```
### Network Slicing Recognition
```

The telecom industry is going through a massive digital transformation with the adoption of ML, AI, feedback-based automation and advanced analytics to handle the next generation applications and services. AI concepts are not new; the algorithms used by Machine Learning and Deep Learning are being currently implemented in various industries and technology verticals. With growing data and immense volume

of information over 5G, the ability to predict data proactively, swiftly and with accuracy, is critically important. Data-driven decision making will be vital in future communication networks due to the traffic explosion and Artificial Intelligence (AI) will accelerate the 5G network performance.

Mobile operators are looking for a programmable solution that will allow them to accommodate multiple independent tenants on the same physical infrastructure and 5G networks allow for end-to-end network resource allocation using the concept of Network Slicing (NS).

Network Slicing will play a vital role in enabling a multitude of 5G applications, use cases, and services. Network slicing functions will provide an end-to-end isolation between slices with an ability to customize each slice based on the service demands (bandwidth, coverage, security, latency, reliability, etc).

Your Task is to build a Machine Learning model that will be able to to proactively detect and eliminate threats based on incoming connections thereby selecting the most appropriate network slice, even in case of a network failure.

LTE/5g - User Equipment categories or classes to define the performance specifications
Packet Loss Rate - number of packets not received divided by the total number of packets sent.
Packet Delay - The time for a packet to be received.
Slice type - network configuration that allows multiple networks (virtualized and independent)
GBR - Guaranteed Bit Rate
Healthcare - Usage in Healthcare (1 or 0)
Industry 4.0 - Usage in Digital Enterprises(1 or 0)
IoT Devices - Usage
Public Safety - Usage for public welfare and safety purposes (1 or 0)
Smart City & Home - usage in daily household chores
Smart Transportation - usage in public transportation
Smartphone - whether used for smartphone cellular data

```
####! pip install neattext
```

```
import pandas as pd
import numpy as np
import neattext.functions as nfx
import seaborn as sn

from sklearn.feature_extraction.text import TfidfVectorizer,CountVectorizer
from sklearn.metrics.pairwise import cosine_similarity,linear_kernel
```

```
##! pip uninstall numpy
###!pip install numpy==1.20
```

```
###!mkdir ~/.kaggle
```

```
###!cp /kaggle.json ~/.kaggle/
```

```
###!chmod 600 ~/.kaggle/kaggle.json
```

```
###! pip install kaggle
###!pip install keras-tuner
```

```
###!kaggle datasets download -d gauravduttakiit/network-slicing-recognition
```

```
###!unzip /content/network-slicing-recognition.zip
```

```
train_dataset = pd.read_csv("/content/train_dataset.csv")
test_dataset = pd.read_csv("/content/test_dataset.csv")
```

```
print(train_dataset.shape, test_dataset.shape)
```

```
(31583, 17) (31584, 16)
```

```
test_dataset['slice Type'] = 0
```

```
train_dataset = train_dataset.reset_index()
test_dataset = test_dataset.reset_index()
train_dataset.rename(columns = { "index" : "ID"}, inplace = True)
test_dataset.rename(columns = { "index" : "ID"}, inplace = True)
```

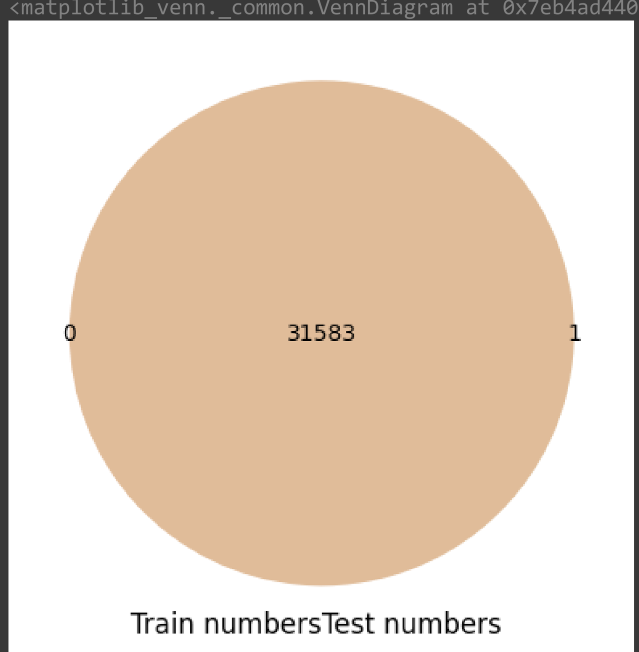
```
train_dataset['slice Type'].value_counts()
```

```
1    16799
3     7392
2     7392
Name: slice Type, dtype: int64
```

```
from matplotlib_venn import venn2, venn2_circles, venn2_unweighted
from matplotlib_venn import venn3, venn3_circles
```

```
set_numbers_train = set(train_dataset[['ID']].drop_duplicates().sort_values(by = 'ID')['ID'].tolist())
set_numbers_test = set(test_dataset[['ID']].drop_duplicates().sort_values(by = 'ID')['ID'].tolist())
venn2((set_numbers_train, set_numbers_test), set_labels = ('Train numbers', 'Test numbers'))
```

```
<matplotlib_venn._common.VennDiagram at 0x7eb4ad440700>
```




```
train_dataset.columns
```

```
Index(['ID', 'LTE/5g Category', 'Time', 'Packet Loss Rate', 'Packet delay',
       'IoT', 'LTE/5G', 'GBR', 'Non-GBR', 'AR/VR/Gaming', 'Healthcare',
       'Industry 4.0', 'IoT Devices', 'Public Safety', 'Smart City & Home',
       'Smart Transportation', 'Smartphone', 'slice Type'],
      dtype='object')
```

```
###! pip install klib
```

```
###!pip install keras-tuner
```

```
import klib
```

```
train_dataset = klib.clean_column_names(train_dataset)
test_dataset = klib.clean_column_names(test_dataset)
```

```
train_dataset = klib.convert_datatypes(train_dataset)
test_dataset = klib.convert_datatypes(test_dataset)
```

```
train_dataset.columns
```

```
Index(['id', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

Anomaly Detection Using One-Class SVM

