup
import time
import requests     # to get images
import shutil       # to save files locally
import datetime
from scipy.stats import norm
import warnings
warnings.filterwarnings('ignore')
import xgboost
from xgboost import XGBClassifier
from imblearn import under_sampling, over_sampling
from imblearn.over_sampling import SMOTE, ADASYN
import random
from random import randint
from sklearn.datasets import *
from IPython.display import Image, display_svg, SVG
import os
from sklearn.pipeline import Pipeline
from dtreeviz.trees import *
from sklearn.tree import plot_tree
os.environ["PATH"] += os.pathsep + "C:\\Users\\tmcro\\anaconda3\\pkgs\\grap
hviz-2.38-hfd603c8_2\\Library\\bin\\graphviz\\"
from sklearn.model_selection import train_test_split
from sklearn.compose import make_column_selector as selector
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from imblearn.pipeline import Pipeline as imbpipeline # https://towardsdata
science.com/the-right-way-of-using-smote-with-cross-validation-92a8d09d00c7
```

```python
from imblearn.pipeline import make_pipeline as make_imb_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline
from sklearn.pipeline import FeatureUnion
```

In [2]:
```python
import pandas as pd
df = pd.read_csv('heart_2020_cleaned.csv')

target_name = "HeartDisease"
y = df[target_name]
X = df.drop(columns=[target_name])
```

In [3]:
```python
# Scoring Metric
def my_custom_score(y_true, y_pred):
    cf = confusion_matrix(y_true, y_pred)
    precision = cf[1,1] / sum(cf[:,1])
    recall    = cf[1,1] / sum(cf[1,:])
    f1_score  = 2*precision*recall / (precision + recall)
    rwf_score = (1+(2**2)) * ((precision * recall) / (((2**2) * precision)
+ recall))
    return rwf_score

my_scorer = make_scorer(my_custom_score, greater_is_better= True)

# Change class metric
class_metric = my_scorer
```

In [4]:
```python
X.dtypes
```

Out[4]:
```
BMI                 float64
Smoking              object
AlcoholDrinking      object
Stroke               object
PhysicalHealth      float64
MentalHealth        float64
DiffWalking          object
Sex                  object
AgeCategory          object
Race                 object
Diabetic             object
PhysicalActivity     object
GenHealth            object
SleepTime           float64
Asthma               object
KidneyDisease        object
SkinCancer           object
dtype: object
```

In [5]:
```python
numerical_columns_selector = selector(dtype_exclude=object)
categorical_columns_selector = selector(dtype_include=object)

numerical_columns = numerical_columns_selector(X)
categorical_columns = categorical_columns_selector(X)
```

In [6]:
```
categorical_columns
```

Out[6]:
```
['Smoking',
 'AlcoholDrinking',
 'Stroke',
 'DiffWalking',
 'Sex',
 'AgeCategory',
 'Race',
 'Diabetic',
 'PhysicalActivity',
 'GenHealth',
 'Asthma',
 'KidneyDisease',
 'SkinCancer']
```

In [7]:
```
numerical_columns
```

Out[7]:
```
['BMI', 'PhysicalHealth', 'MentalHealth', 'SleepTime']
```

In [8]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

In [9]:
```
catcols = [1,2,3,6,7,8,9,10,11,12,14,15,16]
```

In [10]:
```
# To get the column names from onehotencoder
ohe = OneHotEncoder(sparse=False, handle_unknown='ignore')
checker = ohe.fit_transform(X_train[categorical_columns])
```

In [11]:
```
feature_names_categorical = ohe.get_feature_names(categorical_columns)
```

In [12]:
```
feature_names_categorical
```

Out[12]:
```
array(['Smoking_No', 'Smoking_Yes', 'AlcoholDrinking_No',
       'AlcoholDrinking_Yes', 'Stroke_No', 'Stroke_Yes', 'DiffWalking_No',
       'DiffWalking_Yes', 'Sex_Female', 'Sex_Male', 'AgeCategory_18-24',
       'AgeCategory_25-29', 'AgeCategory_30-34', 'AgeCategory_35-39',
       'AgeCategory_40-44', 'AgeCategory_45-49', 'AgeCategory_50-54',
       'AgeCategory_55-59', 'AgeCategory_60-64', 'AgeCategory_65-69',
       'AgeCategory_70-74', 'AgeCategory_75-79',
       'AgeCategory_80 or older', 'Race_American Indian/Alaskan Native',
       'Race_Asian', 'Race_Black', 'Race_Hispanic', 'Race_Other',
       'Race_White', 'Diabetic_No', 'Diabetic_No, borderline diabetes',
       'Diabetic_Yes', 'Diabetic_Yes (during pregnancy)',
       'PhysicalActivity_No', 'PhysicalActivity_Yes',
       'GenHealth_Excellent', 'GenHealth_Fair', 'GenHealth_Good',
       'GenHealth_Poor', 'GenHealth_Very good', 'Asthma_No', 'Asthma_Yes',
       'KidneyDisease_No', 'KidneyDisease_Yes', 'SkinCancer_No',
       'SkinCancer_Yes'], dtype=object)
```

SMOTENC

In [13]:
```
Smote_NC = SMOTENC(categorical_features= catcols, random_state=42)
```

In [14]:
```
print(y_train.value_counts())
# Fit SMOTE to training data
X_train_resampled, y_train_resampled = Smote_NC.fit_resample(X_train, y_tra
in)
# Preview synthetic sample class distribution
print('\n')
print(pd.Series(y_train_resampled).value_counts())
```

```
No     219418
Yes     20428
Name: HeartDisease, dtype: int64


No     219418
Yes    219418
Name: HeartDisease, dtype: int64
```

In [15]:
```
X_train = X_train_resampled
y_train = y_train_resampled
```

In [16]:
```
# Identify Processors
categorical_preprocessor = OneHotEncoder(handle_unknown="ignore")
numerical_preprocessor = StandardScaler()

preprocessor = ColumnTransformer([('one-hot-encoder', categorical_preproces
sor, categorical_columns),
    ('standard_scaler', numerical_preprocessor, numerical_columns)])

smoter = SMOTENC(categorical_features= categorical_columns, random_state=
0)
classifier = LogisticRegression(max_iter=500)
```

Code Additions

In [17]:
```
# SOURCE: The origin of this confusion matrix code was found on medium, '
# from https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30f
ea
def make_confusion_matrix(cf,
                          group_names=None,
                          categories='auto',
                          count=True,
                          percent=True,
                          cbar=True,
                          xyticks=True,
                          xyplotlabels=True,
                          sum_stats=True,
                          figsize=None,
                          cmap='Blues',
                          title=None):

    # CODE TO GENERATE SUMMARY STATISTICS & TEXT FOR SUMMARY STATS
    if sum_stats:
        #Accuracy is sum of diagonal divided by total observations
        accuracy  = np.trace(cf) / float(np.sum(cf))

        #if it is a binary confusion matrix, show some more stats
        if len(cf)==2:
            #Metrics for Binary Confusion Matrices
            a = cf[0,0]
            b = cf[0,1]
            c = cf[1,0]
            d = cf[1,1]
            tn = ((a / (a+b))*100).round(2).astype(str) + '%'
            fp = ((b / (a+b))*100).round(2).astype(str) + '%'
            fn = ((c / (c+d))*100).round(2).astype(str) + '%'
            tp = ((d / (c+d))*100).round(2).astype(str) + '%'
            precision = cf[1,1] / sum(cf[:,1])
            recall    = cf[1,1] / sum(cf[1,:])
            f1_score  = 2*precision*recall / (precision + recall)
            rwf_score = (1+(2**2)) * ((precision * recall) / (((2**2) * pre
cision) + recall))
            stats_text = "\n\nAccuracy={:0.3f}\nPrecision={:0.3f}\nRecall=
{:0.3f}\nF1 Score={:0.3f}\n\nRecall-Weighted F Score={:0.3f}".format(
                accuracy,precision,recall,f1_score, rwf_score)
        else:
            stats_text = "\n\nAccuracy={:0.3f}".format(accuracy)
    else:
        stats_text = ""

    # CODE TO GENERATE TEXT INSIDE EACH SQUARE
    blanks = ['' for i in range(cf.size)]

    if group_names and len(group_names)==cf.size:
        group_labels = ["{}\n".format(value) for value in group_names]
    else:
        group_labels = blanks

    if count:
        group_counts = ["{0:0.0f}\n".format(value) for value in cf.flatten
```

```
()]
    else:
        group_counts = blanks

    if percent:
        group_percentages =  [tn,fp,fn,tp]
        # old = group_percentages = ["{0:.2%}".format(value) for value in c
f.flatten()/np.sum(cf)]
    else:
        group_percentages = blanks

    box_labels = [f"{v1}{v2}{v3}".strip() for v1, v2, v3 in zip(group_label
s,group_counts,group_percentages)]
    box_labels = np.asarray(box_labels).reshape(cf.shape[0],cf.shape[1])

    # SET FIGURE PARAMETERS ACCORDING TO OTHER ARGUMENTS
    if figsize==None:
        #Get default figure size if not set
        figsize = plt.rcParams.get('figure.figsize')

    if xyticks==False:
        #Do not show categories if xyticks is False
        categories=False


    # MAKE THE HEATMAP VISUALIZATION
    plt.figure(figsize=figsize)
    sns.heatmap(cf,annot=box_labels,fmt="",cmap=cmap,cbar=cbar,xticklabels=
categories,yticklabels=categories)

    if xyplotlabels:
        plt.ylabel('True label', weight = 'bold')
        plt.xlabel('Predicted label' + stats_text, weight = 'bold')
    else:
        plt.xlabel(stats_text)