```
from sklearn import svm
```

```
clf = svm.OneClassSVM(nu=0.05, kernel="rbf", gamma=0.1)
clf.fit(train_dataset)
```

```
OneClassSVM
OneClassSVM(gamma=0.1, nu=0.05)
```

```
pred = clf.predict(train_dataset)

# inliers are labeled 1, outliers are labeled -1
normal = train_dataset[pred == 1]
abnormal = train_dataset[pred == -1]
```

```
print(normal.shape, abnormal.shape)
```

```
(18373, 18) (13210, 18)
```

```
normal.columns
```

```
Index(['id', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
normal['slice_type'].value_counts()
```

```
1    9839
2    4294
3    4240
Name: slice_type, dtype: int64
```

```
train_dataset = normal
```

```
print(train_dataset.shape)
print(train_dataset.columns)
```

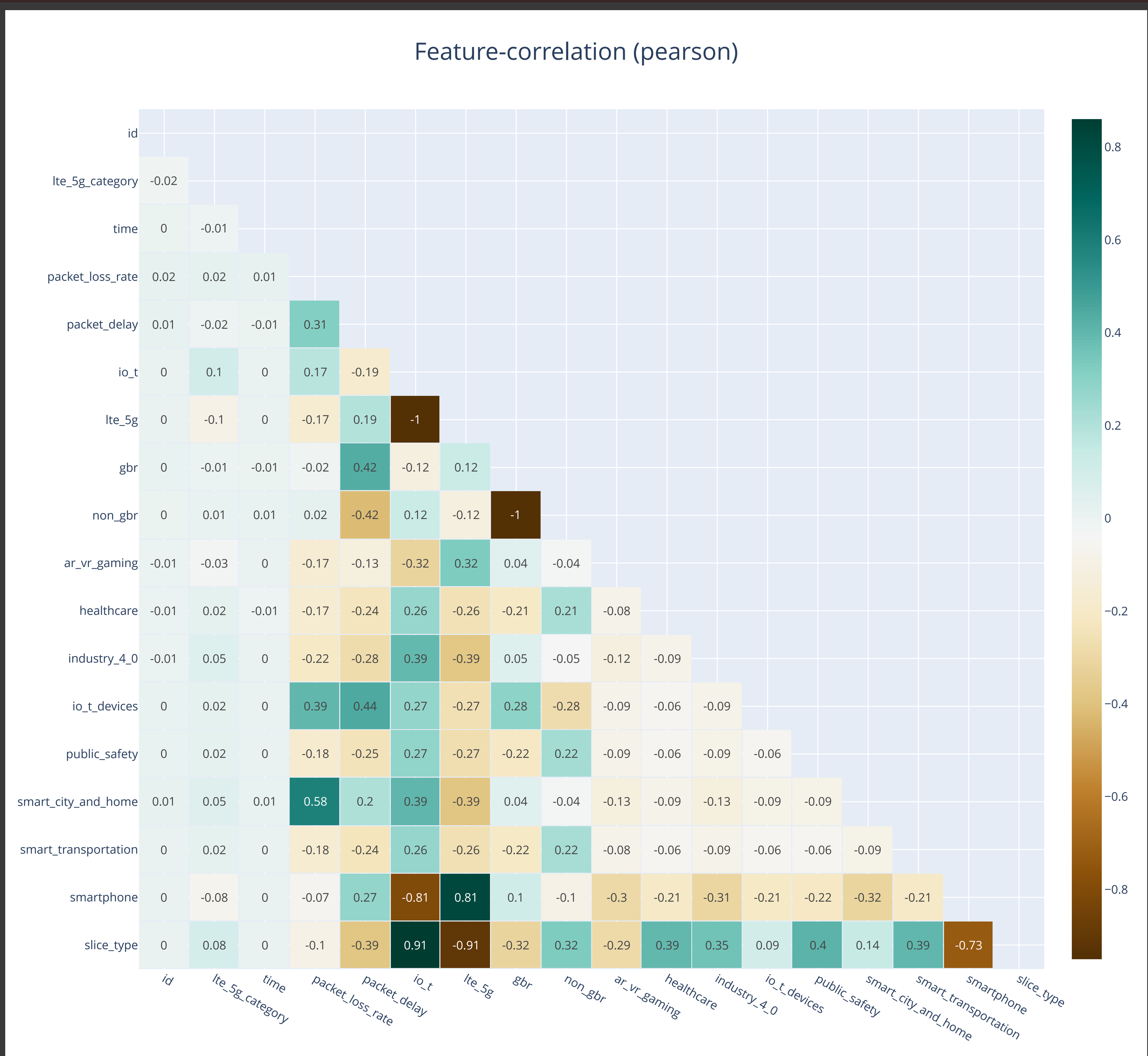
```
(18373, 18)
Index(['id', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
test_dataset['slice_type'] = 0
```