    if title:
        plt.title(title,size = 20, weight = 'bold')
```

In [18]:
```
dfcols = ['Model', 'RWF Score', 'F1',  'Recall',  'Precision',  'Accuracy']
model_summary = pd.DataFrame(columns=dfcols)
model_summary
```

Out[18]:

Model	RWF Score	F1	Recall	Precision	Accuracy

In [19]:
```
# Define Result Saving Initial Function
def save_result(cf, model_name):
            global model_summary
            accuracy  = np.trace(cf) / float(np.sum(cf))
            precision = cf[1,1] / sum(cf[:,1])
            recall    = cf[1,1] / sum(cf[1,:])
            f1_score  = 2*precision*recall / (precision + recall)
            rwf_score = (1+(2**2)) * ((precision * recall) / (((2**2) * pre
cision) + recall))
            row = [(model_name, rwf_score, f1_score, recall, precision, acc
uracy)]
            res = pd.DataFrame(columns = dfcols, data = row)
            yeep = [model_summary, res]
            model_summary = pd.concat(yeep)
            model_summary = model_summary.sort_values('RWF Score', ascendin
g = False)
            model_summary = model_summary.drop_duplicates()
            return model_summary.round(3)
```

In [20]:
```
def run_model(model, model_name):
    model.fit(X_train, y_train)
    model_prediction = model.predict(X_test)
    cf_matrix = confusion_matrix(y_test, model_prediction)
    save_result(cf_matrix, model_name)
    cf = make_confusion_matrix(cf_matrix)
    return model_summary
```

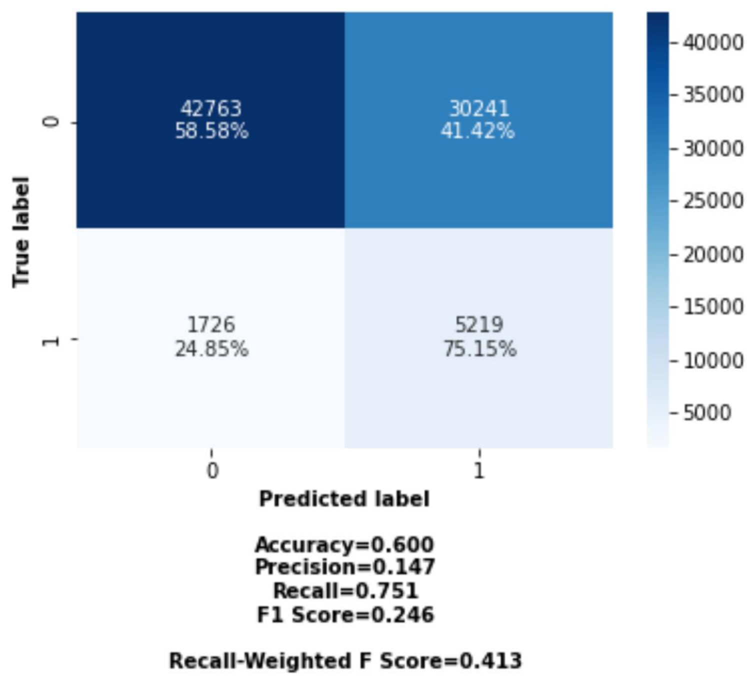
Models to Run

In [25]:
```
# Initial Models
init_decision_tree = make_pipeline(preprocessor, DecisionTreeClassifier(ran
dom_state=0, max_depth=3))
log_reg = make_pipeline(preprocessor, LogisticRegression(random_state=0))
decisionTree = make_pipeline(preprocessor, DecisionTreeClassifier(max_depth
=5, random_state=0))
random_forest = make_pipeline(preprocessor, RandomForestClassifier(n_estima
tors=50, random_state=0))
baggedTrees = make_pipeline(preprocessor, BaggingClassifier(DecisionTreeCla
ssifier(), n_estimators=50, random_state=0))
extraTrees = make_pipeline(preprocessor, ExtraTreesClassifier(n_estimators=
50, random_state=0))
knn = make_pipeline(preprocessor, KNeighborsClassifier(n_neighbors=5))
xgBoost = make_pipeline(preprocessor, XGBClassifier(n_estimators=50, random
_state=0))
```

In [26]:
```python
run_model(init_decision_tree, 'Initial Decision Tree')
```

Out[26]:

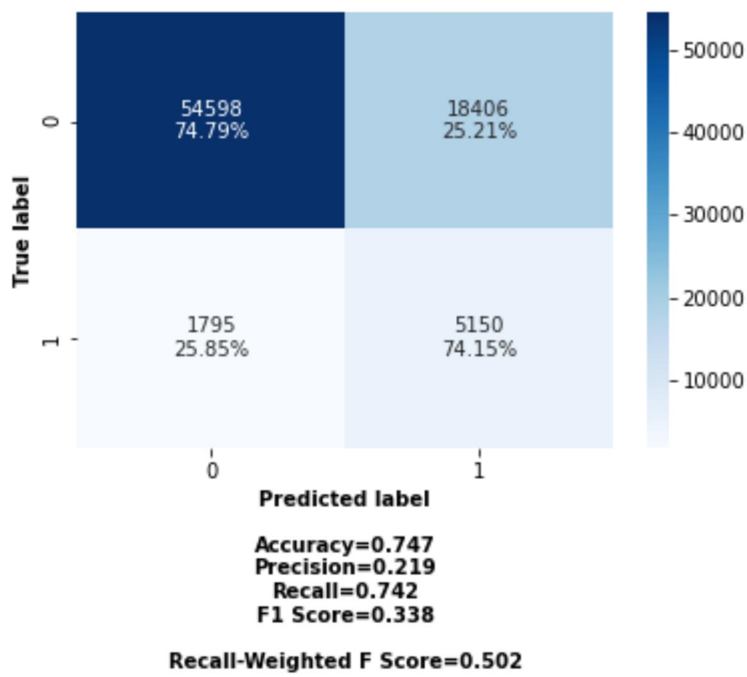
	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158