```
klib.cat_plot(train_dataset)
```

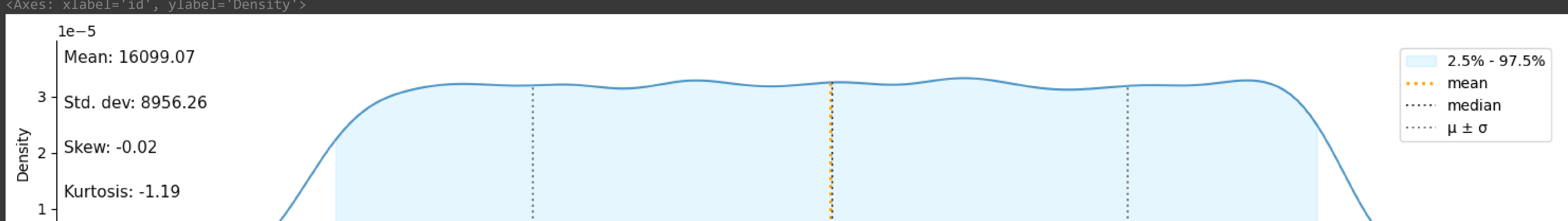
```
No columns with categorical data were detected.
```

```
klib.corr_interactive_plot(train_dataset)
```




```
klib.dist_plot(train_dataset)
```

```
Large dataset detected, using 10000 random samples for the plots. Summary statistics are still based on the entire dataset.
<Axes: xlabel='id', ylabel='Density'>
```




```
klib.missingval_plot(train_dataset)
```

```
No missing values found in the dataset.
```

```
klib.corr_mat(train_dataset)
```

	id	lte_5g_category	time	packet_loss_rate	packet_delay	io_t	lte_5g	gbr	non_gbr
id	1.00	-0.02	-0.00	0.02	0.01	0.00	-0.00	0.00	-0.00
lte_5g_category	-0.02	1.00	-0.01	0.02	-0.02	0.10	-0.10	-0.01	0.01
time	-0.00	-0.01	1.00	0.01	-0.01	0.00	-0.00	-0.01	0.01
packet_loss_rate	0.02	0.02	0.01	1.00	0.31	0.17	-0.17	-0.02	0.02
packet_delay	0.01	-0.02	-0.01	0.31	1.00	-0.19	0.19	0.42	-0.42
io_t	0.00	0.10	0.00	0.17	-0.19	1.00	-1.00	-0.12	0.12
lte_5g	-0.00	-0.10	-0.00	-0.17	0.19	-1.00	1.00	0.12	-0.12
gbr	0.00	-0.01	-0.01	-0.02	0.42	-0.12	0.12	1.00	-1.00
non_gbr	-0.00	0.01	0.01	0.02	-0.42	0.12	-0.12	-1.00	1.00
ar_vr_gaming	-0.01	-0.03	-0.00	-0.17	-0.13	-0.32	0.32	0.04	-0.04
healthcare	-0.01	0.02	-0.01	-0.17	-0.24	0.26	-0.26	-0.21	0.21
industry_4_0	-0.01	0.05	0.00	-0.22	-0.28	0.39	-0.39	0.05	-0.05
io_t_devices	0.00	0.02	-0.00	0.39	0.44	0.27	-0.27	0.28	-0.28
public_safety	0.00	0.02	0.00	-0.18	-0.25	0.27	-0.27	-0.22	0.22
smart_city_and_home	0.01	0.05	0.01	0.58	0.20	0.39	-0.39	0.04	-0.04
smart_transportation	-0.00	0.02	-0.00	-0.18	-0.24	0.26	-0.26	-0.22	0.22
smartphone	0.00	-0.08	0.00	-0.07	0.27	-0.81	0.81	0.10	-0.10
slice_type	-0.00	0.08	-0.00	-0.10	-0.39	0.91	-0.91	-0.32	0.32

	ar_vr_gaming	healthcare	industry_4_0	io_t_devices	public_safety	smart_city_and_home	smart_transportation	smartphone	slice_type
id	-0.01	-0.01	-0.01	0.00	0.00	0.01	-0.00	0.00	-0.00
lte_5g_category	-0.03	0.02	0.05	0.02	0.02	0.05	0.02	-0.08	0.08
time	-0.00	-0.01	0.00	-0.00	0.00	0.01	-0.00	0.00	-0.00
packet_loss_rate	-0.17	-0.17	-0.22	0.39	-0.18	0.58	-0.18	-0.07	-0.10
packet_delay	-0.13	-0.24	-0.28	0.44	-0.25	0.20	-0.24	0.27	-0.39
io_t	-0.32	0.26	0.39	0.27	0.27	0.39	0.26	-0.81	0.91
lte_5g	0.32	-0.26	-0.39	-0.27	-0.27	-0.39	-0.26	0.81	-0.91
gbr	0.04	-0.21	0.05	0.28	-0.22	0.04	-0.22	0.10	-0.32
non_gbr	-0.04	0.21	-0.05	-0.28	0.22	-0.04	0.22	-0.10	0.32
ar_vr_gaming	1.00	-0.08	-0.12	-0.09	-0.09	-0.13	-0.08	-0.30	-0.29
healthcare	-0.08	1.00	-0.09	-0.06	-0.06	-0.09	-0.06	-0.21	0.39
industry_4_0	-0.12	-0.09	1.00	-0.09	-0.09	-0.13	-0.09	-0.31	0.35
io_t_devices	-0.09	-0.06	-0.09	1.00	-0.06	-0.09	-0.06	-0.21	0.09
public_safety	-0.09	-0.06	-0.09	-0.06	1.00	-0.09	-0.06	-0.22	0.40
smart_city_and_home	-0.13	-0.09	-0.13	-0.09	-0.09	1.00	-0.09	-0.32	0.14
smart_transportation	-0.08	-0.06	-0.09	-0.06	-0.06	-0.09	1.00	-0.21	0.39
smartphone	-0.30	-0.21	-0.31	-0.21	-0.22	-0.32	-0.21	1.00	-0.73
slice_type	-0.29	0.39	0.35	0.09	0.40	0.14	0.39	-0.73	1.00