```
In [27]: run_model(log_reg, 'Logistic Regression')
```

Out[27]:

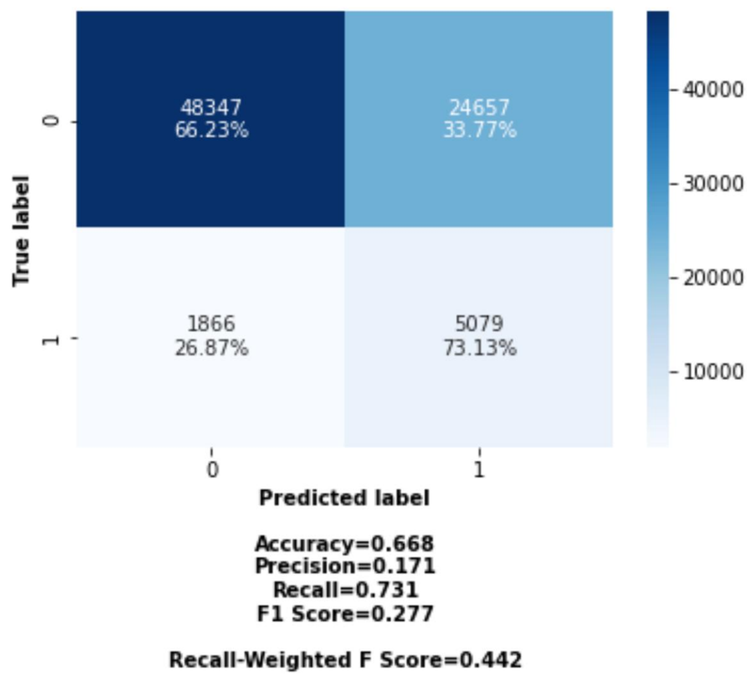
	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158



In [28]:
```
run_model(decisionTree, 'Decision Tree')
```

Out[28]:

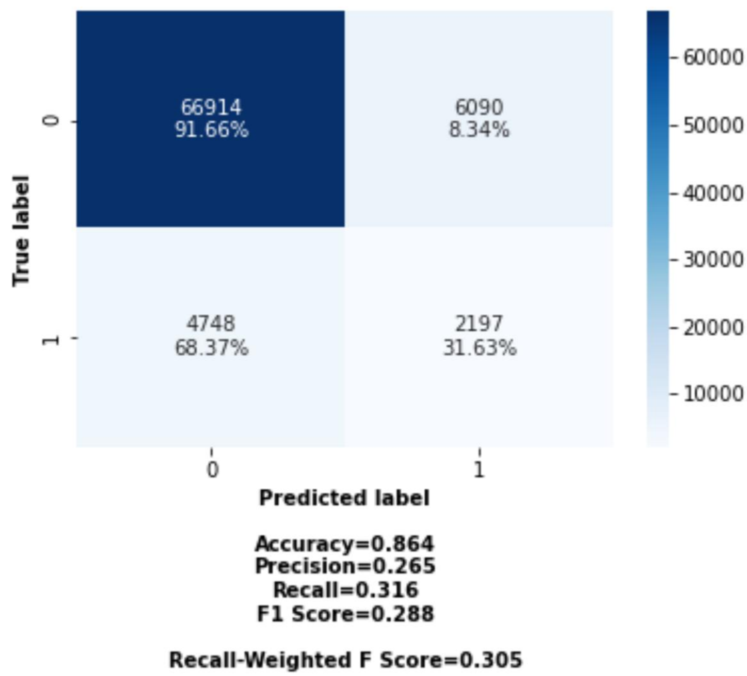
	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Decision Tree	0.441529	0.276928	0.731317	0.170803	0.668251
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158



In [29]:
```
run_model(random_forest, 'Random Forest')
```

Out[29]:

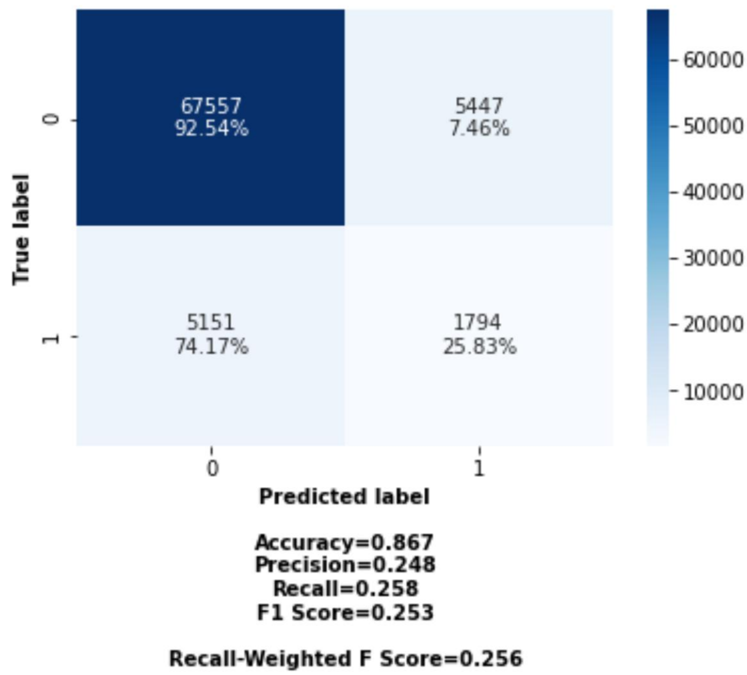
	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Decision Tree	0.441529	0.276928	0.731317	0.170803	0.668251
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158
0	Random Forest	0.304572	0.288472	0.316343	0.265114	0.864439



In [30]:
```
run_model(baggedTrees, 'Bagged Trees')
```

Out[30]:

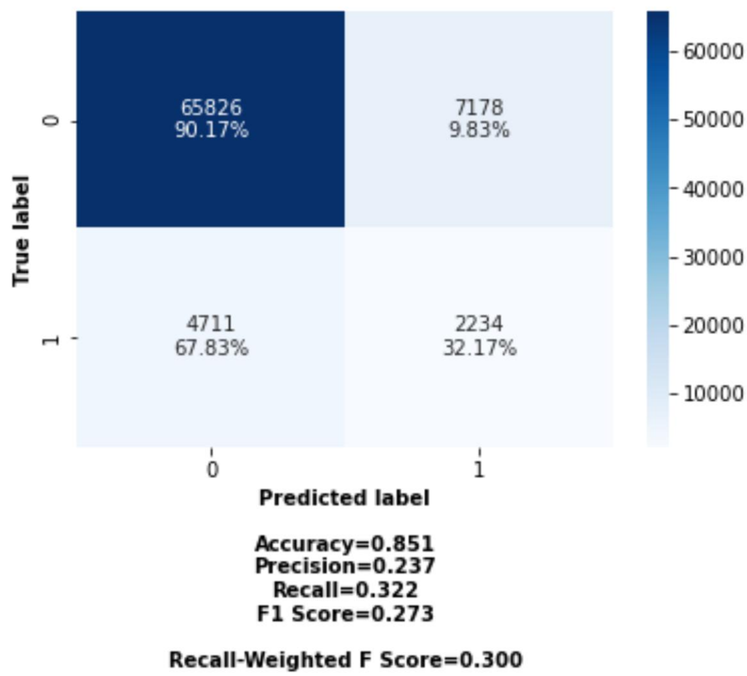
	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Decision Tree	0.441529	0.276928	0.731317	0.170803	0.668251
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158
0	Random Forest	0.304572	0.288472	0.316343	0.265114	0.864439
0	Bagged Trees	0.256132	0.252925	0.258315	0.247756	0.867440



In [31]:
```python
run_model(extraTrees, 'Extra Trees')
```

Out[31]:

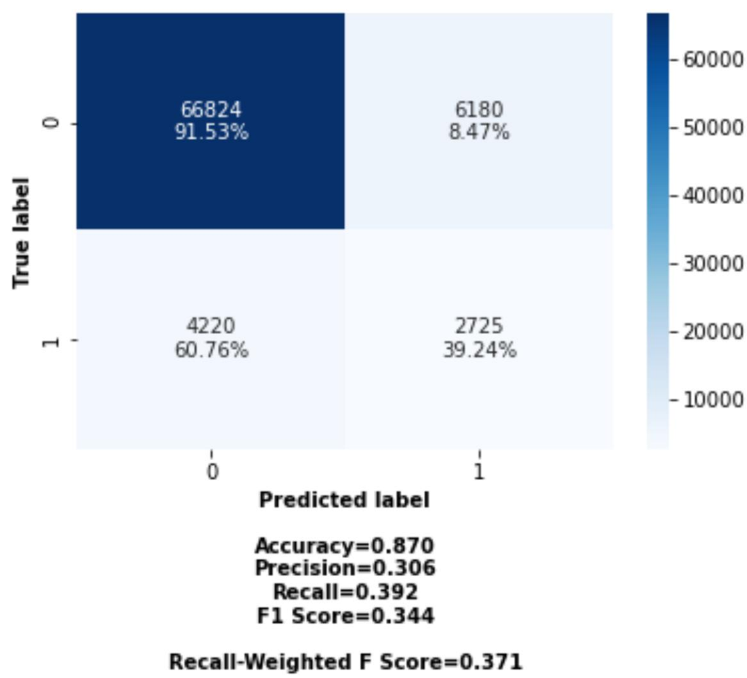
	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Decision Tree	0.441529	0.276928	0.731317	0.170803	0.668251
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158
0	Random Forest	0.304572	0.288472	0.316343	0.265114	0.864439
0	Extra Trees	0.300333	0.273155	0.321670	0.237357	0.851293
0	Bagged Trees	0.256132	0.252925	0.258315	0.247756	0.867440



In [32]:
```python
run_model(xgBoost, 'XGBoost')
```

Out[32]:

	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Decision Tree	0.441529	0.276928	0.731317	0.170803	0.668251
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158
0	XGBoost	0.371405	0.343849	0.392369	0.306008	0.869917
0	Random Forest	0.304572	0.288472	0.316343	0.265114	0.864439