```
train_dataset.columns
```

```
Index(['id', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
# Checking for outliers in the continuous variables
num_train_dataset = train_dataset[['id', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type']]
```

```
train_dataset['slice_type'].value_counts()
```

```
1    9839
2    4294
3    4240
Name: slice_type, dtype: int64
```

```
train_dataset.columns
```

```
Index(['id', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
y_train = train_dataset['slice_type']
x_train = train_dataset.drop('slice_type', axis = 1)
y_test = test_dataset['slice_type']
x_test = test_dataset.drop('slice_type', axis = 1)
```

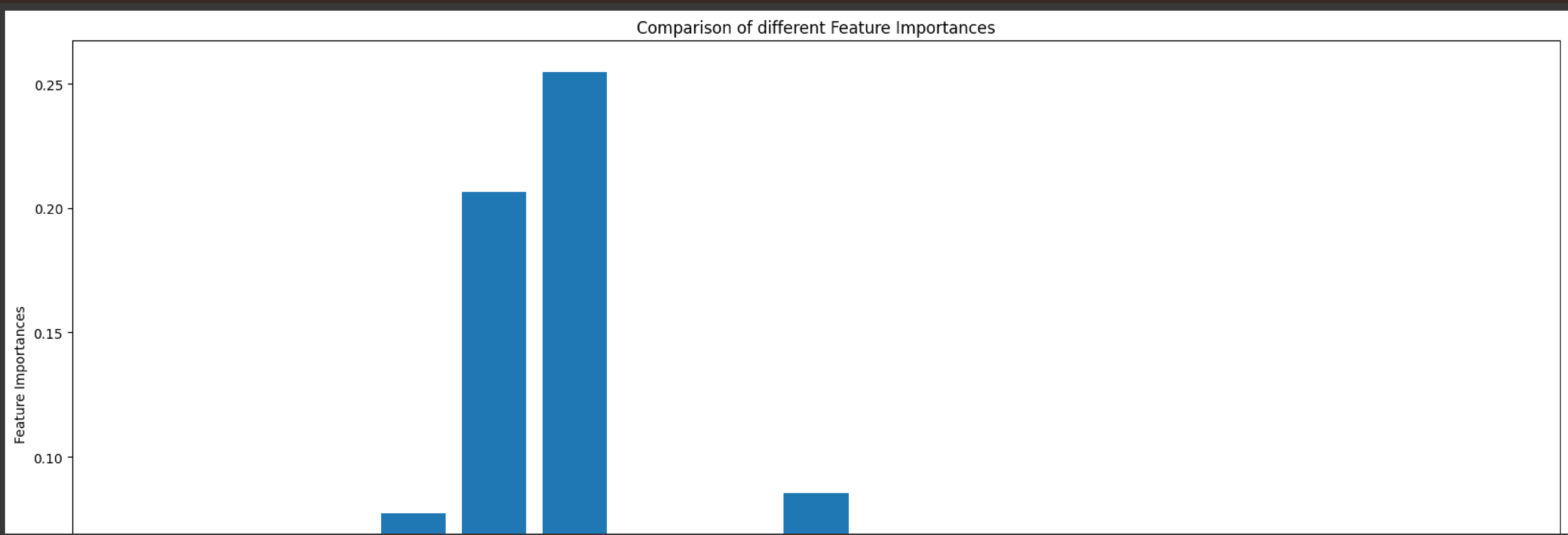
```
from sklearn.ensemble import ExtraTreesClassifier
extra_tree_forest = ExtraTreesClassifier(n_estimators = 5,
                                        criterion ='entropy', max_features = 2)
extra_tree_forest.fit(x_train, y_train)
feature_importance = extra_tree_forest.feature_importances_
feature_importance_normalized = np.std([tree.feature_importances_ for tree in
                                        extra_tree_forest.estimators_],
                                        axis = 0)
```