0	Extra Trees	0.300333	0.273155	0.321670	0.237357	0.851293
0	Bagged Trees	0.256132	0.252925	0.258315	0.247756	0.867440



Iterate the best

In [33]:
```
log_reg['logisticregression'].get_params()
```

Out[33]:
```
{'C': 1.0,
 'class_weight': None,
 'dual': False,
 'fit_intercept': True,
 'intercept_scaling': 1,
 'l1_ratio': None,
 'max_iter': 100,
 'multi_class': 'auto',
 'n_jobs': None,
 'penalty': 'l2',
 'random_state': 0,
 'solver': 'lbfgs',
 'tol': 0.0001,
 'verbose': 0,
 'warm_start': False}
```

In [34]:
```
# Define Grid
rf_grid = [{'logisticregression__C': [1, 2],
        'logisticregression__penalty': ['l2', 'none'],
        'logisticregression__solver': ['newton-cg', 'lbfgs','sag']}]
```

In [35]:
```
logreg_gridsearch = GridSearchCV(estimator=log_reg, param_grid=rf_grid, sco
ring=class_metric, cv=3)
```

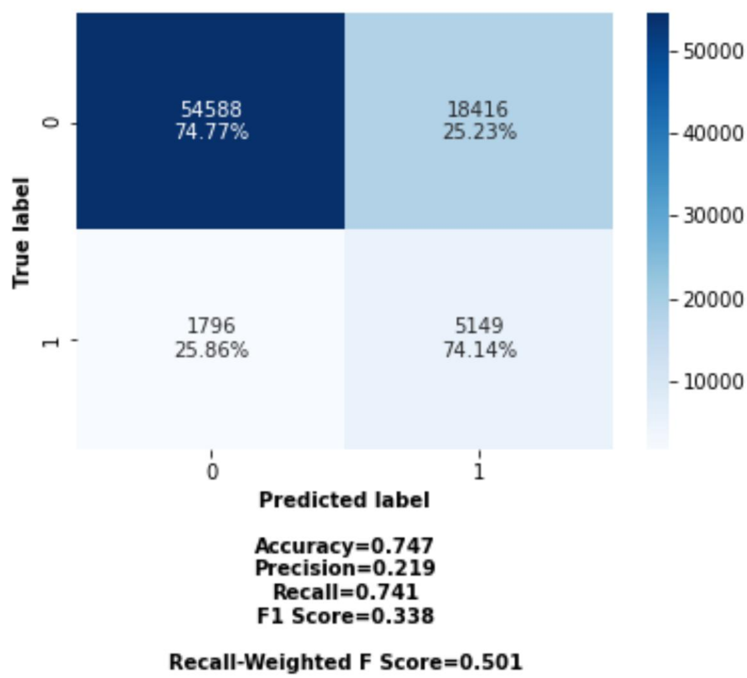
In [36]:
```
log_reg.get_params().keys()
```

Out[36]:
```
dict_keys(['memory', 'steps', 'verbose', 'columntransformer', 'logisticregr
ession', 'columntransformer__n_jobs', 'columntransformer__remainder', 'colu
mntransformer__sparse_threshold', 'columntransformer__transformer_weights',
'columntransformer__transformers', 'columntransformer__verbose', 'columntra
nsformer__one-hot-encoder', 'columntransformer__standard_scaler', 'columntr
ansformer__one-hot-encoder__categories', 'columntransformer__one-hot-encode
r__drop', 'columntransformer__one-hot-encoder__dtype', 'columntransformer__
one-hot-encoder__handle_unknown', 'columntransformer__one-hot-encoder__spar
se', 'columntransformer__standard_scaler__copy', 'columntransformer__standa
rd_scaler__with_mean', 'columntransformer__standard_scaler__with_std', 'log
isticregression__C', 'logisticregression__class_weight', 'logisticregressio
n__dual', 'logisticregression__fit_intercept', 'logisticregression__interce
pt_scaling', 'logisticregression__l1_ratio', 'logisticregression__max_iter
', 'logisticregression__multi_class', 'logisticregression__n_jobs', 'logist