```
import matplotlib.pyplot as plt
```

```
feature_importance_normalized
```

```
array([1.96047907e-06, 3.22411088e-05, 0.00000000e+00, 7.71850427e-02,
       2.06573178e-01, 2.54515106e-01, 0.00000000e+00, 6.79080438e-02,
       8.53867020e-02, 2.29935701e-02, 4.69127328e-03, 4.45481272e-02,
       5.46713374e-02, 6.93306611e-03, 6.74625612e-02, 1.73966301e-03,
       0.00000000e+00])
```

```
plt.figure(figsize = [20,9])
plt.bar(x_train.columns, feature_importance_normalized)
plt.xlabel('Feature Labels')
plt.ylabel('Feature Importances')
plt.xticks(rotation = 90)
plt.title('Comparison of different Feature Importances')
plt.show()
```




```
x_train.columns
```

```
Index(['id', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object')
```

```
x_train2 = x_train[['lte_5g_category', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone']]
```

```
x_test2 = x_test[['lte_5g_category', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone']]
```

```
print(x_train2.shape, x_test2.shape)
```

```
(18373, 15) (31584, 15)
```

```
y_train.value_counts()
```

```
1    9839
2    4294
3    4240
Name: slice_type, dtype: int64
```

```
x_train2 = pd.DataFrame(x_train2)
x_test2 = pd.DataFrame(x_test2)
```

Pearson Correlation

```
x_train2.astype(float).corr()
```

	lte_5g_category	packet_loss_rate	packet_delay	io_t	lte_5g	gbr	non_gbr	ar_vr_gaming	healthcare	industry_4_0	io_t_devices	public_safety	smart_city_and_home	smart_transportation	smartphone
lte_5g_category	1.000000	0.022254	-0.015085	0.095605	-0.095605	-0.007156	0.007156	-0.034010	0.018408	0.045106	0.019458	0.019485	0.047347	0.019787	-0.075152
packet_loss_rate	0.022254	1.000000	0.306436	0.170858	-0.170858	-0.022315	0.022315	-0.168172	-0.174050	-0.216202	0.389878	-0.182358	0.578743	-0.176111	-0.067416
packet_delay	-0.015085	0.306436	1.000000	-0.187910	0.187910	0.424124	-0.424124	-0.127614	-0.238384	-0.284384	0.437355	-0.249763	0.200818	-0.241206	0.268831
io_t	0.095605	0.170858	-0.187910	1.000000	-1.000000	-0.122402	0.122402	-0.321284	0.260863	0.385515	0.265817	0.273314	0.394585	0.263951	-0.807524
lte_5g	-0.095605	-0.170858	0.187910	-1.000000	1.000000	0.122402	-0.122402	0.321284	-0.260863	-0.385515	-0.265817	-0.273314	-0.394585	-0.263951	0.807524
gbr	-0.007156	-0.022315	0.424124	-0.122402	0.122402	1.000000	-1.000000	0.037476	-0.213782	0.045353	0.281337	-0.223986	0.035940	-0.216313	0.099995
non_gbr	0.007156	0.022315	-0.424124	0.122402	-0.122402	-1.000000	1.000000	-0.037476	0.213782	-0.045353	-0.281337	0.223986	-0.035940	0.216313	-0.099995
ar_vr_gaming	-0.034010	-0.168172	-0.127614	-0.321284	0.321284	0.037476	-0.037476	1.000000	-0.083811	-0.123860	-0.085403	-0.087812	-0.126774	-0.084803	-0.299119
healthcare	0.018408	-0.174050	-0.238384	0.260863	-0.260863	-0.213782	0.213782	-0.083811	1.000000	-0.087228	-0.060145	-0.061841	-0.089280	-0.059722	-0.210653
industry_4_0	0.045106	-0.216202	-0.284384	0.385515	-0.385515	0.045353	-0.045353	-0.123860	-0.087228	1.000000	-0.088885	-0.091391	-0.131942	-0.088261	-0.311313
io_t_devices	0.019458	0.389878	0.437355	0.265817	-0.265817	0.281337	-0.281337	-0.085403	-0.060145	-0.088885	1.000000	-0.063016	-0.090976	-0.060857	-0.214654
public_safety	0.019485	-0.182358	-0.249763	0.273314	-0.273314	-0.223986	0.223986	-0.087812	-0.061841	-0.091391	-0.063016	1.000000	-0.093542	-0.062573	-0.220708
smart_city_and_home	0.047347	0.578743	0.200818	0.394585	-0.394585	0.035940	-0.035940	-0.126774	-0.089280	-0.131942	-0.090976	-0.093542	1.000000	-0.090337	-0.318637
smart_transportation	0.019787	-0.176111	-0.241206	0.263951	-0.263951	-0.216313	0.216313	-0.084803	-0.059722	-0.088261	-0.060857	-0.062573	-0.090337	1.000000	-0.213147
smartphone	-0.075152	-0.067416	0.268831	-0.807524	0.807524	0.099995	-0.099995	-0.299119	-0.210653	-0.311313	-0.214654	-0.220708	-0.318637	-0.213147	1.000000