icregression__penalty', 'logisticregression__random_state', 'logisticregres
sion__solver', 'logisticregression__tol', 'logisticregression__verbose', 'l
ogisticregression__warm_start'])
```

In [37]:
```python
#logreg_gridsearch.fit(X_train, y_train)
run_model(logreg_gridsearch, 'Logistic Regression with Grid Search')
```

Out[37]:

	Model	RWF Score	F1	Recall	Precision	Accuracy
0	Logistic Regression	0.501597	0.337694	0.741541	0.218628	0.747326
0	Logistic Regression with Grid Search	0.501412	0.337529	0.741397	0.218502	0.747189
0	Decision Tree	0.441529	0.276928	0.731317	0.170803	0.668251
0	Initial Decision Tree	0.412634	0.246150	0.751476	0.147180	0.600158
0	XGBoost	0.371405	0.343849	0.392369	0.306008	0.869917
0	Random Forest	0.304572	0.288472	0.316343	0.265114	0.864439
0	Extra Trees	0.300333	0.273155	0.321670	0.237357	0.851293
0	Bagged Trees	0.256132	0.252925	0.258315	0.247756	0.867440



Winner: Logistic Regression

In [38]:
```
log_reg.named_steps
```

Out[38]:
```
{'columntransformer': ColumnTransformer(transformers=[('one-hot-encoder',
                                  OneHotEncoder(handle_unknown='ignore'),
                                  ['Smoking', 'AlcoholDrinking', 'Stroke',
                                   'DiffWalking', 'Sex', 'AgeCategory', 'Ra
ce',
                                   'Diabetic', 'PhysicalActivity', 'GenHeal
th',
                                   'Asthma', 'KidneyDisease', 'SkinCancer
']),
                                 ('standard_scaler', StandardScaler(),
                                  ['BMI', 'PhysicalHealth', 'MentalHealth',
                                   'SleepTime'])]),
 'logisticregression': LogisticRegression(random_state=0)}
```

In [39]:
```
coefs = log_reg['logisticregression'].coef_
coefs = list(coefs[0])
len(coefs)
```

Out[39]:
```
50
```

In [40]:
```
numerical_columns
```

Out[40]:
```
['BMI', 'PhysicalHealth', 'MentalHealth', 'SleepTime']
```

In [41]:
```
cat_list= list(feature_names_categorical)
```

In [42]:
```
all_cats = cat_list + numerical_columns
```