```
def correlation(dataset, threshold):
    col_corr = set() # Set of all the names of deleted columns
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if (corr_matrix.iloc[i, j] >= threshold) and (corr_matrix.columns[j] not in col_corr):
                colname = corr_matrix.columns[i] # getting the name of column
                col_corr.add(colname)
                if colname in dataset.columns:
                    del dataset[colname] # deleting the column from the dataset

    print(dataset.columns)
    print(dataset.shape)
```

```
correlation(x_train2, 0.95)
```

```
Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object')
(18373, 15)
```

```
print(x_test2.columns, x_train2.columns)
```

```
Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object') Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object')
```

```
y_train = pd.DataFrame(y_train)
y_test = pd.DataFrame(y_test)
```

```
print(y_test.columns, y_train.columns)
```

```
Index(['slice_type'], dtype='object') Index(['slice_type'], dtype='object')
```

EVAL ML

```
###!pip install evalml
```

```
import evalml
```

```
from sklearn.preprocessing import LabelEncoder
```

```
lbl= LabelEncoder()
```

```
y_test= lbl.fit_transform(y_test)
y_test[:12]
```

```
A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

```
y_train= lbl.fit_transform(y_train)
y_train[:12]
```

```
A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
array([2, 1, 2, 0, 2, 1, 0, 0, 0, 2, 1, 0])
```

```
evalml.problem_types.ProblemTypes.all_problem_types
```

```
[<ProblemTypes.BINARY: 'binary'>,
 <ProblemTypes.MULTICLASS: 'multiclass'>,
 <ProblemTypes.REGRESSION: 'regression'>,
 <ProblemTypes.TIME_SERIES_REGRESSION: 'time series regression'>,
 <ProblemTypes.TIME_SERIES_BINARY: 'time series binary'>,
 <ProblemTypes.TIME_SERIES_MULTICLASS: 'time series multiclass'>,
 <ProblemTypes.MULTISERIES_TIME_SERIES_REGRESSION: 'multiseries time series regression'>]
```

```
from evalml.automl import AutoMLSearch
automl = AutoMLSearch(X_train=x_train2, y_train=y_train, problem_type='MULTICLASS')
automl.search()
```

```
The y_pred values do not sum to one. Starting from 1.5 thiswill result in an error.
The y_pred values do not sum to one. Starting from 1.5 thiswill result in an error.
The y_pred values do not sum to one. Starting from 1.5 thiswill result in an error.
{1: {'Random Forest Classifier w/ Label Encoder + Imputer + RF Classifier Select From Model': 3.5806334018707275,
  'Total time of batch': 3.7166035175323486},
 2: {'LightGBM Classifier w/ Label Encoder + Imputer + Select Columns Transformer': 2.3293821811676025,
  'Extra Trees Classifier w/ Label Encoder + Imputer + Select Columns Transformer': 2.3987269401550293,
  'Elastic Net Classifier w/ Label Encoder + Imputer + Standard Scaler + Select Columns Transformer': 3.3342366218566895,
  'XGBoost Classifier w/ Label Encoder + Imputer + Select Columns Transformer': 12.184428930282593,
  'Logistic Regression Classifier w/ Label Encoder + Imputer + Standard Scaler + Select Columns Transformer': 9.130321502685547,
  'Total time of batch': 30.656388521194458}}
```

```
automl.rankings
```

	id	pipeline_name	search_order	ranking_score	mean_cv_score	standard_deviation_cv_score	percent_better_than_baseline	high_variance_cv	parameters
0	1	Random Forest Classifier w/ Label Encoder + Im...	1	4.440892e-16	4.440892e-16	0.000000e+00	100.000000	False	{'Label Encoder': {'positive_label': None}, 'I...
1	3	Extra Trees Classifier w/ Label Encoder + Impu...	3	4.440892e-16	4.440892e-16	0.000000e+00	100.000000	False	{'Label Encoder': {'positive_label': None}, 'I...
2	2	LightGBM Classifier w/ Label Encoder + Imputer...	2	1.137570e-06	1.137570e-06	2.102637e-11	99.999993	False	{'Label Encoder': {'positive_label': None}, 'I...
3	5	XGBoost Classifier w/ Label Encoder + Imputer ...	5	1.418487e-04	1.418487e-04	4.158776e-07	99.999153	False	{'Label Encoder': {'positive_label': None}, 'I...
4	4	Elastic Net Classifier w/ Label Encoder + Impu...	4	4.380961e-04	4.380961e-04	7.629913e-06	99.997383	False	{'Label Encoder': {'positive_label': None}, 'I...
5	6	Logistic Regression Classifier w/ Label Encode...	6	5.086381e-04	5.086381e-04	1.026568e-05	99.996962	False	{'Label Encoder': {'positive_label': None}, 'I...
6	0	Mode Baseline Multiclass Classification Pipeline	0	1.674177e+01	1.674177e+01	2.945292e-03	0.000000	False	{'Label Encoder': {'positive_label': None}, 'B...

```
automl.best_pipeline
```

```
pipeline = MulticlassClassificationPipeline(component_graph={'Label Encoder': ['Label Encoder', 'X', 'y'], 'Imputer': ['Imputer', 'X', 'Label Encoder.y'], 'RF Classifier Select From Model': ['RF Classifier Select From Model', 'Imputer.x', 'Label Encoder.y'], 'Random Forest Classifier': ['Random Forest Classifier', 'RF Classifier Select From Model.x', 'Label Encoder.y']}, parameters={'Label Encoder':{'positive_label': None}, 'Imputer':{'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy': 'mean', 'boolean_impute_strategy': 'most_frequent', 'categorical_fill_value': None, 'numeric_fill_value': None, 'boolean_fill_value': None}, 'RF Classifier Select From Model':{'number_features': None, 'n_estimators': 10, 'max_depth': None, 'percent_features': 0.5, 'threshold': 'median', 'n_jobs': -1}, 'Random Forest Classifier':{'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}}, random_seed=0)
```

```
best_pipeline=automl.best_pipeline
```

```
automl.describe_pipeline(automl.rankings.iloc[0]["id"])
```

```
INFO:evalml.pipelines.components.component_base.describe:        * max_depth : 6
         * n_jobs : -1
INFO:evalml.pipelines.components.component_base.describe:        * n_jobs : -1

INFO:evalml.automl.automl_search.describe_pipeline:
Training
INFO:evalml.automl.automl_search.describe_pipeline:Training
========
INFO:evalml.automl.automl_search.describe_pipeline:========
Training for multiclass problems.
INFO:evalml.automl.automl_search.describe_pipeline:Training for multiclass problems.
Total training time (including CV): 3.5 seconds
INFO:evalml.automl.automl_search.describe_pipeline:Total training time (including CV): 3.5 seconds

INFO:evalml.automl.automl_search.describe_pipeline:
Cross Validation
INFO:evalml.automl.automl_search.describe_pipeline:Cross Validation
----------------
INFO:evalml.automl.automl_search.describe_pipeline:----------------
             Log Loss Multiclass  MCC Multiclass  AUC Weighted  AUC Macro  AUC Micro  Precision Weighted  Precision Macro  Precision Micro  F1 Weighted  F1 Macro  F1 Micro  Balanced Accuracy Multiclass  Accuracy Multiclass # Training # Validation
0                          0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000     12,248        6,125
1                          0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000     12,249        6,124
2                          0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000     12,249        6,124
mean                       0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000          -            -
std                        0.000           0.000         0.000      0.000      0.000               0.000            0.000            0.000        0.000     0.000     0.000                         0.000                0.000          -            -
coef of var                0.000           0.000         0.000      0.000      0.000               0.000            0.000            0.000        0.000     0.000     0.000                         0.000                0.000          -            -
INFO:evalml.automl.automl_search.describe_pipeline:             Log Loss Multiclass  MCC Multiclass  AUC Weighted  AUC Macro  AUC Micro  Precision Weighted  Precision Macro  Precision Micro  F1 Weighted  F1 Macro  F1 Micro  Balanced Accuracy Multiclass  Accuracy Multiclass # Trainin
0                          0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000     12,248        6,125
1                          0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000     12,249        6,124
2                          0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000     12,249        6,124
mean                       0.000           1.000         1.000      1.000      1.000               1.000            1.000            1.000        1.000     1.000     1.000                         1.000                1.000          -            -
std                        0.000           0.000         0.000      0.000      0.000               0.000            0.000            0.000        0.000     0.000     0.000                         0.000                0.000          -            -
coef of var                0.000           0.000         0.000      0.000      0.000               0.000            0.000            0.000        0.000     0.000     0.000                         0.000                0.000          -            -
```

```python
evalml.problem_types.ProblemTypes.all_problem_types
```

```
[<ProblemTypes.BINARY: 'binary'>,
 <ProblemTypes.MULTICLASS: 'multiclass'>,
 <ProblemTypes.REGRESSION: 'regression'>,
 <ProblemTypes.TIME_SERIES_REGRESSION: 'time series regression'>,
 <ProblemTypes.TIME_SERIES_BINARY: 'time series binary'>,
 <ProblemTypes.TIME_SERIES_MULTICLASS: 'time series multiclass'>,
 <ProblemTypes.MULTISERIES_TIME_SERIES_REGRESSION: 'multiseries time series regression'>]
```

```python
from evalml.objectives import get_optimization_objectives
```

```python
from evalml.problem_types import ProblemTypes

for objective in get_optimization_objectives(ProblemTypes.MULTICLASS):
    print(objective.name)
```

```
MCC Multiclass
Log Loss Multiclass
AUC Weighted
AUC Macro
AUC Micro
Precision Weighted
Precision Macro
Precision Micro
F1 Weighted
F1 Macro
F1 Micro
Balanced Accuracy Multiclass
Accuracy Multiclass
```

```python
automl_auc = AutoMLSearch(X_train=x_train2, y_train=y_train,
                          problem_type='multiclass',
                          objective='F1 Weighted',
                          additional_objectives=['Balanced Accuracy Multiclass', 'Accuracy Multiclass'],
                          max_batches=1,
                          optimize_thresholds=True)

automl_auc.search()
```

```
{1: {'Random Forest Classifier w/ Label Encoder + Imputer + RF Classifier Select From Model': 6.735596418380737,
  'Total time of batch': 6.892743349075317}}
```

```python
automl_auc.rankings
```

	id	pipeline_name	search_order	ranking_score	mean_cv_score	standard_deviation_cv_score	percent_better_than_baseline	high_variance_cv	parameters
0	1	Random Forest Classifier w/ Label Encoder + Im...	1	1.000000	1.000000	0.000000	62.647647	False	{'Label Encoder': {'positive_label': None}, 'I...
1	0	Mode Baseline Multiclass Classification Pipeline	0	0.373524	0.373524	0.000094	0.000000	False	{'Label Encoder': {'positive_label': None}, 'B...

```python
automl_auc.describe_pipeline(automl_auc.rankings.iloc[0]["id"])
```

```
         * categorical_fill_value : None
INFO:evalml.pipelines.components.component_base.describe:        * categorical_fill_value : None
         * numeric_fill_value : None
INFO:evalml.pipelines.components.component_base.describe:        * numeric_fill_value : None
         * boolean_fill_value : None
INFO:evalml.pipelines.components.component_base.describe:        * boolean_fill_value : None
3. RF Classifier Select From Model
INFO:evalml.pipelines.component_graph.describe:3. RF Classifier Select From Model
         * number_features : None
INFO:evalml.pipelines.components.component_base.describe:        * number_features : None
         * n_estimators : 10
INFO:evalml.pipelines.components.component_base.describe:        * n_estimators : 10
         * max_depth : None
INFO:evalml.pipelines.components.component_base.describe:        * max_depth : None
         * percent_features : 0.5
INFO:evalml.pipelines.components.component_base.describe:        * percent_features : 0.5
         * threshold : median
INFO:evalml.pipelines.components.component_base.describe:        * threshold : median
         * n_jobs : -1
INFO:evalml.pipelines.components.component_base.describe:        * n_jobs : -1
4. Random Forest Classifier
INFO:evalml.pipelines.component_graph.describe:4. Random Forest Classifier
         * n_estimators : 100
INFO:evalml.pipelines.components.component_base.describe:        * n_estimators : 100
         * max_depth : 6
INFO:evalml.pipelines.components.component_base.describe:        * max_depth : 6
         * n_jobs : -1
INFO:evalml.pipelines.components.component_base.describe:        * n_jobs : -1

INFO:evalml.automl.automl_search.describe_pipeline:
Training
INFO:evalml.automl.automl_search.describe_pipeline:Training
========
INFO:evalml.automl.automl_search.describe_pipeline:========
Training for multiclass problems.
INFO:evalml.automl.automl_search.describe_pipeline:Training for multiclass problems.
Total training time (including CV): 6.7 seconds
INFO:evalml.automl.automl_search.describe_pipeline:Total training time (including CV): 6.7 seconds

INFO:evalml.automl.automl_search.describe_pipeline:
Cross Validation
INFO:evalml.automl.automl_search.describe_pipeline:Cross Validation
----------------
INFO:evalml.automl.automl_search.describe_pipeline:----------------
             F1 Weighted  Balanced Accuracy Multiclass  Accuracy Multiclass # Training # Validation
0                  1.000                         1.000                1.000     12,248        6,125
1                  1.000                         1.000                1.000     12,249        6,124
2                  1.000                         1.000                1.000     12,249        6,124
mean               1.000                         1.000                1.000          -            -
std                0.000                         0.000                0.000          -            -
coef of var        0.000                         0.000                0.000          -            -
INFO:evalml.automl.automl_search.describe_pipeline:             F1 Weighted  Balanced Accuracy Multiclass  Accuracy Multiclass # Training # Validation
0                  1.000                         1.000                1.000     12,248        6,125
1                  1.000                         1.000                1.000     12,249        6,124
2                  1.000                         1.000                1.000     12,249        6,124
mean               1.000                         1.000                1.000          -            -
std                0.000                         0.000                0.000          -            -
coef of var        0.000                         0.000                0.000          -            -
```

```python
best_pipeline_auc = automl_auc.best_pipeline
```

```python
# get the score on holdout data
best_pipeline_auc.score(x_test2, y_test,  objectives=["F1 Weighted"])
```

```
OrderedDict([('F1 Weighted', 0.6944444444444444)])
```

```python
best_pipeline.save("network_slicing_pipelines.pkl")
```

```python
final_model=best_pipeline_auc.load('network_slicing_pipelines.pkl')
```

```python
final_model.predict_proba(x_test2)
```

	0	1	2
0	1.0	0.0	0.0
1	0.0	0.0	1.0
2	0.0	1.0	0.0
3	0.0	1.0	0.0
4	1.0	0.0	0.0
...	...	...	...
31579	0.0	0.0	1.0
31580	0.0	0.0	1.0
31581	0.0	0.0	1.0
31582	1.0	0.0	0.0
31583	0.0	0.0	1.0

31584 rows × 3 columns

```
y_pred = final_model.predict(x_test2)
```

```
y_pred = pd.DataFrame(y_pred)
```

```
y_pred.value_counts()
```

```
0    16800
1     7392
2     7392
dtype: int64
```

```
y_train = pd.DataFrame(y_train)
```

```
from sklearn.metrics import classification_report
```

```
print(classification_report(y_test, y_pred, labels=[0, 1, 2]))
```

```
              precision    recall  f1-score   support

           0       1.00      0.53      0.69     31584
           1       0.00      0.00      0.00         0
           2       0.00      0.00      0.00         0

    accuracy                           0.53     31584
   macro avg       0.33      0.18      0.23     31584
weighted avg       1.00      0.53      0.69     31584

Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
```

Start coding or generate with AI.