```
In [43]: all_cats
```

```
Out[43]: ['Smoking_No',
 'Smoking_Yes',
 'AlcoholDrinking_No',
 'AlcoholDrinking_Yes',
 'Stroke_No',
 'Stroke_Yes',
 'DiffWalking_No',
 'DiffWalking_Yes',
 'Sex_Female',
 'Sex_Male',
 'AgeCategory_18-24',
 'AgeCategory_25-29',
 'AgeCategory_30-34',
 'AgeCategory_35-39',
 'AgeCategory_40-44',
 'AgeCategory_45-49',
 'AgeCategory_50-54',
 'AgeCategory_55-59',
 'AgeCategory_60-64',
 'AgeCategory_65-69',
 'AgeCategory_70-74',
 'AgeCategory_75-79',
 'AgeCategory_80 or older',
 'Race_American Indian/Alaskan Native',
 'Race_Asian',
 'Race_Black',
 'Race_Hispanic',
 'Race_Other',
 'Race_White',
 'Diabetic_No',
 'Diabetic_No, borderline diabetes',
 'Diabetic_Yes',
 'Diabetic_Yes (during pregnancy)',
 'PhysicalActivity_No',
 'PhysicalActivity_Yes',
 'GenHealth_Excellent',
 'GenHealth_Fair',
 'GenHealth_Good',
 'GenHealth_Poor',
 'GenHealth_Very good',
 'Asthma_No',
 'Asthma_Yes',
 'KidneyDisease_No',
 'KidneyDisease_Yes',
 'SkinCancer_No',
 'SkinCancer_Yes',
 'BMI',
 'PhysicalHealth',
 'MentalHealth',
 'SleepTime']
```

In [44]:
```
log_reg['logisticregression'].coef_
```

Out[44]:
```
array([[-4.05333675e-01, -2.90920559e-02,  3.37922741e-01,
        -7.72348472e-01, -6.18184131e-01,  1.83758400e-01,
        -3.03145729e-01, -1.31280001e-01, -6.00230712e-01,
         1.65804981e-01, -2.16451588e+00, -2.27540768e+00,
        -2.01627123e+00, -1.44242048e+00, -8.19559992e-01,
        -4.64338740e-01,  2.44673437e-01,  6.01561770e-01,
         1.01634869e+00,  1.28097544e+00,  1.61177442e+00,
         1.81754057e+00,  2.17521394e+00, -6.26414042e-01,
        -7.51741889e-01,  6.32556488e-02,  3.01197732e-01,
        -4.49489479e-01,  1.02876630e+00,  5.26667578e-01,
        -4.80360117e-01,  1.00643036e+00, -1.48716355e+00,
        -2.57080607e-01, -1.77345124e-01, -1.34099153e+00,
         6.31534785e-01,  2.00928726e-03,  9.89670893e-01,
        -7.16649164e-01, -2.70863747e-01, -1.63561984e-01,
        -2.54662829e-01, -1.79762902e-01, -1.43987311e-01,
        -2.90438420e-01,  9.58713097e-02, -1.40068493e-02,
         9.92067232e-02, -6.18929764e-02]])
```

In [45]:
```
data1 = log_reg['logisticregression'].coef_
cols = all_cats
data = pd.DataFrame(data1, columns=cols)
data = data.T
data
```

Out[45]:

	0
Smoking_No	-0.405334
Smoking_Yes	-0.029092
AlcoholDrinking_No	0.337923
AlcoholDrinking_Yes	-0.772348
Stroke_No	-0.618184
Stroke_Yes	0.183758
DiffWalking_No	-0.303146
DiffWalking_Yes	-0.131280
Sex_Female	-0.600231
Sex_Male	0.165805
AgeCategory_18-24	-2.164516
AgeCategory_25-29	-2.275408
AgeCategory_30-34	-2.016271
AgeCategory_35-39	-1.442420
AgeCategory_40-44	-0.819560
AgeCategory_45-49	-0.464339
AgeCategory_50-54	0.244673
AgeCategory_55-59	0.601562
AgeCategory_60-64	1.016349
AgeCategory_65-69	1.280975
AgeCategory_70-74	1.611774
AgeCategory_75-79	1.817541
AgeCategory_80 or older	2.175214
Race_American Indian/Alaskan Native	-0.626414
Race_Asian	-0.751742
Race_Black	0.063256
Race_Hispanic	0.301198
Race_Other	-0.449489
Race_White	1.028766
Diabetic_No	0.526668
Diabetic_No, borderline diabetes	-0.480360

	0
Diabetic_Yes	1.006430
Diabetic_Yes (during pregnancy)	-1.487164
PhysicalActivity_No	-0.257081
PhysicalActivity_Yes	-0.177345
GenHealth_Excellent	-1.340992
GenHealth_Fair	0.631535
GenHealth_Good	0.002009
GenHealth_Poor	0.989671
GenHealth_Very good	-0.716649
Asthma_No	-0.270864
Asthma_Yes	-0.163562
KidneyDisease_No	-0.254663
KidneyDisease_Yes	-0.179763
SkinCancer_No	-0.143987

In [46]:
```
data = data.reset_index()
```

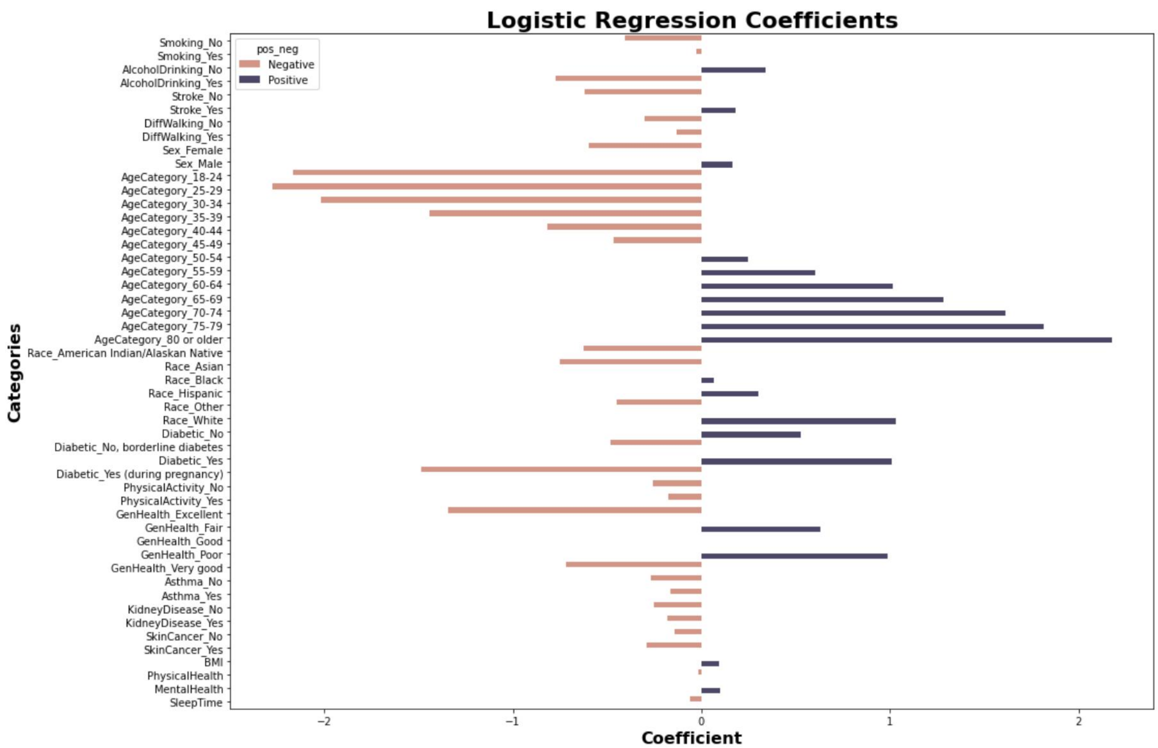
In [55]:
```
plt.figure(figsize=(16,12))

conds = [(data[0] > 0),
        (data[0] < 0)]

vals = ['Positive', 'Negative']
data['pos_neg'] = np.select(conds, vals)
color_dict = {'Positive': '#49416D', 'Negative': '#E08D79'}

ax = sns.barplot(x=0,y= 'index', data=data, hue = 'pos_neg', palette= color
_dict)
plt.ylabel('Categories', size = 16, weight = 'bold')
plt.xlabel('Coefficient', size = 16, weight = 'bold')
plt.title('Logistic Regression Coefficients', size = 22, weight = 'bold')
```

Out[55]:
```
Text(0.5, 1.0, 'Logistic Regression Coefficients')
```



In [ ]: