c_yeast_multilabel_classifier

February 13, 2023

1 Multi-label Classification

1.1 Import Packages

[ ]:
```
from IPython.display import display, HTML, Image

import pandas as pd
import numpy as np
import csv
import matplotlib.pyplot as plt
import copy
import random


from sklearn.base import BaseEstimator, ClassifierMixin, clone
from sklearn.utils.validation import check_X_y, check_array, check_is_fitted

from sklearn.model_selection import train_test_split

from sklearn.model_selection import GridSearchCV

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC

from sklearn.metrics import make_scorer
from sklearn import metrics
from sklearn.metrics import hamming_loss

# to avoid future warnings for sklearn
import warnings
warnings.filterwarnings("ignore")
```

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

[ ]:
```
from sklearn.utils import shuffle


def shuffle_index(num_samples):
    a = range(0, num_samples)
    a = shuffle(a)
    length = int((num_samples + 1) / 2)
    train_index = a[:length]
    test_index = a[length:]
    return [train_index, test_index]


def load_csv(data_csv, label_csv):
    """
    :param csv_file_name:
    :return: Data
    """

    with open(data_csv, encoding='utf-8') as f:
        data = np.loadtxt(f, str, delimiter=",")
    with open(label_csv, encoding='utf-8') as f:
        label = np.loadtxt(f, str, delimiter=",")
    label = label.astype("int")
    num_samples = len(data)

    train_index, test_index = shuffle_index(num_samples)

    X_train = data[train_index]
    y_train = label[train_index]
    X_test = data[test_index]
    y_test = label[test_index]

    return X_train, y_train, X_test, y_test
```

[ ]:
```
data_path = r'/content/drive/MyDrive/dataset/yeast_data.csv'
label_path = r'/content/drive/MyDrive/dataset/yeast_label.csv'
```

[ ]:
```
# Read the CSV file
X = pd.read_csv(data_path)


header = []

for i in range(0, X.shape[1]):
```

```python
    header.append('Att'+str(i))
print(header)
X.to_csv("data.csv", header=header, index=False)

X = pd.read_csv('data.csv')

print("Dataset.shape: " + str(X.shape))
y = pd.read_csv(label_path)

header = []

for i in range(0, y.shape[1]):
    header.append('Class'+str(i))
print(header)

y.to_csv("label.csv", header=header, index=False)

y = pd.read_csv('label.csv')


print("X.shape: " + str(X.shape))
display(X.head())
print("y.shape: " + str(y.shape))
display(y.head())
print("Descriptive stats:")
X.describe()
```

```
['Att0', 'Att1', 'Att2', 'Att3', 'Att4', 'Att5', 'Att6', 'Att7', 'Att8', 'Att9',
'Att10', 'Att11', 'Att12', 'Att13', 'Att14', 'Att15', 'Att16', 'Att17', 'Att18',
'Att19', 'Att20', 'Att21', 'Att22', 'Att23', 'Att24', 'Att25', 'Att26', 'Att27',
'Att28', 'Att29', 'Att30', 'Att31', 'Att32', 'Att33', 'Att34', 'Att35', 'Att36',
'Att37', 'Att38', 'Att39', 'Att40', 'Att41', 'Att42', 'Att43', 'Att44', 'Att45',
'Att46', 'Att47', 'Att48', 'Att49', 'Att50', 'Att51', 'Att52', 'Att53', 'Att54',
'Att55', 'Att56', 'Att57', 'Att58', 'Att59', 'Att60', 'Att61', 'Att62', 'Att63',
'Att64', 'Att65', 'Att66', 'Att67', 'Att68', 'Att69', 'Att70', 'Att71', 'Att72',
'Att73', 'Att74', 'Att75', 'Att76', 'Att77', 'Att78', 'Att79', 'Att80', 'Att81',
'Att82', 'Att83', 'Att84', 'Att85', 'Att86', 'Att87', 'Att88', 'Att89', 'Att90',
'Att91', 'Att92', 'Att93', 'Att94', 'Att95', 'Att96', 'Att97', 'Att98', 'Att99',
'Att100', 'Att101', 'Att102']
Dataset.shape: (2416, 103)
['Class0', 'Class1', 'Class2', 'Class3', 'Class4', 'Class5', 'Class6', 'Class7',
'Class8', 'Class9', 'Class10', 'Class11', 'Class12', 'Class13']
X.shape: (2416, 103)
```

```
       Att0      Att1      Att2      Att3      Att4      Att5      Att6  \
0 -0.022711 -0.050504 -0.035691 -0.065434 -0.084316 -0.378560  0.038212
1 -0.090407  0.021198  0.208712  0.102752  0.119315  0.041729 -0.021728
2 -0.085235  0.009540 -0.013228  0.094063 -0.013592 -0.030719 -0.116062
```

```
3 -0.088765 -0.026743  0.002075 -0.043819 -0.005465  0.004306 -0.055865
4  0.052386 -0.077969 -0.065555 -0.044628 -0.005428  0.120818  0.051850

       Att7      Att8      Att9  …     Att93     Att94     Att95     Att96  \
0  0.085770  0.182613 -0.055544  … -0.001198  0.030594 -0.021814  0.010430
1  0.019603 -0.063853 -0.053756  …  0.195777  0.022294  0.012583  0.002233
2 -0.131674 -0.165448 -0.123053  …  0.001189 -0.066241 -0.046999 -0.066604
3 -0.071484 -0.159025 -0.111348  … -0.035045 -0.080882  0.028468 -0.073576
4  0.072627  0.107119  0.034214  … -0.056235  0.187005 -0.053345  0.162630

      Att97     Att98     Att99    Att100    Att101    Att102
0 -0.013809 -0.009248 -0.027318 -0.014191  0.022783  0.123785
1 -0.002072 -0.010981  0.007615 -0.063378 -0.084181 -0.034402
2 -0.055773 -0.041941  0.051066  0.004976  0.193972  0.131866
3  0.050630  0.084832 -0.019570 -0.021650 -0.068326 -0.091155
4  0.141881 -0.055852 -0.075871 -0.066165 -0.027733  0.069023

[5 rows x 103 columns]
```

```
y.shape: (2416, 14)
```

```
   Class0  Class1  Class2  Class3  Class4  Class5  Class6  Class7  Class8  \
0       0       0       0       0       0       0       1       1       0
1       0       1       1       0       0       0       0       0       0
2       0       0       1       1       0       0       0       0       0
3       1       1       0       0       0       0       0       0       0
4       0       0       1       1       0       0       0       0       0

   Class9  Class10  Class11  Class12  Class13
0       0        0        1        1        0
1       0        0        1        1        0
2       0        0        1        1        1
3       0        0        0        0        0
4       0        0        1        1        0
```

```
Descriptive stats:
```

[ ]:

```
              Att0         Att1         Att2         Att3         Att4  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean      0.001135    -0.000494    -0.000283     0.000262     0.001194
std       0.097413     0.097864     0.097758     0.096989     0.096915
min      -0.371146    -0.472632    -0.339195    -0.467945    -0.367044
25%      -0.053689    -0.058771    -0.057598    -0.057170    -0.058476
50%       0.003468    -0.003537     0.002850    -0.000172     0.005518
75%       0.057256     0.048045     0.060880     0.054533     0.065772
max       0.520272     0.614114     0.353241     0.568960     0.307649

              Att5         Att6         Att7         Att8         Att9  …  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000  …
```

```
mean      0.000525     0.001077     0.000418     0.001065    -0.000027  ...
std       0.097296     0.097179     0.096823     0.096345     0.096821  ...
min      -0.509447    -0.319928    -0.594498    -0.369712    -0.767128  ...
25%      -0.060135    -0.058491    -0.062855    -0.063560    -0.065011  ...
50%       0.000386     0.006126     0.001423     0.003452     0.002378  ...
75%       0.059962     0.068844     0.061512     0.064962     0.063160  ...
max       0.336971     0.351401     0.454591     0.419852     0.420876  ...

             Att93        Att94        Att95        Att96        Att97  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean     -0.000790     0.000472    -0.000501     0.000683     0.000340
std       0.093332     0.096703     0.096226     0.096651     0.096297
min      -0.455191    -0.283594    -0.279408    -0.226420    -0.225374
25%      -0.054157    -0.056452    -0.056422    -0.059432    -0.058030
50%      -0.012933    -0.023597    -0.024312    -0.023023    -0.021937
75%       0.027762     0.034969     0.036229     0.041436     0.035745
max       0.609175     0.542867     0.547134     0.385928     0.540493

             Att98        Att99       Att100       Att101       Att102
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean     -0.001491    -0.001026    -0.001522     0.000235     0.007556
std       0.094388     0.096914     0.094227     0.093142     0.099359
min      -0.501572    -0.236589    -0.267052    -0.194079    -0.237752
25%      -0.053600    -0.063331    -0.059546    -0.054079    -0.077199
50%      -0.018219    -0.033615    -0.023481    -0.012015     0.022072
75%       0.019640     0.038968     0.025432     0.028014     0.103146
max       0.569250     0.509963     0.587358     0.700340     0.163431

[8 rows x 103 columns]
```

[ ]:

```

```

1.1.1 Split into Train and Test Set

[ ]:

```
# Normalise the data
X = (X-X.min())/(X.max()-X.min())

# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0,␣
 ↪train_size=0.7)

print("X_train.shape: " + str(X_train.shape))
print("X_test.shape: " + str(X_test.shape))
print("y_train.shape: " + str(y_train.shape))
print("y_test.shape: " + str(y_test.shape))
```

```
X_train.shape: (1691, 103)
```

```
X_test.shape: (725, 103)
y_train.shape: (1691, 14)
y_test.shape: (725, 14)
```

[ ]:

```

```

1.2 Task 1: Implement the Binary Relevance Algorithm

[ ]:

```
class BinaryRelevanceClassifier(BaseEstimator, ClassifierMixin):
    def __init__(self, base_classifier=LogisticRegression()):
        self.base_classifier=base_classifier

    def fit(self, X, y):
        """Build a Binary Relevance classifier from the training set (X, y).
        Parameters
        ----------
        X : array-like or sparse matrix, shape = [n_samples, n_features]
            The training input samples. Internally, it will be converted to
            ``dtype=np.float32`` and if a sparse matrix is provided
            to a sparse ``csc_matrix``.
        y : array-like, shape = [n_samples, n_labels]
            The target values (class labels) as integers or strings.
        """

        # list of individual classifiers
        self.models = []

        # for every class label
        for label in list(y.columns):
            # Check that X and y have correct shape
            x_checked, y_checked = check_X_y(X, y[label])
            # every classifier is independent of the others
            # hence we create a copy of the base classifier instance
            base_model = clone(self.base_classifier)
            # fit the base model - one model each for Y1, Y2....Y14
            basel_model = base_model.fit(x_checked, y_checked)
            # add the fitted model list of individual classifiers
            self.models.append(base_model)

    # The predict function to make a set of predictions for a set of query␣
↪instances
    def predict(self, X):
        # check if the models list has been set up
        check_is_fitted(self, ['models'])
        X = check_array(X)

        all_preds = pd.DataFrame()
```

```
        i=0
        # list of individual classifier predictions
        preds = []

        # predict against each fitted model - one model per label
        for model in self.models:
            pred = model.predict(X)
            # add the prediction to the dataframe
            preds.append(pd.DataFrame({'Class'+ str(i+1): pred}))
            i+=1

        # dataframe with predictions for all class labels
        all_preds = pd.concat(preds, axis=1)
        # standard sklearn classifiers return predictions as numpy arrays
        # hence convert the dataframe to a numpy array
        return all_preds.to_numpy()



    def predict_proba(self,X):
        # check if the models list has been set up
        check_is_fitted(self, ['models'])
        X = check_array(X)

        all_preds = pd.DataFrame()
        i = 0

        for model in self.models:
            # Call predict_proba of the each base model
            pred = model.predict_proba(X)
            # Add the probabilities of 1 to the dataframe
            all_preds['Class'+str(i+1)] = [one_prob[1] for one_prob in pred]
            i+=1

        #return probabilities
        return all_preds.to_numpy()
```

1.2.1 Predictions against the test data

[ ]:
```
# instantiate the classifier
br_clf = BinaryRelevanceClassifier(LogisticRegression())
# fit
br_clf.fit(X_train, y_train)
# predict
y_pred = br_clf.predict(X_test)
print("y_pred.shape: " + str(y_pred.shape))
```

```
y_pred.shape: (725, 14)
```

1.2.2 Custom Accuracy Measure for Classifiers

The Accuracy measure used here has been described in - "A Literature Survey on Algorithms for Multi-label Learning" by "Mohammad S Sorower".

[ ]:
```
def accuracy_score(y_test, y_pred):
    # y_pred is a numpy array, y_test is a dataframe
    # to compare the two, convert to a single type
    y_test = y_test.to_numpy()

    # shape of test and preds must be equal
    assert y_test.shape == y_pred.shape
    i=0
    # list of scores for each training sample
    scores = []

    # for each test sample
    while i < len(y_test):
        count=0
        # count the number of matches in the sample
        # y_test[i] -> row values in test set (true values)
        # y_pred[i] -> row values in predictions set (predicted values)
        for p, q in zip(y_test[i], y_pred[i]):
            if p == q:
                count += 1

        # accuracy score for the sample = no. of correctly predicted labels/
 ↪total no. of labels
        scores.append(count / y_pred.shape[1])
        i+=1

    # final accuracy = avg. accuracy over all test samples =
    # sum of the accuracy of all training samples/no. of training samples
    return round((sum(scores)/len(y_test)), 5)
```

[ ]:
```
print("Accuracy of Binary Relevance Classifier: " + str(accuracy_score(y_test,␣
 ↪y_pred)))
```

```
Accuracy of Binary Relevance Classifier: 0.78542
```

1.2.3 Experiment with different Base Classifiers - GridSearch

[ ]:
```
cv_folds=5

# Set up the parameter grid to search
```

```
param_grid ={'base_classifier': [DecisionTreeClassifier(criterion='entropy',␣
 ↪max_depth=15, min_samples_leaf=2),
                                 RandomForestClassifier(criterion='entropy'),
                                 LogisticRegression(max_iter=20000),␣
 ↪GaussianNB(), KNeighborsClassifier(), SVC()] }

# Perform the search
# Using the custom accuracy function defined earlier
tuned_model = GridSearchCV(BinaryRelevanceClassifier(), \
                            param_grid, scoring=make_scorer(accuracy_score),␣
 ↪verbose = 2, n_jobs = -1, cv=cv_folds)
tuned_model.fit(X_train, y_train)

# Print details of the best model
print("Best Parameters Found: ")
display(tuned_model.best_params_)
display(tuned_model.best_score_)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Best Parameters Found:
```

```
{'base_classifier': SVC()}
```

```
0.815366
```

1.2.4 Evaluate the best model against the Test Data

[ ]:
```
# instantiate the classifier
br_clf = BinaryRelevanceClassifier(LogisticRegression(max_iter=20000))
# fit
br_clf.fit(X_train, y_train)
# predict
y_pred = br_clf.predict(X_test)
print("y_pred.shape: " + str(y_pred.shape))
```

```
y_pred.shape: (725, 14)
```

[ ]:
```
print("Accuracy of Binary Relevance Classifier - Best Model: " +␣
 ↪str(accuracy_score(y_test, y_pred)))
```

```
Accuracy of Binary Relevance Classifier - Best Model: 0.78562
```

1.3 Task 2: Implement the Binary Relevance Algorithm with Under-Sampling

[ ]:
```
class BinaryRelevanceClassifierUS(BaseEstimator, ClassifierMixin):
    def __init__(self, base_classifier=LogisticRegression(max_iter=20000)):
        self.base_classifier=base_classifier
```

```
    def fit(self, X, y):
        """Build a Binary Relevance classifier with Under sampling from the␣
↪training set (X, y).
        Parameters
        ----------
        X : array-like or sparse matrix, shape = [n_samples, n_features]
            The training input samples. Internally, it will be converted to
            ``dtype=np.float32`` and if a sparse matrix is provided
            to a sparse ``csc_matrix``.
        y : array-like, shape = [n_samples]
            The target values (class labels) as integers or strings.
        """

        # list of individual classifiers
        self.models = []

        # for each class label
        for label in list(y.columns):

            X_cp = X.copy()
            # pick the column values for the label
            y_cp = y[label]

            # sampling is done on both X and y, hence join the two dataframes
            X_y_data = pd.concat([X_cp, y_cp], axis=1)

            # counters for 0 values and 1 values
            n_val0, n_val1 = 0,0

            j=0
            # for each sample
            while j<len(X_y_data):
                # if value for the label is 0
                if(X_y_data.iloc[j][label] == 0):
                    n_val0+=1
                else:
                    # value 1
                    n_val1+=1
                j+=1

            # under sample the majority class
            # randomly pick samples from majority class equal to the number of␣
↪samples in the minority class
            # both the classes will have the same number of samples
            if n_val0 > n_val1:
                # majority 0 values
                val1 = X_y_data[X_y_data[label]==1]
```

```
            val0 = X_y_data[X_y_data[label]==0].sample(n_val1)

            X_y_data = pd.concat([val0, val1], axis=0)

        elif n_val1 > n_val0:
            # majority 1 values
            val1 = X_y_data[X_y_data[label]==1].sample(n_val0)
            val0 = X_y_data[X_y_data[label]==0]

            X_y_data = pd.concat([val0, val1], axis=0)

        # split back into X and y
        X_cp = X_y_data.iloc[:, :-1]
        y_cp = X_y_data.iloc[:, -1]

        base_model = clone(self.base_classifier)
        # fit the base model - one model each for Y1, Y2....Y14
        a, b = check_X_y(X_cp, y_cp)
        base_model.fit(a, b)
        # list of individual classifiers classifiers
        self.models.append(base_model)


    # The predict function to make a set of predictions for a set of query␣
↪instances
    def predict(self, X):
        # check if the models list has been set up
        check_is_fitted(self, ['models'])
        X = check_array(X)

        all_preds = pd.DataFrame()
        i=0
        # list of individual classifier predictions
        preds = []

        # for every fitted model
        for model in self.models:
            # predict for X
            pred = model.predict(X)
            # add to the list of predictions
            preds.append(pd.DataFrame({'Class'+ str(i+1): pred}))
            i+=1

        # store predictions for each label in a single dataframe
        all_preds = pd.concat(preds, axis=1)
        # standard sklearn classifiers return predictions as numpy arrays
        # hence convert the dataframe to a numpy array
```

```
        return all_preds.to_numpy()


    def predict_proba(self,X):
        # check if the models list has been set up
        check_is_fitted(self, ['models'])
        X = check_array(X)

        all_preds = pd.DataFrame()
        i = 0

        for model in self.models:
            # Call predict_proba of the each base model
            pred = model.predict_proba(X)
            # Add the probabilities of 1 to the dataframe
            all_preds['Class'+str(i+1)] = [one_prob[1] for one_prob in pred]
            i+=1

        #return probabilities
        return all_preds.to_numpy()
```

1.3.1 Prediction against the Test Data

[ ]:
```
brus_clf = BinaryRelevanceClassifierUS()
# fit
brus_clf.fit(X_train, y_train)
# predict
y_pred = brus_clf.predict(X_test)
print("y_pred.shape=" + str(y_pred.shape))
```

```
y_pred.shape=(725, 14)
```

1.3.2 Calculate the Accuracy

[ ]:
```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy of Binary Relevance Classifier with Under-sampling: " +␣
 ↪str(accuracy))
```

```
Accuracy of Binary Relevance Classifier with Under-sampling: 0.60709
```

1.3.3 Experiment with different Base Classifiers - GridSearch

[ ]:
```
cv_folds=5

# Set up the parameter grid to search
param_grid ={'base_classifier': [DecisionTreeClassifier(criterion='entropy',␣
 ↪max_depth=15, min_samples_leaf=2),
```

```
                                    RandomForestClassifier(criterion='entropy'),
                                    LogisticRegression(max_iter=20000),␣
 ↪GaussianNB(), KNeighborsClassifier(), SVC()] }

# Perform the search
tuned_model = GridSearchCV(BinaryRelevanceClassifierUS(), \
                              param_grid, scoring=make_scorer(accuracy_score),␣
 ↪verbose = 2, n_jobs = -1, cv=cv_folds)
tuned_model.fit(X_train, y_train)

# Print details
print("Best Parameters Found: ")
display(tuned_model.best_params_)
display(tuned_model.best_score_)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Best Parameters Found:
```

```
{'base_classifier': RandomForestClassifier(criterion='entropy')}
```

```
0.648602
```

1.3.4 Evaluate the best model against the Test Data

[ ]:
```
brus_clf =␣
 ↪BinaryRelevanceClassifierUS(RandomForestClassifier(criterion='entropy'))
# fit
brus_clf.fit(X_train, y_train)
# predict
y_pred = brus_clf.predict(X_test)
print("y_pred.shape=" + str(y_pred.shape))
```

```
y_pred.shape=(725, 14)
```

[ ]:
```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy of Binary Relevance Classifier with Under-sampling - Best Model:
 ↪ " + str(accuracy))
```

```
Accuracy of Binary Relevance Classifier with Under-sampling - Best Model:
0.62877
```

1.4 Task 3: Compare the Performance of Different Binary Relevance Approaches

1.4.1 Accuracy and F-1 Scores

[ ]:
```
# list of base models
base_models = [DecisionTreeClassifier(criterion='entropy', max_depth=15,␣
↪min_samples_leaf=2),
               RandomForestClassifier(criterion='entropy'),
               LogisticRegression(max_iter=20000), GaussianNB(),␣
↪KNeighborsClassifier(n_neighbors=4), SVC()]
base_model_names = ["Decision Tree", "Random Forest", "Logistic Regression",␣
↪"GaussianNB", "kNN", "SVM"]

# store accuracy scores
br_clf_accuracies = dict()
br_clfus_accuracies = dict()

# store F1 scores
br_clf_f1 = dict()
br_clfus_f1 = dict()

# store hamming scores
br_clf_ham = dict()
br_clfus_ham = dict()

i=0
for clf in base_models:
    # without undersampling
    br_clf = BinaryRelevanceClassifier(clf)
    br_clf.fit(X_train, y_train)
    br_y_pred = br_clf.predict(X_test)

    # find accuracy using custom accuracy function defined
    accuracy = accuracy_score(y_test, br_y_pred)
    br_clf_accuracies[base_model_names[i]] = accuracy

    # find f1 score using sklearn
    y_pred_df = pd.DataFrame(br_y_pred)
    f1_score_br = metrics.f1_score(y_test, y_pred_df, average='macro')
    br_clf_f1[base_model_names[i]] = f1_score_br

    # hamming
    hamming = hamming_loss(y_test, br_y_pred)
    br_clf_ham[base_model_names[i]] = hamming

    # with undersampling
    brus_clf = BinaryRelevanceClassifierUS(clf)
```

```
    brus_clf.fit(X_train, y_train)
    brus_y_pred = brus_clf.predict(X_test)

    # find accuracy using custom accuracy function defined
    accuracy_us = accuracy_score(y_test, brus_y_pred)
    br_clfus_accuracies[base_model_names[i]] = accuracy_us

    # find f1 score using sklearn
    y_pred_df = pd.DataFrame(brus_y_pred)
    f1_score_us = metrics.f1_score(y_test, y_pred_df, average='macro')
    br_clfus_f1[base_model_names[i]] = f1_score_us

    # hamming score
    hamming_us = hamming_loss(y_test, brus_y_pred)
    br_clfus_ham[base_model_names[i]] = hamming_us

    i+=1

print("===================Accuracy Scores=====================")
print("Binary Relevance")
display(br_clf_accuracies)
print("Binary Relevance with Under-Sampling")
display(br_clfus_accuracies)

print("======================F1 Scores========================")
print("Binary Relevance")
display(br_clf_f1)
print("Binary Relevance with Under-Sampling")
display(br_clfus_f1)

print("======================Hamming Loss========================")
print("Binary Relevance")
display(br_clf_ham)
print("Binary Relevance with Under-Sampling")
display(br_clfus_ham)
```

```
===================Accuracy Scores=====================
Binary Relevance

{'Decision Tree': 0.71419,
 'Random Forest': 0.79675,
 'Logistic Regression': 0.78562,
 'GaussianNB': 0.67596,
 'kNN': 0.7799,
 'SVM': 0.79498}

Binary Relevance with Under-Sampling

{'Decision Tree': 0.57488,
```

```
 'Random Forest': 0.63429,
 'Logistic Regression': 0.62118,
 'GaussianNB': 0.60227,
 'kNN': 0.66867,
 'SVM': 0.62631}
```

```
======================F1 Scores========================
Binary Relevance
```

```
{'Decision Tree': 0.37205137865718785,
 'Random Forest': 0.33961609493205847,
 'Logistic Regression': 0.33938178009885295,
 'GaussianNB': 0.4316627679083272,
 'kNN': 0.353415071415573,
 'SVM': 0.32787742663955644}
```

```
Binary Relevance with Under-Sampling
```

```
{'Decision Tree': 0.3896751873697854,
 'Random Forest': 0.45648651643790894,
 'Logistic Regression': 0.44346054877187635,
 'GaussianNB': 0.4250478803948921,
 'kNN': 0.427125836416144,
 'SVM': 0.45050218652543356}
```

```
======================Hamming Loss========================
Binary Relevance
```

```
{'Decision Tree': 0.2858128078817734,
 'Random Forest': 0.2032512315270936,
 'Logistic Regression': 0.21438423645320198,
 'GaussianNB': 0.32403940886699506,
 'kNN': 0.22009852216748768,
 'SVM': 0.20502463054187192}
```

```
Binary Relevance with Under-Sampling
```

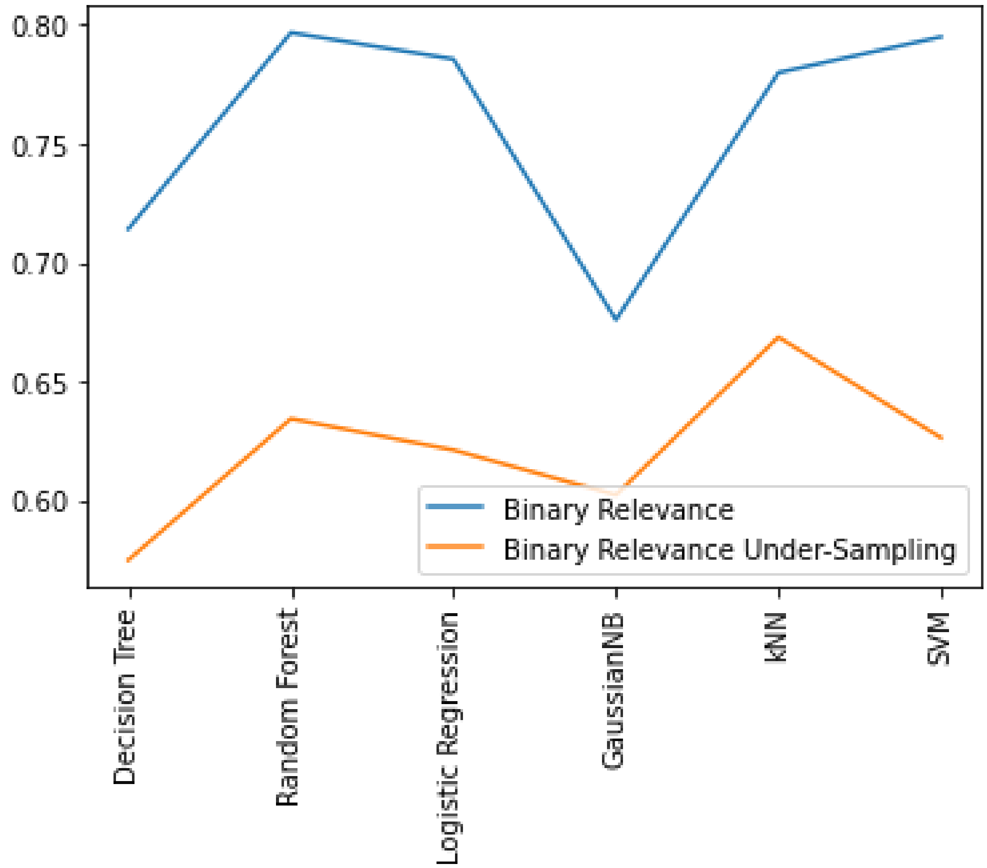
```
{'Decision Tree': 0.42512315270935963,
 'Random Forest': 0.3657142857142857,
 'Logistic Regression': 0.3788177339901478,
 'GaussianNB': 0.39773399014778327,
 'kNN': 0.3313300492610837,
 'SVM': 0.3736945812807882}
```

1.4.2 Plot the Accuracy Scores

[ ]:

```
plt.plot(list(br_clf_accuracies.keys()), list(br_clf_accuracies.values()))
plt.plot(list(br_clfus_accuracies.keys()), list(br_clfus_accuracies.values()))
plt.xticks(rotation=90)
plt.legend(['Binary Relevance','Binary Relevance Under-Sampling'])
```

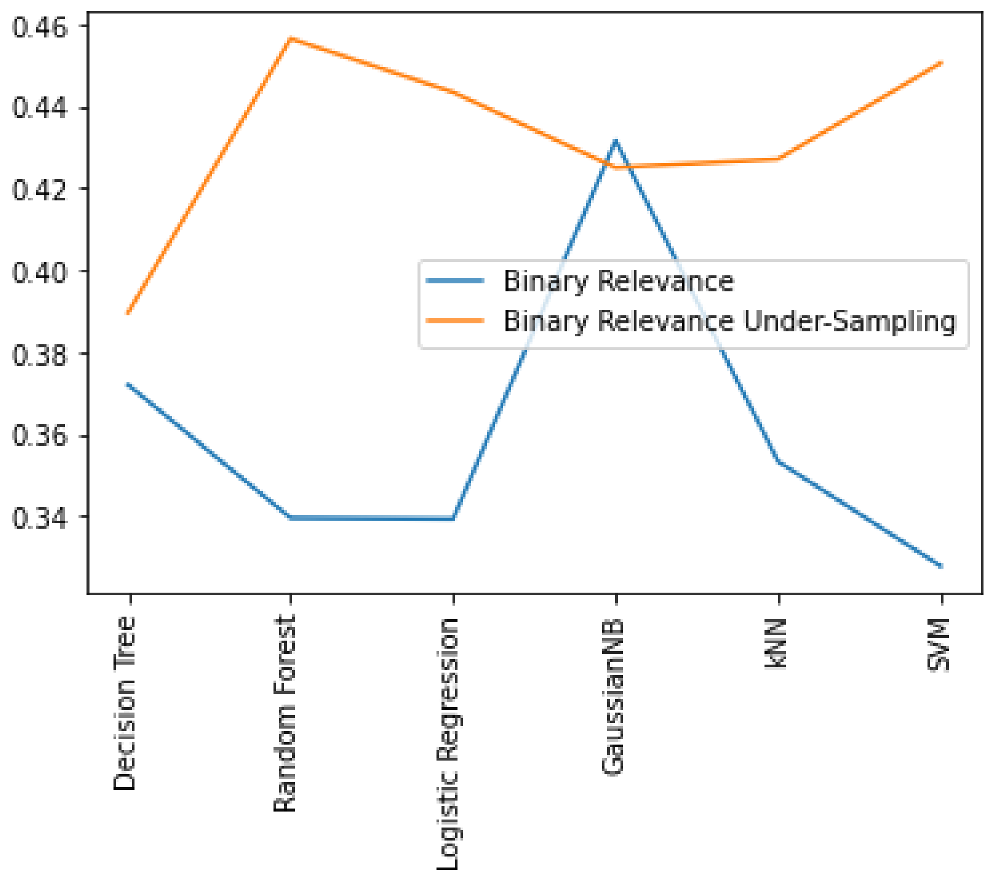
[ ]: <matplotlib.legend.Legend at 0x7f4a394fafa0>



1.4.3 Plot the F-1 Scores

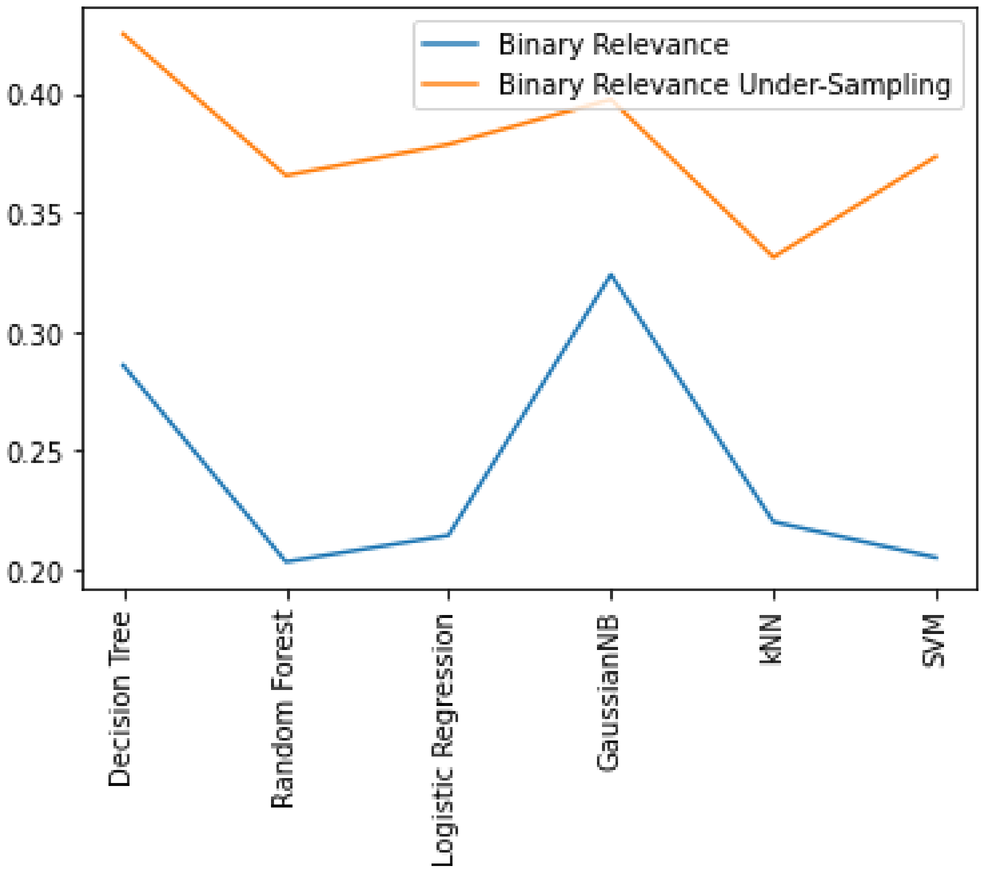
[ ]:
```
plt.plot(list(br_clf_f1.keys()), list(br_clf_f1.values()))
plt.plot(list(br_clfus_f1.keys()), list(br_clfus_f1.values()))
plt.xticks(rotation=90)
plt.legend(['Binary Relevance','Binary Relevance Under-Sampling'])
```

[ ]: <matplotlib.legend.Legend at 0x7f4a393c4760>



[ ]:
```
plt.plot(list(br_clf_ham.keys()), list(br_clf_ham.values()))
plt.plot(list(br_clfus_ham.keys()), list(br_clfus_ham.values()))
plt.xticks(rotation=90)
plt.legend(['Binary Relevance','Binary Relevance Under-Sampling'])
```

[ ]: <matplotlib.legend.Legend at 0x7f4a38e940a0>



1.5 Task 4: Implement the Classifier Chains Algorithm

[ ]:
```
data_path = r'/content/drive/MyDrive/dataset/yeast_data.csv'
label_path = r'/content/drive/MyDrive/dataset/yeast_label.csv'
#X_train, y_train, X_test, y_test = load_csv(data_path, label_path)
```

[ ]:
```
# Read the CSV file
X = pd.read_csv(data_path)


header = []

for i in range(1, X.shape[1]+1):
    header.append('Att'+str(i))
print(header)
X.to_csv("enron_data.csv", header=header, index=False)

X = pd.read_csv('enron_data.csv')
```

```
print("Dataset.shape: " + str(X.shape))
y = pd.read_csv(label_path)

header = []

for i in range(1, y.shape[1]+1):
    header.append('Class'+str(i))
print(header)

y.to_csv("enron_label.csv", header=header, index=False)

y = pd.read_csv('enron_label.csv')


print("X.shape: " + str(X.shape))
display(X.head())
print("y.shape: " + str(y.shape))
display(y.head())
print("Descriptive stats:")
X.describe()
```

```
['Att1', 'Att2', 'Att3', 'Att4', 'Att5', 'Att6', 'Att7', 'Att8', 'Att9',
'Att10', 'Att11', 'Att12', 'Att13', 'Att14', 'Att15', 'Att16', 'Att17', 'Att18',
'Att19', 'Att20', 'Att21', 'Att22', 'Att23', 'Att24', 'Att25', 'Att26', 'Att27',
'Att28', 'Att29', 'Att30', 'Att31', 'Att32', 'Att33', 'Att34', 'Att35', 'Att36',
'Att37', 'Att38', 'Att39', 'Att40', 'Att41', 'Att42', 'Att43', 'Att44', 'Att45',
'Att46', 'Att47', 'Att48', 'Att49', 'Att50', 'Att51', 'Att52', 'Att53', 'Att54',
'Att55', 'Att56', 'Att57', 'Att58', 'Att59', 'Att60', 'Att61', 'Att62', 'Att63',
'Att64', 'Att65', 'Att66', 'Att67', 'Att68', 'Att69', 'Att70', 'Att71', 'Att72',
'Att73', 'Att74', 'Att75', 'Att76', 'Att77', 'Att78', 'Att79', 'Att80', 'Att81',
'Att82', 'Att83', 'Att84', 'Att85', 'Att86', 'Att87', 'Att88', 'Att89', 'Att90',
'Att91', 'Att92', 'Att93', 'Att94', 'Att95', 'Att96', 'Att97', 'Att98', 'Att99',
'Att100', 'Att101', 'Att102', 'Att103']
Dataset.shape: (2416, 103)
['Class1', 'Class2', 'Class3', 'Class4', 'Class5', 'Class6', 'Class7', 'Class8',
'Class9', 'Class10', 'Class11', 'Class12', 'Class13', 'Class14']
X.shape: (2416, 103)

       Att1      Att2      Att3      Att4      Att5      Att6      Att7  \
0 -0.022711 -0.050504 -0.035691 -0.065434 -0.084316 -0.378560  0.038212
1 -0.090407  0.021198  0.208712  0.102752  0.119315  0.041729 -0.021728
2 -0.085235  0.009540 -0.013228  0.094063 -0.013592 -0.030719 -0.116062
3 -0.088765 -0.026743  0.002075 -0.043819 -0.005465  0.004306 -0.055865
4  0.052386 -0.077969 -0.065555 -0.044628 -0.005428  0.120818  0.051850

       Att8      Att9     Att10  …     Att94     Att95     Att96     Att97  \
0  0.085770  0.182613 -0.055544  … -0.001198  0.030594 -0.021814  0.010430
1  0.019603 -0.063853 -0.053756  …  0.195777  0.022294  0.012583  0.002233
```

```
2 -0.131674 -0.165448 -0.123053  …  0.001189 -0.066241 -0.046999 -0.066604
3 -0.071484 -0.159025 -0.111348  … -0.035045 -0.080882  0.028468 -0.073576
4  0.072627  0.107119  0.034214  … -0.056235  0.187005 -0.053345  0.162630

      Att98     Att99    Att100    Att101    Att102    Att103
0 -0.013809 -0.009248 -0.027318 -0.014191  0.022783  0.123785
1 -0.002072 -0.010981  0.007615 -0.063378 -0.084181 -0.034402
2 -0.055773 -0.041941  0.051066  0.004976  0.193972  0.131866
3  0.050630  0.084832 -0.019570 -0.021650 -0.068326 -0.091155
4  0.141881 -0.055852 -0.075871 -0.066165 -0.027733  0.069023

[5 rows x 103 columns]
```

```
y.shape: (2416, 14)
```

```
   Class1  Class2  Class3  Class4  Class5  Class6  Class7  Class8  Class9  \
0       0       0       0       0       0       0       1       1       0
1       0       1       1       0       0       0       0       0       0
2       0       0       1       1       0       0       0       0       0
3       1       1       0       0       0       0       0       0       0
4       0       0       1       1       0       0       0       0       0

   Class10  Class11  Class12  Class13  Class14
0        0        0        1        1        0
1        0        0        1        1        0
2        0        0        1        1        1
3        0        0        0        0        0
4        0        0        1        1        0
```

```
Descriptive stats:
```

[ ]:

```
              Att1         Att2         Att3         Att4         Att5  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean      0.001135    -0.000494    -0.000283     0.000262     0.001194
std       0.097413     0.097864     0.097758     0.096989     0.096915
min      -0.371146    -0.472632    -0.339195    -0.467945    -0.367044
25%      -0.053689    -0.058771    -0.057598    -0.057170    -0.058476
50%       0.003468    -0.003537     0.002850    -0.000172     0.005518
75%       0.057256     0.048045     0.060880     0.054533     0.065772
max       0.520272     0.614114     0.353241     0.568960     0.307649

              Att6         Att7         Att8         Att9        Att10  …  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000  …
mean      0.000525     0.001077     0.000418     0.001065    -0.000027  …
std       0.097296     0.097179     0.096823     0.096345     0.096821  …
min      -0.509447    -0.319928    -0.594498    -0.369712    -0.767128  …
25%      -0.060135    -0.058491    -0.062855    -0.063560    -0.065011  …
50%       0.000386     0.006126     0.001423     0.003452     0.002378  …
75%       0.059962     0.068844     0.061512     0.064962     0.063160  …
```

```
max       0.336971     0.351401     0.454591     0.419852     0.420876  …

                Att94        Att95        Att96        Att97        Att98  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean     -0.000790     0.000472    -0.000501     0.000683     0.000340
std       0.093332     0.096703     0.096226     0.096651     0.096297
min      -0.455191    -0.283594    -0.279408    -0.226420    -0.225374
25%      -0.054157    -0.056452    -0.056422    -0.059432    -0.058030
50%      -0.012933    -0.023597    -0.024312    -0.023023    -0.021937
75%       0.027762     0.034969     0.036229     0.041436     0.035745
max       0.609175     0.542867     0.547134     0.385928     0.540493

                Att99       Att100       Att101       Att102       Att103
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean     -0.001491    -0.001026    -0.001522     0.000235     0.007556
std       0.094388     0.096914     0.094227     0.093142     0.099359
min      -0.501572    -0.236589    -0.267052    -0.194079    -0.237752
25%      -0.053600    -0.063331    -0.059546    -0.054079    -0.077199
50%      -0.018219    -0.033615    -0.023481    -0.012015     0.022072
75%       0.019640     0.038968     0.025432     0.028014     0.103146
max       0.569250     0.509963     0.587358     0.700340     0.163431

[8 rows x 103 columns]
```

[ ]:
```python
# Normalise the data
X = (X-X.min())/(X.max()-X.min())

# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0,␣
 ↪train_size=0.7)

print("X_train.shape: " + str(X_train.shape))
print("X_test.shape: " + str(X_test.shape))
print("y_train.shape: " + str(y_train.shape))
print("y_test.shape: " + str(y_test.shape))
```

```
X_train.shape: (1691, 103)
X_test.shape: (725, 103)
y_train.shape: (1691, 14)
y_test.shape: (725, 14)
```

[ ]:
```python
class ClassifierChains(BaseEstimator, ClassifierMixin):
    def __init__(self, base_classifier=LogisticRegression(max_iter=20000),␣
 ↪order=None):
        self.base_classifier=base_classifier
        self.order = order
```

```
    def fit(self, X, y):
        """
        Build a Classifier Chain from the training set (X, y).
        Parameters
        ----------
        X : array-like or sparse matrix, shape = [n_samples, n_features]
            The training input samples. Internally, it will be converted to
            ``dtype=np.float32`` and if a sparse matrix is provided
            to a sparse ``csc_matrix``.
        y : array-like, shape = [n_samples, n_labels]
            The target values (class labels) as integers or strings.

        """

        # check the order parameter
        if self.order is None:
            # default value - natural order for number of labels
            self.order = list(range(y.shape[1]))
        elif self.order == 'random':
            # random order
            self.order = list(range(y.shape[1]))
            random.shuffle(self.order)
        else:
            # order specified
            if(len(self.order)==y.shape[1]):
                # expect order from 1, hence reduce 1 to consider zero indexing
                self.order = [o - 1 for o in self.order]


        # list of base models for each class
        self.models = [clone(self.base_classifier) for clf in range(y.shape[1])]

        # create a copy of X
        X_joined = X.copy()
       # X_joined.reset_index(drop=True, inplace=True)

        # create a new dataframe with X and y-in the order specified
        # if order = [2,4,5,6...] -> X_joined= X, y2, y4, y5...
        for val in self.order:
            X_joined = pd.concat([X_joined, y['Class'+str(val+1)]], axis=1)


        # for each ith model, fit the model on X + y0 to yi-1 (in the order␣
↪specified)
        # if order = [2,4,6,....] fit 1st model on X for y2, fit second model␣
↪on X+y2 for y4...
        for chain_index, model in enumerate(self.models):
```

```
            # select values of the class in order
            y_vals = y.loc[:, 'Class'+str(self.order[chain_index]+1)]
            # pick values for training - X+y upto the current label
            t_X = X_joined.iloc[:, :(X.shape[1]+chain_index)]
            check_X_y(t_X, y_vals)
            # fit the model
            model.fit(t_X, y_vals)



    # The predict function to make a set of predictions for a set of query␣
↪instances
    def predict(self, X):

        # check if the models list has been set up
        check_is_fitted(self, ['models'])

        # dataframe to maintain previous predictions
        pred_chain = pd.DataFrame(columns=['Class'+str(o+1) for o in self.
↪order])

        X_copy = X.copy()
        X_joined = X.copy()

        # use default indexing
        X_joined.reset_index(drop=True, inplace=True)
        X_copy.reset_index(drop=True, inplace=True)

        i=0

        # for each ith model, predict based on X + predictions of all models␣
↪upto i-1
        # happens in the specified order since models are already fitted␣
↪according to the order
        for chain_index, model in enumerate(self.models):
            # select previous predictions - all columns upto the current index
            prev_preds = pred_chain.iloc[:, :chain_index]
            # join the previous predictions with X
            X_joined = pd.concat([X_copy, prev_preds], axis=1)
            # predict on the base model
            pred = model.predict(X_joined)
            # add the new prediction to the pred chain
            pred_chain['Class'+str(self.order[i]+1)] = pred
            i+=1

        # re-arrange the columns in natural order to return the predictions
```

```
        pred_chain = pred_chain.loc[:, ['Class'+str(j+1) for j in range(0,␣
↪len(self.order))]]
        # all sklearn implementations return numpy array
        # hence convert the dataframe to numpy array
        return pred_chain.to_numpy()



    # Function to predict probabilities of 1s
    def predict_proba(self, X):
        # check if the models list has been set up
        check_is_fitted(self, ['models'])

        # dataframe to maintain previous predictions
        pred_chain = pd.DataFrame(columns=['Class'+str(o+1) for o in self.
↪order])
        # dataframe to maintain probabilities of class labels
        pred_probs = pd.DataFrame(columns=['Class'+str(o+1) for o in self.
↪order])
        X_copy = X.copy()
        X_joined = X.copy()

        # use default indexing
        X_joined.reset_index(drop=True, inplace=True)
        X_copy.reset_index(drop=True, inplace=True)

        i=0

        # for each ith model, predict based on X + predictions of all models␣
↪upto i-1
        # happens in the specified order since models are already fitted␣
↪according to the order
        for chain_index, model in enumerate(self.models):

            # select previous predictions - all columns upto the current index
            prev_preds = pred_chain.iloc[:, :chain_index]
            # join the previous predictions with X
            X_joined = pd.concat([X_copy, prev_preds], axis=1)
            # predict on the base model
            pred = model.predict(X_joined)
            # predict probabilities
            pred_proba = model.predict_proba(X_joined)
            # add the new prediction to the pred chain
            pred_chain['Class'+str(self.order[i]+1)] = pred
            # save the probabilities of 1 according to label order
            pred_probs['Class'+str(self.order[i]+1)] = [one_prob[1] for␣
↪one_prob in pred_proba]
```

```
            i+=1

        # re-arrange the columns in natural order to return the probabilities
        pred_probs = pred_probs.loc[:, ['Class'+str(j+1) for j in range(0,␣
↪len(self.order))]]
        # all sklearn implementations return numpy array
        # hence convert the dataframe to numpy array
        return pred_probs.to_numpy()
```

1.5.1 Predictions against the Test data

[ ]:
```
#cc = ClassifierChains(order=[1,2,3,4,5,6,7,8,9,10,11,12,13,14])
cc = ClassifierChains()
# fit
cc.fit(X_train, y_train)
```

[ ]:
```
# predict
cc_pred = cc.predict(X_test)
```

1.5.2 Calculate the Accuracy

[ ]:
```
print("Accuracy of Classifier Chains: " + str(accuracy_score(y_test, cc_pred)))
```

```
Accuracy of Classifier Chains: 0.773
```

1.5.3 Experiment with different Base Classifiers - GridSearch

[ ]:
```
cv_folds=5

# generate 20 random orders for class labels
#rand_orders = [list(range(1, y_test.shape[1]+1)) for i in list(range(1, 20))]

#for lst in rand_orders:
 #   random.shuffle(lst)

# make sure natural order is present
#rand_orders.append([1,2,3,4,5,6,7,8,9,10,11,12,13,14])

# Set up the parameter grid to search
param_grid ={'base_classifier': [DecisionTreeClassifier(criterion='entropy',␣
↪max_depth=15, min_samples_leaf=2),
                                 RandomForestClassifier(criterion='entropy'),
                                 LogisticRegression(max_iter=20000),␣
↪GaussianNB(), KNeighborsClassifier(n_neighbors=4), SVC()],
            }#'order': rand_orders}
```

```
# Perform the search
tuned_model = GridSearchCV(ClassifierChains(), \
                              param_grid, scoring=make_scorer(accuracy_score),␣
↪verbose = 2, n_jobs = -1, cv=cv_folds)
tuned_model.fit(X_train, y_train)

# Print details
print("Best Parameters Found: ")
display(tuned_model.best_params_)
display(tuned_model.best_score_)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Best Parameters Found:

{'base_classifier': RandomForestClassifier(criterion='entropy')}

0.814264
```

[ ]:
```
# store the best parameters
best = tuned_model.best_params_
```

1.5.4 Evaluate the best model against the Test Data

[ ]:
```
#cc = ClassifierChains(base_classifier=best['base_classifier'],␣
↪order=best['order'])
cc = ClassifierChains(base_classifier=best['base_classifier'])
cc.fit(X_train, y_train)
```

[ ]:
```
cc_pred = cc.predict(X_test)
```

[ ]:
```
print("Accuracy of Classifier Chains - Best Model: " +␣
↪str(accuracy_score(y_test, cc_pred)))
```

```
Accuracy of Classifier Chains - Best Model: 0.78926
```

1.6 Task 5: Evaluate the Performance of the Classifier Chains Algorithm

1.6.1 Accuracy and F1 Scores of Classifier Chains

[ ]:
```
# list of base models
base_models = [DecisionTreeClassifier(criterion='entropy', max_depth=15,␣
↪min_samples_leaf=2),
               RandomForestClassifier(criterion='entropy'),
               LogisticRegression(max_iter=20000), GaussianNB(),␣
↪KNeighborsClassifier(), SVC()]
base_model_names = ["Decision Tree", "Random Forest", "Logistic Regression",␣
↪"GaussianNB", "kNN", "SVM"]
```

```python
cc_accuracies = dict()
cc_f1 = dict()
cc_ham = dict()

i=0
for clf in base_models:
    #cc = ClassifierChains(clf, order=best['order'])
    cc = ClassifierChains(clf)
    cc.fit(X_train, y_train)
    cc_pred = cc.predict(X_test)
    # accuracy score
    accuracy = accuracy_score(y_test, cc_pred)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = metrics.f1_score(y_test, pd.DataFrame(cc_pred),␣
 ↪average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # Hamming Score
    hamming = hamming_loss(y_test, cc_pred)
    cc_ham[base_model_names[i]] = hamming
    i+=1

print("====================Classifier Chains Accuracy====================")
display(cc_accuracies)
print("===================Classifier Chains F1 Scores====================")
display(cc_f1)
print("===================Classifier Chains Hamming Loss====================")
display(cc_ham)
```

```
====================Classifier Chains Accuracy====================

{'Decision Tree': 0.72355,
 'Random Forest': 0.7931,
 'Logistic Regression': 0.773,
 'GaussianNB': 0.66069,
 'kNN': 0.77567,
 'SVM': 0.78453}

===================Classifier Chains F1 Scores====================

{'Decision Tree': 0.3874364422201807,
 'Random Forest': 0.36661888724519287,
 'Logistic Regression': 0.37746896974583016,
 'GaussianNB': 0.41998209248639107,
 'kNN': 0.4322904271162943,
 'SVM': 0.3603761599984326}

===================Classifier Chains Hamming Loss====================

{'Decision Tree': 0.2764532019704434,
```

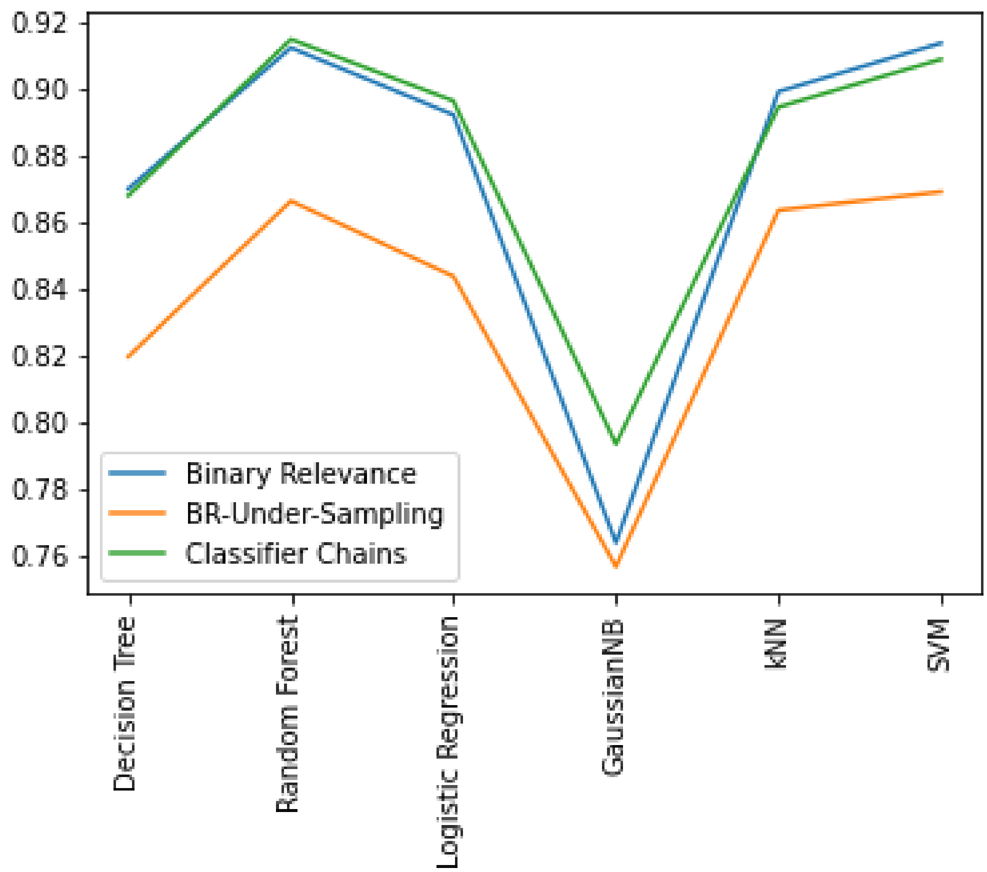
```
'Random Forest': 0.20689655172413793,
'Logistic Regression': 0.22699507389162563,
'GaussianNB': 0.3393103448275862,
'kNN': 0.22433497536945812,
'SVM': 0.2154679802955665}
```

1.6.2 Comparison with Binary Relevance Approaches

Accuracy Scores

[ ]:
```
plt.plot(list(br_clf_accuracies.keys()), list(br_clf_accuracies.values()))
plt.plot(list(br_clfus_accuracies.keys()), list(br_clfus_accuracies.values()))
plt.plot(list(cc_accuracies.keys()), list(cc_accuracies.values()))
plt.xticks(rotation=90)
plt.legend(['Binary Relevance','BR-Under-Sampling', 'Classifier Chains'])
```

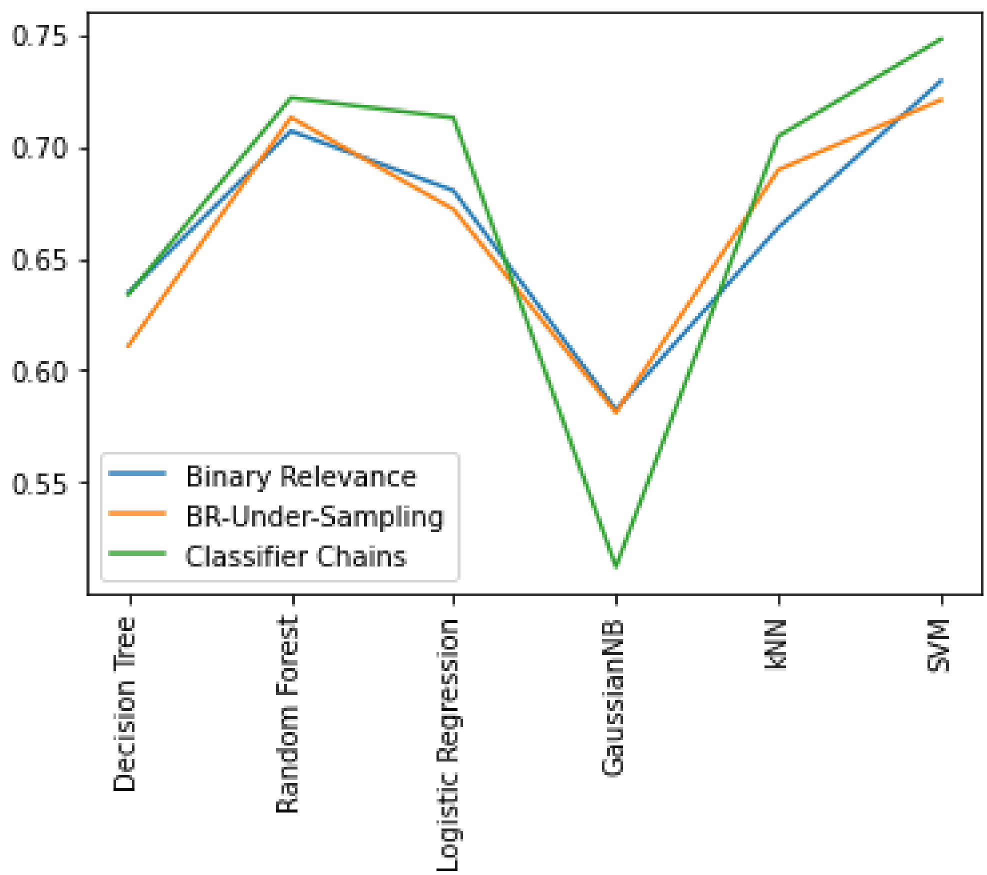
[ ]:
```
<matplotlib.legend.Legend at 0x7f3309ff4af0>
```



F1 Scores

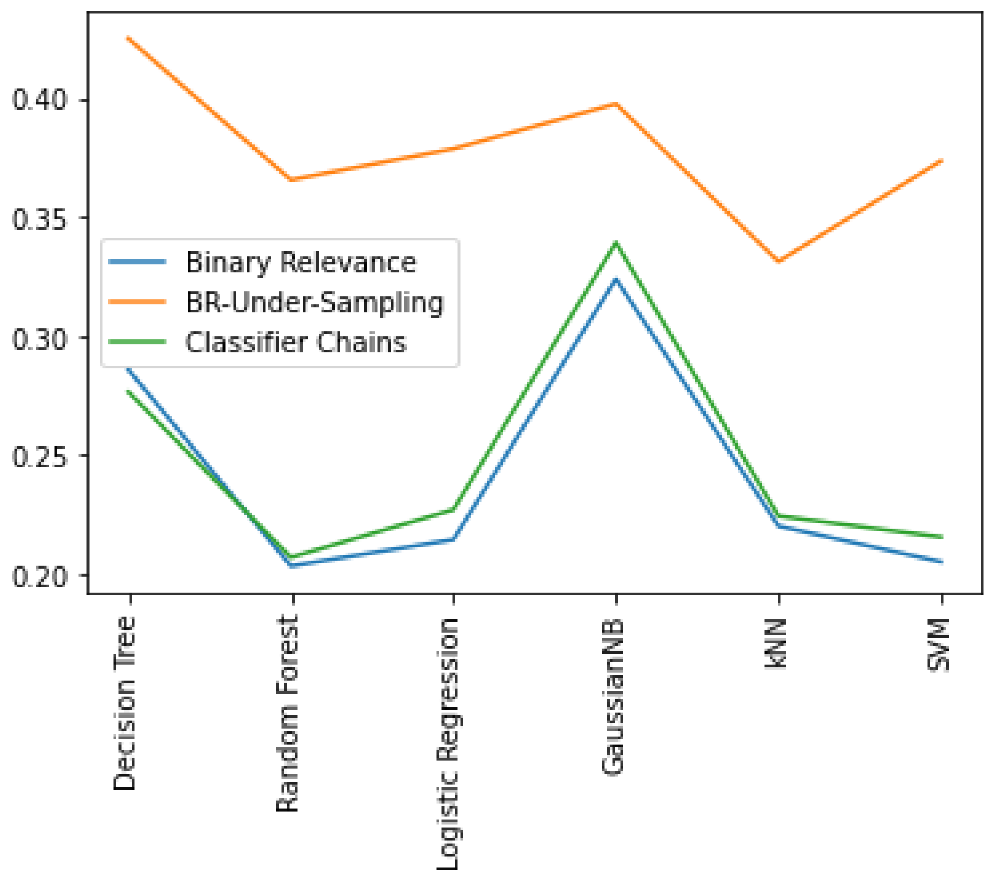
```
[ ]: plt.plot(list(br_clf_f1.keys()), list(br_clf_f1.values()))
     plt.plot(list(br_clfus_f1.keys()), list(br_clfus_f1.values()))
     plt.plot(list(cc_f1.keys()), list(cc_f1.values()))
     plt.xticks(rotation=90)
     plt.legend(['Binary Relevance','BR-Under-Sampling', 'Classifier Chains'])
```

```
[ ]: <matplotlib.legend.Legend at 0x7f33058af7f0>
```




```
[ ]: plt.plot(list(br_clf_ham.keys()), list(br_clf_ham.values()))
     plt.plot(list(br_clfus_ham.keys()), list(br_clfus_ham.values()))
     plt.plot(list(cc_ham.keys()), list(cc_ham.values()))
     plt.xticks(rotation=90)
     plt.legend(['Binary Relevance','BR-Under-Sampling', 'Classifier Chains'])
```

```
[ ]: <matplotlib.legend.Legend at 0x7f4a3931db50>
```



1.7 Task 6: Reflect on the Performance of the Different Models Evaluated

Consider **BR=Binary Relevance Classifier, BRUS=Binary Relevance Classifier with Under Sampling, CC=Classifier Chains.**

From the above experiment we can conclude that:

- BR works much better than BRUS. This is because with undersampling, relevant training samples may be lost which affect the accuracy.
- BRUS gives better F1 scores for all the base models as compared to BR. Lower F1 score is an indication that the data is highly biased which means high precision and low recall. So when the data gets more balanced after undersampling, we achieve better F1 scores.
- CC works better than BR and BRUS because it takes label dependency into consideration while making predictions. BR on the other hand fits and predicts independently of other labels. To my surprise, in this experiment we can obseve that CC outperforms BR only in case of RandomForest as the base model.
- The performance of CC depends on the label order as while making current predictions, we consider the results and labels of previous predictions. To experiment with label ordering, random 20 label orders were used in grid search. To my observation, the results accross different runs are inconsistent pertaining to label orders.(refer the above plots)

- In terms of complexity, BR is simple and faster as compared to CC. In terms of performance, CC has better performance than BR due to reasons mentioned above.
- While dealing with Yeast Dataset, CC works slightly better than BR which is a surprise. So, while dealing with Yeast Dataset, we can use BR as an adequate model if complexity and speed is a concern.

[ ]:

[ ]:

2 References:

[1] Read, J., Pfahringer, B., Holmes, G. and Frank, E. (2011). Classifier chains for multi-label classification. Machine Learning, [online] 85(3), pp.333-359. Available at: https://link.springer.com/content/pdf/10.1007/s10994-011-5256-5.pdf.

[2] A Literature Survey on Algorithms for Multi-label Learning by Mohammad S Sorower. Available at: https://pdfs.semanticscholar.org/6b56/91db1e3a79af5e3c136d2dd322016a687a0b.pdf

[ ]:

```
!pip install mllearn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting mllearn
  Downloading mllearn-1.2.3-py3-none-any.whl (14 kB)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.8/dist-
packages (from mllearn) (1.0.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages
(from mllearn) (1.21.6)
Collecting liac-arff
  Downloading liac-arff-2.5.0.tar.gz (13 kB)
  Preparing metadata (setup.py) … done
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.8/dist-
packages (from scikit-learn->mllearn) (1.7.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.8/dist-
packages (from scikit-learn->mllearn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from scikit-learn->mllearn) (3.1.0)
Building wheels for collected packages: liac-arff
  Building wheel for liac-arff (setup.py) … done
  Created wheel for liac-arff: filename=liac_arff-2.5.0-py3-none-any.whl
size=11732
sha256=5edfb22d597781706ad5a0aca460991a5339be5f634996b940e12be47c7dc080
  Stored in directory: /root/.cache/pip/wheels/a2/de/68/bf3972de3ecb31e32bef59a7
f4c75f0687a3674c476b347c14
Successfully built liac-arff
Installing collected packages: liac-arff, mllearn
Successfully installed liac-arff-2.5.0 mllearn-1.2.3
```

```
[ ]: !pip install scikit-multilearn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting scikit-multilearn
  Downloading scikit_multilearn-0.2.0-py3-none-any.whl (89 kB)
                           89.4/89.4 KB
4.8 MB/s eta 0:00:00
Installing collected packages: scikit-multilearn
Successfully installed scikit-multilearn-0.2.0
```

```
[ ]: import numpy as np
from mllearn.problem_transform import BinaryRelevance
from mllearn.problem_transform import CalibratedLabelRanking
from mllearn.problem_transform import ClassifierChain
from mllearn.problem_transform import RandomKLabelsets
from mllearn.alg_adapt import MLKNN
from skmultilearn.adapt import MLkNN
from mllearn.alg_adapt import MLDecisionTree
from mllearn.metrics import hamming_loss
from mllearn.metrics import subset_acc
#from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score

from mllearn.metrics import accuracy
from mllearn.metrics import precision
from mllearn.metrics import recall
from mllearn.metrics import F_beta

from sklearn.dummy import DummyClassifier

from sklearn.metrics import zero_one_loss
import sklearn.metrics as metrics
from sklearn.model_selection import train_test_split

import arff
import pandas as pd
from sklearn.preprocessing import StandardScaler

from IPython.display import display, HTML, Image

import matplotlib.pyplot as plt
import copy
import random

from sklearn.base import BaseEstimator, ClassifierMixin, clone
from sklearn.utils.validation import check_X_y, check_array, check_is_fitted
```

```python
from sklearn.model_selection import GridSearchCV

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC

from sklearn.metrics import make_scorer


# to avoid future warnings for sklearn
import warnings
warnings.filterwarnings("ignore")
```

[ ]:
```python
def accuracy_score(y_test, y_pred):
    # y_pred is a numpy array, y_test is a dataframe
    # to compare the two, convert to a single type
    #y_test = y_test.to_numpy()

    # shape of test and preds must be equal
    assert y_test.shape == y_pred.shape
    i=0
    # list of scores for each training sample
    scores = []

    # for each test sample
    while i < len(y_test):
        count=0
        # count the number of matches in the sample
        # y_test[i] -> row values in test set (true values)
        # y_pred[i] -> row values in predictions set (predicted values)
        for p, q in zip(y_test[i], y_pred[i]):
            if p == q:
                count += 1

        # accuracy score for the sample = no. of correctly predicted labels/
↪total no. of labels
        scores.append(count / y_pred.shape[1])
        i+=1

    # final accuracy = avg. accuracy over all test samples =
    # sum of the accuracy of all training samples/no. of training samples
    return round((sum(scores)/len(y_test)), 5)
```

```
[ ]: X_train, y_train, X_test, y_test = X_train.to_numpy(), y_train.to_numpy(),␣
      ↪X_test.to_numpy(), y_test.to_numpy()
```

```
[ ]: print(X_train.shape)
     print(y_train.shape)
     print(X_test.shape)
     print(y_test.shape)
```

```
(1691, 103)
(1691, 14)
(725, 103)
(725, 14)
```

```
[ ]: #  MLLearn Library
```

```
[ ]: dummy_clf = DummyClassifier(strategy="most_frequent")
     dummy_clf.fit(X_train, y_train)

     #dummy_clf.fit(X_train, y_train)
     predictions = dummy_clf.predict(X_test)
     print(predictions.shape)
     print('The hamming_loss of Dummy Classifier is %f' % hamming_loss(y_test,␣
      ↪predictions))
     print('The subset_acc of Dummy Classifier is %f' % subset_acc(y_test,␣
      ↪predictions))
     print('zero-one-loss of Dummy Classifier is %f'% zero_one_loss(y_test,␣
      ↪predictions))
     print('The F_beta Result is %f' % F_beta(y_test, predictions))
     print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))


     classif = BinaryRelevance()
     classif.fit(X_train, y_train)
     predictions = classif.predict(X_test)
     print('The hamming_loss of BinaryRelevance is %f' % hamming_loss(y_test,␣
      ↪predictions))
     print('The subset_acc of BinaryRelevance is %f' % subset_acc(y_test,␣
      ↪predictions))
     print('zero-one-loss of BinaryRelevance is %f'% zero_one_loss(y_test,␣
      ↪predictions))
     print('The F_beta Result is %f' % F_beta(y_test, predictions))
     print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))

     classif = ClassifierChain()
     classif.fit(X_train, y_train)
     predictions = classif.predict(X_test)
```

```python
print('The hamming_loss of Classifier Chain is %f' % hamming_loss(y_test,␣
↪predictions))
print('The subset_acc of Classifier Chain is %f' % subset_acc(y_test,␣
↪predictions))
print('zero-one-loss of ClassifierChain is %f'% zero_one_loss(y_test,␣
↪predictions))
print('The F_beta Result is %f' % F_beta(y_test, predictions))
print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))

classif = CalibratedLabelRanking()
classif.fit(X_train, y_train)
predictions = classif.predict(X_test)
print('The hamming_loss of CalibratedLabelRanking is %f' % hamming_loss(y_test,␣
↪predictions))
print('The subset_acc of CalibratedLabelRanking is %f' % subset_acc(y_test,␣
↪predictions))
print('zero-one-loss of CalibratedLabelRanking is %f'% zero_one_loss(y_test,␣
↪predictions))
print('The F_beta Result is %f' % F_beta(y_test, predictions))
print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))

classif = RandomKLabelsets()
classif.fit(X_train, y_train)
predictions = classif.predict(X_test)
print('The hamming_loss of Random K-Labelsets is %f' % hamming_loss(y_test,␣
↪predictions))
print('The subset_acc of Random K-Labelsets is %f' % subset_acc(y_test,␣
↪predictions))
print('zero-one-loss of RandomKLabelsets is %f'% zero_one_loss(y_test,␣
↪predictions))
print('The F_beta Result is %f' % F_beta(y_test, predictions))
print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))
```

```
(725, 14)
The hamming_loss of Dummy Classifier is 0.238818
The subset_acc of Dummy Classifier is 0.012414
zero-one-loss of Dummy Classifier is 0.987586
The F_beta Result is 0.438496
The F1 Result is 0.119067
The hamming_loss of BinaryRelevance is 0.205025
The subset_acc of BinaryRelevance is 0.143448
zero-one-loss of BinaryRelevance is 0.856552
The F_beta Result is 0.616597
The F1 Result is 0.327877
The hamming_loss of Classifier Chain is 0.215468
The subset_acc of Classifier Chain is 0.188966
zero-one-loss of ClassifierChain is 0.811034
```

```
The F_beta Result is 0.600635
The F1 Result is 0.360376
The hamming_loss of CalibratedLabelRanking is 0.204631
The subset_acc of CalibratedLabelRanking is 0.144828
zero-one-loss of CalibratedLabelRanking is 0.855172
The F_beta Result is 0.614439
The F1 Result is 0.326719
The hamming_loss of Random K-Labelsets is 0.203842
The subset_acc of Random K-Labelsets is 0.162759
zero-one-loss of RandomKLabelsets is 0.837241
The F_beta Result is 0.620017
The F1 Result is 0.335364
```

[ ]:

```
base_models = [BinaryRelevance(), ClassifierChain(), CalibratedLabelRanking(),␣
 ↪RandomKLabelsets()]
base_model_names = ["Binary Relevance", "Classifier Chain", 'Calibrated Label␣
 ↪Ranking', 'Random K-Labelsets']

cc_accuracies = dict()
cc_f1 = dict()
cc_hamming = dict()

i=0
for cc in base_models:

    cc.fit(X_train, y_train)
    cc_pred = cc.predict(X_test)
    # accuracy score
    accuracy = accuracy_score(y_test, cc_pred)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = metrics.f1_score(y_test, pd.DataFrame(cc_pred),␣
 ↪average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # Hamming
    hamming = hamming_loss(y_test, cc_pred)
    cc_hamming[base_model_names[i]] = hamming
    i+=1

print("====================MLLearn Accuracy====================")
display(cc_accuracies)
print("===================MLLearn F1 Scores====================")
display(cc_f1)
print("====================MLLearn Hamming Loss====================")
display(cc_hamming)
```

```
====================MLLearn Accuracy====================
```

```
{'Binary Relevance': 0.79498,
 'Classifier Chain': 0.78453,
 'Calibrated Label Ranking': 0.79537,
 'Random K-Labelsets': 0.79685}
```

```
==================MLLearn F1 Scores====================
```

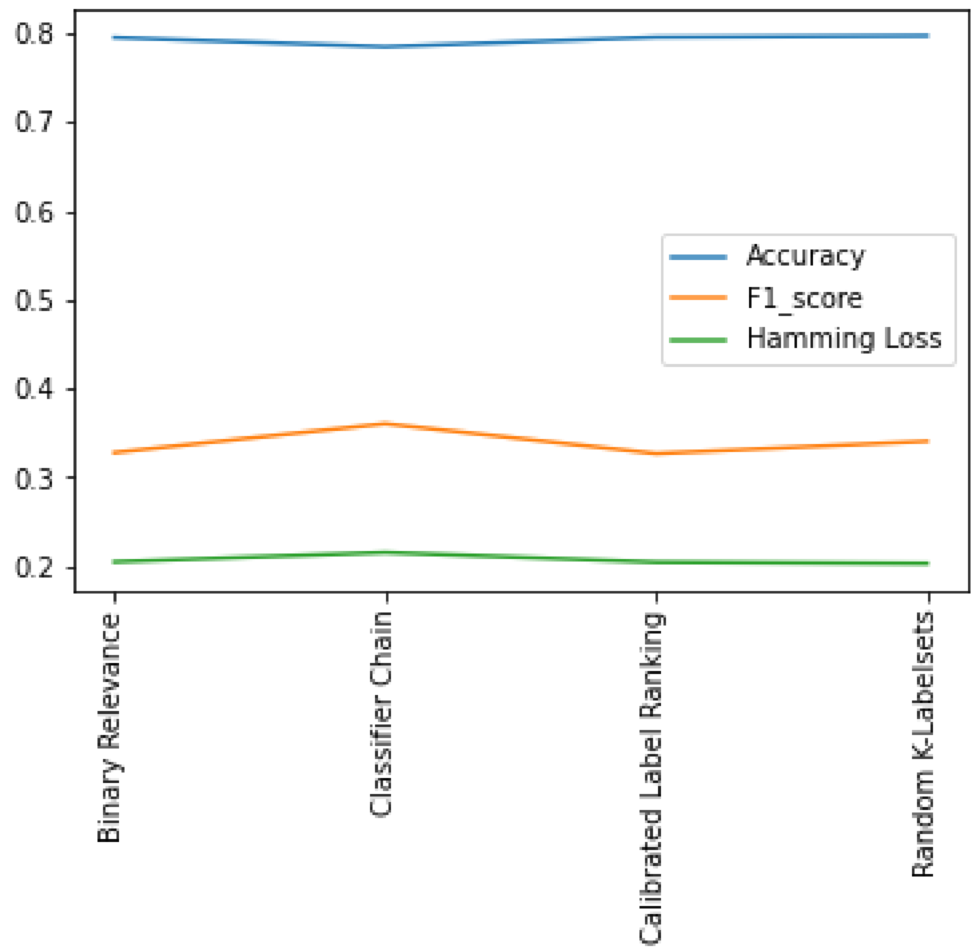
```
{'Binary Relevance': 0.32787742663955644,
 'Classifier Chain': 0.3603761599984326,
 'Calibrated Label Ranking': 0.3267194329097088,
 'Random K-Labelsets': 0.3405642892839444}
```

```
====================MLLearn Hamming Loss====================
```

```
{'Binary Relevance': 0.20502463054187192,
 'Classifier Chain': 0.2154679802955665,
 'Calibrated Label Ranking': 0.20463054187192117,
 'Random K-Labelsets': 0.20315270935960592}
```

[ ]:
```
plt.plot(list(cc_accuracies.keys()), list(cc_accuracies.values()))
plt.plot(list(cc_f1.keys()), list(cc_f1.values()))
plt.plot(list(cc_hamming.keys()), list(cc_hamming.values()))
plt.xticks(rotation=90)
plt.legend(['Accuracy', 'F1_score', 'Hamming Loss', ])
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f4a38f75f10>
```



[ ]:

```

```

[ ]:

```

```

[ ]:

```
# Recursive Feature Elimination
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression

# create a base classifier used to evaluate a subset of attributes
model = LogisticRegression()
# create the RFE model and select 3 attributes
rfe = RFE(model)
rfe = rfe.fit(X_train, y_train[:,:1])
# summarize the selection of the attributes
print(rfe.support_)
print(rfe.ranking_)
```

```python
print('Xshape:', X_train.shape)
```

```
[False  True  True  True False False  True  True False  True False  True
  True False False False False False False  True False False  True False
  True  True False  True False  True  True  True  True  True False False
 False  True  True  True  True False  True  True  True False  True  True
  True False  True  True False  True  True False  True False  True  True
  True False False  True  True False  True False False False False False
  True  True  True False  True False False  True False False False  True
 False False  True False  True False  True  True False False False False
 False False False False False False False False  True False False  True
  True  True False False False False False  True False  True False  True
  True  True False  True False  True False False False False  True False
 False False False  True  True  True  True False False False  True  True
  True  True  True  True False  True  True  True  True  True False  True
 False  True  True  True False False  True False False False  True False
 False False  True  True False  True False  True  True  True False  True
  True False  True False False False  True False False False  True  True
  True False False  True False  True  True  True  True False  True False
 False False False False  True  True False  True  True False False  True
  True  True False  True False False False  True  True  True  True  True
 False  True  True  True False False  True  True  True  True False  True
  True  True False  True False  True False  True  True  True False False
 False False False False False  True False False False False False False
 False  True False False False False False  True  True  True  True False
  True False  True  True False  True  True False False  True  True  True
 False False  True  True  True  True]
[108   1   1   1   5 106   1   1   9   1  73   1   1  10 115   2  32 134
  74   1  61  79   1  31   1   1 138   1 132   1   1   1   1   1 123  77
  26   1   1   1   1  17   1   1   1  38   1   1   1  59   1   1 131   1
   1  50   1  93   1   1   1  24  22   1   1  57   1 126  25  23  55 119
   1   1   1  11   1  12  70   1 142  71  18   1 105 137   1  48   1  97
   1   1  20  21  49  39 136  78 117  91  69 141  68   4   1  80  52   1
   1   1 116  86 124  89   7   1 144   1  85   1   1   1  95   1  33   1
  51  88 128  98   1 125  14  99 143   1   1   1   1  45   6  42   1   1
   1   1   1   1   3   1   1   1   1   1  58   1  40   1   1   1 147 127
   1 130  76  60   1 112 100 129   1   1 121   1  16   1   1   1  35   1
   1  67   1 120  87  53   1 146  56 145   1   1   1 140  72   1  29   1
   1   1   1  82   1 111  62 109  44  30   1   1 101   1   1 133  34   1
   1   1  65   1  81  47  96   1   1   1   1   1  54   1   1   1  27 113
   1   1   1   1 118   1   1   1 122   1 107   1  28   1   1   1  36  94
 102  43   8  19 104   1  64  13  15  90  66 110  46   1 135  83  84  41
  75   1   1   1   1 148   1 139   1   1 103   1   1 114  63   1   1   1
  37  92   1   1   1   1]
Xshape: (1684, 294)
```

[ ]:
```
# report which features were selected by RFE
#from sklearn.datasets import make_classification
from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier
# define dataset
#X, y = make_classification(n_samples=1000, n_features=10, n_informative=5,␣
 ↪n_redundant=5, random_state=1)
# define RFE
rfe = RFE(estimator=DecisionTreeClassifier(), n_features_to_select=50)
# fit RFE
rfe.fit(X_train, y_train[:,:1])
# summarize all features
for i in range(X_train.shape[1]):
    print('Column: %d, Selected %s, Rank: %.3f' % (i, rfe.support_[i], rfe.
 ↪ranking_[i]))
```

```
Column: 0, Selected False, Rank: 245.000
Column: 1, Selected False, Rank: 244.000
Column: 2, Selected False, Rank: 243.000
Column: 3, Selected False, Rank: 242.000
Column: 4, Selected False, Rank: 241.000
Column: 5, Selected False, Rank: 240.000
Column: 6, Selected False, Rank: 235.000
Column: 7, Selected False, Rank: 234.000
Column: 8, Selected True, Rank: 1.000
Column: 9, Selected False, Rank: 21.000
Column: 10, Selected False, Rank: 20.000
Column: 11, Selected False, Rank: 19.000
Column: 12, Selected True, Rank: 1.000
Column: 13, Selected False, Rank: 17.000
Column: 14, Selected True, Rank: 1.000
Column: 15, Selected False, Rank: 18.000
Column: 16, Selected False, Rank: 13.000
Column: 17, Selected False, Rank: 28.000
Column: 18, Selected False, Rank: 26.000
Column: 19, Selected False, Rank: 35.000
Column: 20, Selected False, Rank: 11.000
Column: 21, Selected False, Rank: 22.000
Column: 22, Selected False, Rank: 34.000
Column: 23, Selected False, Rank: 46.000
Column: 24, Selected False, Rank: 33.000
Column: 25, Selected False, Rank: 56.000
Column: 26, Selected False, Rank: 8.000
Column: 27, Selected False, Rank: 38.000
Column: 28, Selected True, Rank: 1.000
Column: 29, Selected True, Rank: 1.000
Column: 30, Selected False, Rank: 47.000
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Column: 31, Selected False, Rank: 43.000
Column: 32, Selected True, Rank: 1.000
Column: 33, Selected False, Rank: 52.000
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Column: 36, Selected True, Rank: 1.000
Column: 37, Selected True, Rank: 1.000
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Column: 42, Selected False, Rank: 71.000
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Column: 44, Selected True, Rank: 1.000
Column: 45, Selected True, Rank: 1.000
Column: 46, Selected False, Rank: 58.000
Column: 47, Selected False, Rank: 103.000
Column: 48, Selected False, Rank: 113.000
Column: 49, Selected False, Rank: 63.000
Column: 50, Selected False, Rank: 118.000
Column: 51, Selected False, Rank: 9.000
Column: 52, Selected False, Rank: 79.000
Column: 53, Selected False, Rank: 64.000
Column: 54, Selected False, Rank: 91.000
Column: 55, Selected False, Rank: 95.000
Column: 56, Selected False, Rank: 62.000
Column: 57, Selected False, Rank: 101.000
Column: 58, Selected False, Rank: 100.000
Column: 59, Selected False, Rank: 105.000
Column: 60, Selected False, Rank: 102.000
Column: 61, Selected False, Rank: 110.000
Column: 62, Selected False, Rank: 98.000
Column: 63, Selected False, Rank: 2.000
Column: 64, Selected False, Rank: 117.000
Column: 65, Selected False, Rank: 96.000
Column: 66, Selected False, Rank: 80.000
Column: 67, Selected True, Rank: 1.000
Column: 68, Selected False, Rank: 126.000
Column: 69, Selected False, Rank: 123.000
Column: 70, Selected False, Rank: 111.000
Column: 71, Selected False, Rank: 72.000
Column: 72, Selected False, Rank: 134.000
Column: 73, Selected False, Rank: 161.000
Column: 74, Selected True, Rank: 1.000
Column: 75, Selected True, Rank: 1.000
Column: 76, Selected False, Rank: 139.000
Column: 77, Selected False, Rank: 70.000
Column: 78, Selected False, Rank: 150.000
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Column: 79, Selected False, Rank: 170.000
Column: 80, Selected False, Rank: 162.000
Column: 81, Selected False, Rank: 145.000
Column: 82, Selected False, Rank: 177.000
Column: 83, Selected False, Rank: 152.000
Column: 84, Selected False, Rank: 149.000
Column: 85, Selected False, Rank: 155.000
Column: 86, Selected False, Rank: 12.000
Column: 87, Selected False, Rank: 163.000
Column: 88, Selected False, Rank: 142.000
Column: 89, Selected True, Rank: 1.000
Column: 90, Selected False, Rank: 166.000
Column: 91, Selected False, Rank: 159.000
Column: 92, Selected False, Rank: 107.000
Column: 93, Selected False, Rank: 180.000
Column: 94, Selected False, Rank: 116.000
Column: 95, Selected True, Rank: 1.000
Column: 96, Selected False, Rank: 169.000
Column: 97, Selected False, Rank: 120.000
Column: 98, Selected False, Rank: 185.000
Column: 99, Selected False, Rank: 146.000
Column: 100, Selected True, Rank: 1.000
Column: 101, Selected False, Rank: 192.000
Column: 102, Selected False, Rank: 188.000
Column: 103, Selected False, Rank: 104.000
Column: 104, Selected False, Rank: 217.000
Column: 105, Selected False, Rank: 167.000
Column: 106, Selected True, Rank: 1.000
Column: 107, Selected False, Rank: 99.000
Column: 108, Selected False, Rank: 205.000
Column: 109, Selected False, Rank: 207.000
Column: 110, Selected False, Rank: 135.000
Column: 111, Selected False, Rank: 184.000
Column: 112, Selected False, Rank: 190.000
Column: 113, Selected False, Rank: 189.000
Column: 114, Selected False, Rank: 221.000
Column: 115, Selected False, Rank: 193.000
Column: 116, Selected False, Rank: 153.000
Column: 117, Selected False, Rank: 173.000
Column: 118, Selected False, Rank: 154.000
Column: 119, Selected False, Rank: 175.000
Column: 120, Selected False, Rank: 237.000
Column: 121, Selected False, Rank: 176.000
Column: 122, Selected False, Rank: 183.000
Column: 123, Selected False, Rank: 172.000
Column: 124, Selected True, Rank: 1.000
Column: 125, Selected False, Rank: 219.000
Column: 126, Selected False, Rank: 143.000
```

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Column: 130, Selected False, Rank: 223.000
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Column: 132, Selected False, Rank: 31.000
Column: 133, Selected False, Rank: 6.000
Column: 134, Selected False, Rank: 49.000
Column: 135, Selected True, Rank: 1.000
Column: 136, Selected False, Rank: 195.000
Column: 137, Selected False, Rank: 197.000
Column: 138, Selected False, Rank: 198.000
Column: 139, Selected False, Rank: 201.000
Column: 140, Selected False, Rank: 200.000
Column: 141, Selected False, Rank: 209.000
Column: 142, Selected False, Rank: 211.000
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Column: 144, Selected False, Rank: 215.000
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Column: 156, Selected False, Rank: 224.000
Column: 157, Selected False, Rank: 222.000
Column: 158, Selected False, Rank: 220.000
Column: 159, Selected False, Rank: 218.000
Column: 160, Selected False, Rank: 216.000
Column: 161, Selected False, Rank: 214.000
Column: 162, Selected False, Rank: 210.000
Column: 163, Selected False, Rank: 208.000
Column: 164, Selected False, Rank: 204.000
Column: 165, Selected False, Rank: 196.000
Column: 166, Selected True, Rank: 1.000
Column: 167, Selected False, Rank: 187.000
Column: 168, Selected False, Rank: 186.000
Column: 169, Selected False, Rank: 181.000
Column: 170, Selected False, Rank: 182.000
Column: 171, Selected True, Rank: 1.000
Column: 172, Selected False, Rank: 174.000
Column: 173, Selected False, Rank: 3.000
Column: 174, Selected False, Rank: 168.000
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Column: 175, Selected False, Rank: 165.000
Column: 176, Selected False, Rank: 157.000
Column: 177, Selected False, Rank: 160.000
Column: 178, Selected False, Rank: 158.000
Column: 179, Selected True, Rank: 1.000
Column: 180, Selected False, Rank: 147.000
Column: 181, Selected True, Rank: 1.000
Column: 182, Selected False, Rank: 144.000
Column: 183, Selected False, Rank: 138.000
Column: 184, Selected True, Rank: 1.000
Column: 185, Selected False, Rank: 7.000
Column: 186, Selected True, Rank: 1.000
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Column: 191, Selected False, Rank: 86.000
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Column: 194, Selected False, Rank: 55.000
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Column: 214, Selected True, Rank: 1.000
Column: 215, Selected False, Rank: 171.000
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Column: 217, Selected False, Rank: 5.000
Column: 218, Selected True, Rank: 1.000
Column: 219, Selected False, Rank: 69.000
Column: 220, Selected False, Rank: 78.000
Column: 221, Selected False, Rank: 37.000
Column: 222, Selected False, Rank: 4.000
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Column: 223, Selected False, Rank: 77.000
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Column: 225, Selected True, Rank: 1.000
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Column: 229, Selected False, Rank: 88.000
Column: 230, Selected True, Rank: 1.000
Column: 231, Selected True, Rank: 1.000
Column: 232, Selected False, Rank: 148.000
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Column: 234, Selected False, Rank: 106.000
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Column: 236, Selected False, Rank: 114.000
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Column: 239, Selected False, Rank: 137.000
Column: 240, Selected False, Rank: 203.000
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Column: 244, Selected False, Rank: 112.000
Column: 245, Selected True, Rank: 1.000
Column: 246, Selected False, Rank: 124.000
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Column: 248, Selected False, Rank: 127.000
Column: 249, Selected False, Rank: 67.000
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Column: 265, Selected False, Rank: 191.000
Column: 266, Selected False, Rank: 83.000
Column: 267, Selected True, Rank: 1.000
Column: 268, Selected False, Rank: 130.000
Column: 269, Selected False, Rank: 151.000
Column: 270, Selected False, Rank: 89.000
```

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Column: 271, Selected False, Rank: 141.000
Column: 272, Selected False, Rank: 179.000
Column: 273, Selected False, Rank: 108.000
Column: 274, Selected False, Rank: 129.000
Column: 275, Selected False, Rank: 136.000
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Column: 280, Selected False, Rank: 109.000
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Column: 285, Selected True, Rank: 1.000
Column: 286, Selected False, Rank: 85.000
Column: 287, Selected False, Rank: 60.000
Column: 288, Selected False, Rank: 36.000
Column: 289, Selected False, Rank: 14.000
Column: 290, Selected False, Rank: 23.000
Column: 291, Selected False, Rank: 32.000
Column: 292, Selected True, Rank: 1.000
Column: 293, Selected False, Rank: 233.000
```

[ ]:
```python
from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier

sec_col = []

for i in range(0,14):

    rfe = RFE(estimator=DecisionTreeClassifier(), n_features_to_select=100)
    # fit RFE
    rfe.fit(X_train, y_train[:,i:i+1])

    selected_columns = []
    # summarize all features
    for j in range(X_train.shape[1]):
        #print('Column: %d, Selected %s, Rank: %.3f' % (i, rfe.support_[i], rfe.
 ↪ranking_[i]))
        if rfe.support_[j]:
            selected_columns.append(j)
    #print(selected_columns)
    sec_col.append(selected_columns)
print(sec_col)
```

```
[[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22,
23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 40, 41, 42, 43,
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44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 81, 82, 83, 84, 85, 86, 87, 88, 89, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102], [0, 1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 66, 67, 68, 69, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102], [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 51, 52, 53, 54, 55, 56, 57, 58, 59, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32, 33, 34, 35, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 95, 96, 97, 98, 99, 100, 101, 102], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,

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78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97,
98, 99, 100, 101, 102]]
```

[ ]:
```
def flatten_nested_lists(matrix):
    l = []
    for row in matrix:
        for x in row:
            l.append(x)
        return l

flat_list = flatten_nested_lists(sec_col)
print(len(flat_list))
print(flat_list)
```

```
100
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22,
23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 40, 41, 42, 43,
44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63,
64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83,
84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101]
```

[ ]:
```
X_new = np.zeros((X_train.shape[0], 100))
X_new_test = np.zeros((X_test.shape[0], 100))
print(X_new.shape)
for i, v in enumerate(flat_list):
    X_new[:,i] = X_train[:, v]
    X_new_test[:, i] = X_test[:, v]
```

```
(1691, 100)
```

[ ]:
```
X_train = X_new
X_test = X_new_test
```

[ ]:
```
def accuracy_score(y_test, y_pred):
    # y_pred is a numpy array, y_test is a dataframe
    # to compare the two, convert to a single type
    #y_test = y_test.to_numpy()

    # shape of test and preds must be equal
    assert y_test.shape == y_pred.shape
    i=0
    # list of scores for each training sample
    scores = []

    # for each test sample
    while i < len(y_test):
        count=0
        # count the number of matches in the sample
        # y_test[i] -> row values in test set (true values)
        # y_pred[i] -> row values in predictions set (predicted values)
        for p, q in zip(y_test[i], y_pred[i]):
            if p == q:
                count += 1

        # accuracy score for the sample = no. of correctly predicted labels/
 ↪total no. of labels
        scores.append(count / y_pred.shape[1])
        i+=1

    # final accuracy = avg. accuracy over all test samples =
    # sum of the accuracy of all training samples/no. of training samples
    return round((sum(scores)/len(y_test)), 5)
```

[ ]:
```
dummy_clf = DummyClassifier(strategy="most_frequent")
dummy_clf.fit(X_train, y_train)

dummy_clf.fit(X_train, y_train)
predictions = dummy_clf.predict(X_test)
print('The hamming_loss of Dummy Classifier is %f' % hamming_loss(y_test,␣
 ↪predictions))
print('The subset_acc of Dummy Classifier is %f' % subset_acc(y_test,␣
 ↪predictions))
print('zero-one-loss of Dummy Classifier is %f'% zero_one_loss(y_test,␣
 ↪predictions))
print('The F_beta Result is %f' % F_beta(y_test, predictions))
print('acc-score is %f ' % accuracy_score(y_test, predictions))
print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))
```

```
classif = BinaryRelevance()
classif.fit(X_train, y_train)
predictions = classif.predict(X_test)
print('The hamming_loss of BR is %f' % hamming_loss(y_test, predictions))
print('The subset_acc of BR is %f' % subset_acc(y_test, predictions))
print('zero-one-loss of BR is %f'% zero_one_loss(y_test, predictions))
print('The F_beta Result of BR is %f' % F_beta(y_test, predictions))
print('acc-score of BR is %f ' % accuracy_score(y_test, predictions))
print('The F1 Result BR is %f' % f1_score(y_test, predictions, average="macro"))


classif = ClassifierChain()
classif.fit(X_train, y_train)
predictions = classif.predict(X_test)
print('The hamming_loss of CC is %f' % hamming_loss(y_test, predictions))
print('The subset_acc of Classifier Chain is %f' % subset_acc(y_test,␣
 ↪predictions))
print('zero-one-loss of Classifier Chain is %f'% zero_one_loss(y_test,␣
 ↪predictions))
print('The F_beta Result of Classifier Chain is %f' % F_beta(y_test,␣
 ↪predictions))
print('acc-score of Classifier Chain is %f ' % accuracy_score(y_test,␣
 ↪predictions))
print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))

classif = CalibratedLabelRanking()
classif.fit(X_train, y_train)
predictions = classif.predict(X_test)
print('The hamming_loss of CalibratedLabelRanking is %f' % hamming_loss(y_test,␣
 ↪predictions))
print('The subset_acc of CalibratedLabelRanking is %f' % subset_acc(y_test,␣
 ↪predictions))
print('zero-one-loss of CalibratedLabelRanking is %f'% zero_one_loss(y_test,␣
 ↪predictions))
print('The F_beta Result of CalibratedLabelRanking is %f' % F_beta(y_test,␣
 ↪predictions))
print('acc-score of CalibratedLabelRanking is %f ' % accuracy_score(y_test,␣
 ↪predictions))
print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))

classif = RandomKLabelsets()
classif.fit(X_train, y_train)
predictions = classif.predict(X_test)
print('The hamming_loss of Random K-Labelsets is %f' % hamming_loss(y_test,␣
 ↪predictions))
```

```
print('The subset_acc of Random K-Labelsets is %f' % subset_acc(y_test,␣
 ↪predictions))
print('zero-one-loss of RandomKLabelsets is %f'% zero_one_loss(y_test,␣
 ↪predictions))
print('The F_beta Result of RandomKLabelsets is %f' % F_beta(y_test,␣
 ↪predictions))
print('acc-score of RandomKLabelsets is %f ' % accuracy_score(y_test,␣
 ↪predictions))
print('The F1 Result is %f' % f1_score(y_test, predictions, average="macro"))
```

```
The hamming_loss of Dummy Classifier is 0.238818
The subset_acc of Dummy Classifier is 0.012414
zero-one-loss of Dummy Classifier is 0.987586
The F_beta Result is 0.438496
acc-score is 0.761180
The F1 Result is 0.119067
The hamming_loss of CalibratedLabelRanking is 0.214286
The subset_acc of CalibratedLabelRanking is 0.188966
zero-one-loss of CalibratedLabelRanking is 0.811034
The F_beta Result of CalibratedLabelRanking is 0.602623
acc-score of CalibratedLabelRanking is 0.785710
The F1 Result is 0.357900
The hamming_loss of CalibratedLabelRanking is 0.205517
The subset_acc of CalibratedLabelRanking is 0.143448
zero-one-loss of CalibratedLabelRanking is 0.856552
The F_beta Result of CalibratedLabelRanking is 0.612894
acc-score of CalibratedLabelRanking is 0.794480
The F1 Result is 0.324440
The hamming_loss of Random K-Labelsets is 0.205419
The subset_acc of Random K-Labelsets is 0.186207
zero-one-loss of RandomKLabelsets is 0.813793
The F_beta Result of RandomKLabelsets is 0.626598
acc-score of RandomKLabelsets is 0.794580
The F1 Result is 0.344099
```

[ ]:

```
```

[ ]:

```
```

[ ]:

```
# Read the CSV file
X = pd.read_csv(data_path)


header = []

for i in range(1, X.shape[1]+1):
    header.append('Att'+str(i))
```

```
print(header)
X.to_csv("enron_data.csv", header=header, index=False)

X = pd.read_csv('enron_data.csv')

print("Dataset.shape: " + str(X.shape))
y = pd.read_csv(label_path)

header = []

for i in range(1, y.shape[1]+1):
    header.append('Class'+str(i))
print(header)

y.to_csv("enron_label.csv", header=header, index=False)

y = pd.read_csv('enron_label.csv')


print("X.shape: " + str(X.shape))
display(X.head())
print("y.shape: " + str(y.shape))
display(y.head())
print("Descriptive stats:")
X.describe()

# Normalise the data
X = (X-X.min())/(X.max()-X.min())

# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0,␣
 ↪train_size=0.7)

print("X_train.shape: " + str(X_train.shape))
print("X_test.shape: " + str(X_test.shape))
print("y_train.shape: " + str(y_train.shape))
print("y_test.shape: " + str(y_test.shape))
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-f5997cea261b> in <module>
      1 # Read the CSV file
----> 2 X = pd.read_csv(data_path)
      3
      4
      5 header = []
```

```
NameError: name 'pd' is not defined
```

```
[ ]: X_train, y_train, X_test, y_test = X_train.to_numpy(), y_train.to_numpy(),␣
     ↪X_test.to_numpy(), y_test.to_numpy()
```

```
[ ]: # list of base models
     base_models = [DecisionTreeClassifier(criterion='entropy', max_depth=15,␣
      ↪min_samples_leaf=2),
                    RandomForestClassifier(criterion='entropy'),
                    LogisticRegression(max_iter=20000), GaussianNB(),␣
      ↪KNeighborsClassifier(), SVC()]
     base_model_names = ["Decision Tree", "Random Forest", "Logistic Regression",␣
      ↪"GaussianNB", "kNN", "SVM"]

     cc_accuracies = dict()
     cc_f1 = dict()
     cc_hamming = dict()

     i=0
     for clf in base_models:

         cc = RandomKLabelsets(clf)
         cc.fit(X_train, y_train)
         cc_pred = cc.predict(X_test)
         # accuracy score
         accuracy = accuracy_score(y_test, cc_pred)
         cc_accuracies[base_model_names[i]] = accuracy
         # F1 score
         cc_f1_score = metrics.f1_score(y_test, pd.DataFrame(cc_pred),␣
      ↪average='macro')
         cc_f1[base_model_names[i]] = cc_f1_score
         # hamming loss
         hamming = hamming_loss(y_test, cc_pred)
         cc_hamming[base_model_names[i]] = hamming

         i+=1

     print("====================RandomKLabelsets Accuracy====================")
     display(cc_accuracies)
     print("===================RandomKLabelsets F1 Scores====================")
     display(cc_f1)
     print("===================RandomKLabelsets Hamming Loss␣
      ↪Scores====================")
     display(cc_hamming)
```

```
====================RandomKLabelsets Accuracy====================
```

```
{'Decision Tree': 0.76256,
 'Random Forest': 0.79389,
 'Logistic Regression': 0.78532,
 'GaussianNB': 0.71113,
 'kNN': 0.77734,
 'SVM': 0.79773}
```

```
===================RandomKLabelsets F1 Scores====================
```

```
{'Decision Tree': 0.3227284172701236,
 'Random Forest': 0.35400214742276226,
 'Logistic Regression': 0.3527910618504751,
 'GaussianNB': 0.4387325555622241,
 'kNN': 0.3802160697698428,
 'SVM': 0.34668815834432926}
```

```
===================RandomKLabelsets Hamming Loss Scores====================
```

```
{'Decision Tree': 0.2374384236453202,
 'Random Forest': 0.20610837438423646,
 'Logistic Regression': 0.21467980295566502,
 'GaussianNB': 0.28886699507389163,
 'kNN': 0.22266009852216748,
 'SVM': 0.20226600985221674}
```

[ ]:
```
print('max value with key:', max(zip(cc_accuracies.values(), cc_accuracies.
 ↪keys())))
```

```
max value with key: (0.79773, 'SVM')
```

[ ]:
```
# Gini as entropy
base_models = [DecisionTreeClassifier(criterion='entropy', max_depth=15,␣
 ↪min_samples_leaf=2),DecisionTreeClassifier(criterion='gini', max_depth=15,␣
 ↪min_samples_leaf=2) ,
               RandomForestClassifier(criterion='entropy'),
               LogisticRegression(max_iter=20000), GaussianNB(),␣
 ↪KNeighborsClassifier(), SVC()]
base_model_names = ["Decision Tree", "Decision Tree Gini" ,"Random Forest",␣
 ↪"Logistic Regression", "GaussianNB", "kNN", "SVM"]

cc_accuracies = dict()
cc_f1 = dict()
cc_hamming = dict()

i=0
for clf in base_models:
    #cc = ClassifierChains(clf, order=best['order'])
    cc = RandomKLabelsets(clf)
    cc.fit(X_train, y_train)
```

```
    cc_pred = cc.predict(X_test)
    # accuracy score
    accuracy = accuracy_score(y_test, cc_pred)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = metrics.f1_score(y_test, pd.DataFrame(cc_pred),␣
 ↪average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # hamming
    hamming = hamming_loss(y_test, cc_pred)
    cc_hamming[base_model_names[i]] = hamming
    i+=1

print("====================RandomKLabelsets Accuracy====================")
display(cc_accuracies)
print("===================RandomKLabelsets F1 Scores====================")
display(cc_f1)
```

```
====================RandomKLabelsets Accuracy====================

{'Decision Tree': 0.76768,
 'Decision Tree Gini': 0.76975,
 'Random Forest': 0.79842,
 'Logistic Regression': 0.78631,
 'GaussianNB': 0.69941,
 'kNN': 0.77665,
 'SVM': 0.79596}

===================RandomKLabelsets F1 Scores====================

{'Decision Tree': 0.3217318779311745,
 'Decision Tree Gini': 0.33096494570826307,
 'Random Forest': 0.3536695760134327,
 'Logistic Regression': 0.361919641204045,
 'GaussianNB': 0.437434681516474,
 'kNN': 0.38448270272221385,
 'SVM': 0.33970914743358216}
```

[ ]:
```
# list of base models
base_models = [DecisionTreeClassifier(criterion='entropy', max_depth=15,␣
 ↪min_samples_leaf=2),
               RandomForestClassifier(criterion='entropy'),
               LogisticRegression(max_iter=20000), GaussianNB(),␣
 ↪KNeighborsClassifier(), SVC()]
base_model_names = ["Decision Tree", "Random Forest", "Logistic Regression",␣
 ↪"GaussianNB", "kNN", "SVM"]

cc_accuracies = dict()
```

```
cc_f1 = dict()
cc_hamming = dict()

i=0
for clf in base_models:

    cc = CalibratedLabelRanking(clf)
    cc.fit(X_train, y_train)
    cc_pred = cc.predict(X_test)
    # accuracy score
    accuracy = accuracy_score(y_test, cc_pred)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = metrics.f1_score(y_test, pd.DataFrame(cc_pred),␣
 ↪average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # Hamming
    hamming = hamming_loss(y_test, cc_pred)
    cc_hamming[base_model_names[i]] = hamming
    i+=1

print("====================CLR Accuracy====================")
display(cc_accuracies)
print("===================CLR F1 Scores====================")
display(cc_f1)
print("====================CLR Hamming Loss====================")
display(cc_hamming)
```

```
====================CLR Accuracy====================

{'Decision Tree': 0.76158,
 'Random Forest': 0.79468,
 'Logistic Regression': 0.78532,
 'GaussianNB': 0.68867,
 'kNN': 0.78631,
 'SVM': 0.79537}

===================CLR F1 Scores====================

{'Decision Tree': 0.3494104664458881,
 'Random Forest': 0.3283483614712321,
 'Logistic Regression': 0.3337487074214078,
 'GaussianNB': 0.4319639759881852,
 'kNN': 0.40129635355831345,
 'SVM': 0.3267194329097088}

====================CLR Hamming Loss====================

{'Decision Tree': 0.23842364532019705,
 'Random Forest': 0.20532019704433496,
```

```
'Logistic Regression': 0.21467980295566502,
'GaussianNB': 0.31133004926108376,
'kNN': 0.21369458128078817,
'SVM': 0.20463054187192117}
```

[ ]:

[ ]:

#Sklearn multilabel classification package

[ ]:
```
from skmultilearn.problem_transform import ClassifierChain
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC

parameters = [
    {
        'classifier': [MultinomialNB()],
        'classifier__alpha': [0.7, 1.0],
    },
    {
        'classifier': [SVC()],
        'classifier__kernel': ['rbf', 'linear', 'poly', 'sigmoid'],
        'classifier__C': [0.2, 0.5, 0.7, 0.8, 1],
        'classifier__gamma': ['scale', 'auto']
    },
    {
        'classifier': [RandomForestClassifier()],
        'classifier__criterion': ['gini', 'entropy'],
        'classifier__n_estimators': [10, 20, 30, 40, 50, 80, 150, 200],
        'classifier__max_features': ['sqrt', 'log'],
    },
    {
        'classifier': [DecisionTreeClassifier()],
        'classifier__criterion': ['gini', 'entropy', 'log_loss'],

    },
    {
        'classifier': [KNeighborsClassifier()],
        'classifier__algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
        'classifier__metric': ['minkowski'],
        'classifier__n_neighbors': [3, 4, 5, 8, 10],
        'classifier__weights': ['uniform', 'distance'],

    },
]
```

```
from sklearn.model_selection import KFold

kf = KFold(n_splits=10)
for train_index, test_index in kf.split(X, y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]


clf = GridSearchCV(ClassifierChain(), parameters, scoring='accuracy')
clf.fit(X_train, y_train)

print (clf.best_params_, clf.best_score_)
```

```
{'classifier': KNeighborsClassifier(n_neighbors=8, weights='distance'),
'classifier__algorithm': 'auto', 'classifier__metric': 'minkowski',
'classifier__n_neighbors': 8, 'classifier__weights': 'distance'}
0.23954022988505747
```

[ ]:
```
predictions = clf.predict(X_test)
print
print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% metrics.hamming_loss(y_test, predictions))
print('Accuracy Score  is %f' % metrics.accuracy_score(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
print('The F_beta Result of RandomKLabelsets is %f' % metrics.
 ↪fbeta_score(y_test, predictions, average='macro', beta=0.5))
```

```
zero-one-loss is 0.734440
hamming-loss is 0.209544
Accuracy Score  is 0.265560
F1_score is 0.438836
The F_beta Result of RandomKLabelsets is 0.451170
```

[ ]:
```

```

[ ]:
```
from skmultilearn.problem_transform import BinaryRelevance

from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier

parameters = [
    {
        'classifier': [MultinomialNB()],
        'classifier__alpha': [0.7, 1.0],
    },
    {
```

```
        'classifier': [SVC()],
        'classifier__kernel': ['rbf', 'linear', 'poly', 'sigmoid'],
        'classifier__C': [0.2, 0.5, 0.7, 0.8, 1],
        'classifier__gamma': ['scale', 'auto']
    },
    {
        'classifier': [RandomForestClassifier()],
        'classifier__criterion': ['gini', 'entropy'],
        'classifier__n_estimators': [10, 20, 30, 40, 50, 80, 150, 200],
        'classifier__max_features': ['sqrt', 'log'],
    },
    {
        'classifier': [DecisionTreeClassifier()],
        'classifier__criterion': ['gini', 'entropy', 'log_loss'],
    },
    {
        'classifier': [KNeighborsClassifier()],
        'classifier__algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
        'classifier__metric': ['minkowski'],
        'classifier__n_neighbors': [3, 4, 5, 8, 10],
        'classifier__weights': ['uniform', 'distance'],

    },
]

from sklearn.model_selection import KFold

kf = KFold(n_splits=10)
print(type(X))
print(type(y))
for train_index, test_index in kf.split(X.to_numpy(), y.to_numpy()):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

clf = GridSearchCV(BinaryRelevance(), parameters, scoring='accuracy')
clf.fit(X_train, y_train)

print (clf.best_params_, clf.best_score_)
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>
{'classifier': MultinomialNB(alpha=0.7), 'classifier__alpha': 0.7}
0.013793103448275862
```

[ ]:
```
import sklearn.metrics as metrics

#metrics.hamming_loss(y_test, prediction)
```

```
predictions = clf.predict(X_test)
print('zero-one-loss is %f'% zero_one_loss(y_test.to_numpy(), predictions))
#print(predictions)
print('hamming-loss is %f'% metrics.hamming_loss(y_test, predictions))
#print('Accuracy Score  is %f' % accuracy_score(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
#print('The F_beta Result of RandomKLabelsets is %f' % F_beta(y_test.
 ↪to_numpy(), predictions))
```

```
zero-one-loss is 0.983402
hamming-loss is 0.225252
F1_score is 0.137457
```

[ ]:

```
from skmultilearn.problem_transform import LabelPowerset
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier

parameters = [
    {
        'classifier': [MultinomialNB()],
        'classifier__alpha': [0.7, 1.0],
    },
    {
        'classifier': [SVC()],
        'classifier__kernel': ['rbf', 'linear', 'poly', 'sigmoid'],
        'classifier__C': [0.2, 0.5, 0.7, 0.8, 1],
        'classifier__gamma': ['scale', 'auto']
    },
    {
        'classifier': [RandomForestClassifier()],
        'classifier__criterion': ['gini', 'entropy'],
        'classifier__n_estimators': [10, 20, 30, 40, 50, 80, 150, 200],
        'classifier__max_features': ['sqrt', 'log'],
    },
    {
        'classifier': [DecisionTreeClassifier()],
        'classifier__criterion': ['gini', 'entropy', 'log_loss'],
    },
    {
        'classifier': [KNeighborsClassifier()],
        'classifier__algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
        'classifier__metric': ['minkowski'],
        'classifier__n_neighbors': [3, 4, 5, 8, 10],
        'classifier__weights': ['uniform', 'distance'],

    },
```

```
]

from sklearn.model_selection import KFold

kf = KFold(n_splits=10)
print(type(X))
print(type(y))
for train_index, test_index in kf.split(X.to_numpy(), y.to_numpy()):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

clf = GridSearchCV(LabelPowerset(), parameters, scoring='accuracy')
clf.fit(X_train, y_train)

print (clf.best_params_, clf.best_score_)
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>
{'classifier': RandomForestClassifier(max_features='sqrt', n_estimators=200),
'classifier__criterion': 'gini', 'classifier__max_features': 'sqrt',
'classifier__n_estimators': 200} 0.6541958897840593
```

[ ]:
```
from skmultilearn.problem_transform import LabelPowerset
clf = LabelPowerset(classifier = RandomForestClassifier(n_estimators=100,␣
  ↪criterion="gini", max_features="sqrt"))
clf.fit(X_train, y_train)
predictions = clf.predict(X_test)
print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% metrics.hamming_loss(y_test, predictions))
print('Accuracy Score  is %f' % metrics.accuracy_score(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
print('The F_beta Result of RandomKLabelsets is %f' % metrics.
  ↪fbeta_score(y_test, predictions, average='macro', beta=0.5))
```

```
zero-one-loss is 0.684647
hamming-loss is 0.179312
Accuracy Score  is 0.315353
F1_score is 0.436128
The F_beta Result of RandomKLabelsets is 0.483287
```

[ ]:
```
predictions = clf.predict(X_test)

print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Accuracy Score  is %f' % accuracy_score(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

```
print('The F_beta Result of RandomKLabelsets is %f' % F_beta(y_test,
 predictions))
```

[ ]:
```
ClassifierChain(classifier=SVC(), require_dense=[True, True]).get_params().
 keys()
```

[ ]:
```
dict_keys(['classifier', 'classifier__C', 'classifier__break_ties',
'classifier__cache_size', 'classifier__class_weight', 'classifier__coef0',
'classifier__decision_function_shape', 'classifier__degree',
'classifier__gamma', 'classifier__kernel', 'classifier__max_iter',
'classifier__probability', 'classifier__random_state', 'classifier__shrinking',
'classifier__tol', 'classifier__verbose', 'require_dense', 'order'])
```

[ ]:
```
ClassifierChain(classifier=DecisionTreeClassifier(), require_dense=[True,
 True]).get_params().keys()
```

[ ]:
```
dict_keys(['classifier', 'classifier__ccp_alpha', 'classifier__class_weight',
'classifier__criterion', 'classifier__max_depth', 'classifier__max_features',
'classifier__max_leaf_nodes', 'classifier__min_impurity_decrease',
'classifier__min_samples_leaf', 'classifier__min_samples_split',
'classifier__min_weight_fraction_leaf', 'classifier__random_state',
'classifier__splitter', 'require_dense', 'order'])
```

[ ]:
```
from sklearn.naive_bayes import GaussianNB
```

[ ]:
```
ClassifierChain(classifier=GaussianNB(), require_dense=[True, True]).
 get_params().keys()
```

[ ]:
```
dict_keys(['classifier', 'classifier__priors', 'classifier__var_smoothing',
'require_dense', 'order'])
```

[ ]:
```

```

[ ]:
```
ClassifierChain(classifier=KNeighborsClassifier(), require_dense=[True, True]).
 get_params().keys()
```

[ ]:
```
dict_keys(['classifier', 'classifier__algorithm', 'classifier__leaf_size',
'classifier__metric', 'classifier__metric_params', 'classifier__n_jobs',
'classifier__n_neighbors', 'classifier__p', 'classifier__weights',
'require_dense', 'order'])
```

[ ]:
```

```

##Meka with Sklearn

[ ]:
```
from skmultilearn.ext import download_meka
```

```
meka_classpath = download_meka()
meka_classpath
from skmultilearn.ext import Meka

meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.BR", # Binary Relevance
        weka_classifier = "weka.classifiers.bayes.NaiveBayesMultinomial", #␣
 ↪with Naive Bayes single-label classifier
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)
meka

meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

hamming_loss(y_test, predictions)
```

```
MEKA 1.9.2 not found, downloading
Unzipping MEKA 1.9.2 to /root/scikit_ml_learn_data/meka/
```

[ ]: 0.23773399014778326

[ ]:
```
meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.BR", # Binary Relevance
        weka_classifier = "weka.classifiers.meta.AdaBoostM1", # with Naive␣
 ↪Bayes single-label classifier
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)
meka

meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

hamming_loss(y_test, predictions)
```

[ ]: 0.1415050784856879

[ ]:
```
print(type(y_test))
```

```
<class 'numpy.ndarray'>
```

[ ]:
```
def accuracy_score(y_test, y_pred):
    # y_pred is a numpy array, y_test is a dataframe
```

```
    # to compare the two, convert to a single type
    #y_test = y_test.to_numpy()

    # shape of test and preds must be equal
    assert y_test.shape == y_pred.shape
    i=0
    # list of scores for each training sample
    scores = []

    # for each test sample
    while i < len(y_test):
        count=0
        # count the number of matches in the sample
        # y_test[i] -> row values in test set (true values)
        # y_pred[i] -> row values in predictions set (predicted values)
        for p, q in zip(y_test[i], y_pred[i]):
            if p == q:
                count += 1

        # accuracy score for the sample = no. of correctly predicted labels/
↪total no. of labels
        scores.append(count / y_pred.shape[1])
        i+=1

    # final accuracy = avg. accuracy over all test samples =
    # sum of the accuracy of all training samples/no. of training samples
    return round((sum(scores)/len(y_test)), 5)
```

[ ]:

```

```

[ ]:

```
print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Accuracy Score  is %f' % subset_acc(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))

#print('The F_beta Result of RandomKLabelsets is %f' % F_beta(y_test,␣
↪predictions))
```

```
zero-one-loss is 0.610803
hamming-loss is 0.141505
Accuracy Score  is 0.389197
F1_score is 0.615844
```

[ ]:

```
meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.BR", # Binary Relevance
        weka_classifier = "weka.classifiers.meta.AdaBoostM1", # with Naive␣
↪Bayes single-label classifier
```

```
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)
meka

meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Subset Accuracy Score  is %f' % subset_acc(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

```
zero-one-loss is 0.610803
hamming-loss is 0.141505
Subset Accuracy Score  is 0.389197
F1_score is 0.615844
```

[ ]:
```
meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.BR", #
        weka_classifier = "weka.classifiers.trees.RandomForest", #
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)

meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Subset Accuracy Score  is %f' % subset_acc(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

[ ]:
```
meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.BR", #
        weka_classifier = "weka.classifiers.trees.J48", #
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)

meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
```

```
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Subset Accuracy Score  is %f' % subset_acc(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

```
zero-one-loss is 0.565097
hamming-loss is 0.134118
Subset Accuracy Score  is 0.434903
F1_score is 0.633334
```

[ ]:
```
weka_clf = ['weka.classifiers.lazy.IBk',
'weka.classifiers.trees.RandomForest',
'weka.classifiers.bayes.NaiveBayes',
'weka.classifiers.rules.ZeroR', 'weka.classifiers.functions.SMO',  "weka.
↪classifiers.trees.J48", 'weka.classifiers.meta.AdaBoostM1', 'weka.
↪classifiers.bayes.NaiveBayesMultinomial']

for clf in weka_clf:
    meka = Meka(
            meka_classifier = "meka.classifiers.multilabel.BR", #
            weka_classifier = clf, #
            meka_classpath = meka_classpath, #obtained via download_meka
            java_command = '/usr/bin/java' # path to java executable
    )

    meka.fit(X_train, y_train)
    predictions = meka.predict(X_test)



    print(f"zero-one-loss of {meka.weka_classifier} is {zero_one_loss(y_test,␣
↪predictions)}")
    print(f"hamming loss of {meka.weka_classifier} is {metrics.
↪hamming_loss(y_test, predictions)}")
    print(f"f1 score of {meka.weka_classifier} is {f1_score(y_test,␣
↪predictions, average='macro')}")
    print(f"subset accuracy of {meka.weka_classifier} is {metrics.
↪accuracy_score(y_test, predictions)}")
```

```
zero-one-loss of weka.classifiers.lazy.IBk is 1.0
hamming loss of weka.classifiers.lazy.IBk is 0.7048014226437463
f1 score of weka.classifiers.lazy.IBk is 0.4129109406213942
subset accuracy of weka.classifiers.lazy.IBk is 0.0
zero-one-loss of weka.classifiers.trees.RandomForest is 0.8049792531120332
hamming loss of weka.classifiers.trees.RandomForest is 0.17842323651452283
f1 score of weka.classifiers.trees.RandomForest is 0.4433687054844513
subset accuracy of weka.classifiers.trees.RandomForest is 0.1950207468879668
zero-one-loss of weka.classifiers.bayes.NaiveBayes is 0.8796680497925311
```

```
hamming loss of weka.classifiers.bayes.NaiveBayes is 0.27771191464137523
f1 score of weka.classifiers.bayes.NaiveBayes is 0.4433125154922345
subset accuracy of weka.classifiers.bayes.NaiveBayes is 0.12033195020746888
zero-one-loss of weka.classifiers.rules.ZeroR is 0.9875518672199171
hamming loss of weka.classifiers.rules.ZeroR is 0.2569650266745702
f1 score of weka.classifiers.rules.ZeroR is 0.25023840585296436
subset accuracy of weka.classifiers.rules.ZeroR is 0.012448132780082987
zero-one-loss of weka.classifiers.functions.SMO is 0.8174273858921162
hamming loss of weka.classifiers.functions.SMO is 0.1813870776526378
f1 score of weka.classifiers.functions.SMO is 0.33747208502842946
subset accuracy of weka.classifiers.functions.SMO is 0.1825726141078838
zero-one-loss of weka.classifiers.trees.J48 is 0.9211618257261411
hamming loss of weka.classifiers.trees.J48 is 0.24659158269116777
f1 score of weka.classifiers.trees.J48 is 0.3857488578458212
subset accuracy of weka.classifiers.trees.J48 is 0.07883817427385892
zero-one-loss of weka.classifiers.meta.AdaBoostM1 is 0.8879668049792531
hamming loss of weka.classifiers.meta.AdaBoostM1 is 0.2098399525785418
f1 score of weka.classifiers.meta.AdaBoostM1 is 0.36499208105093583
subset accuracy of weka.classifiers.meta.AdaBoostM1 is 0.11203319502074689
zero-one-loss of weka.classifiers.bayes.NaiveBayesMultinomial is
0.8838174273858921
hamming loss of weka.classifiers.bayes.NaiveBayesMultinomial is
0.2077652637818613
f1 score of weka.classifiers.bayes.NaiveBayesMultinomial is 0.3212475095965762
subset accuracy of weka.classifiers.bayes.NaiveBayesMultinomial is
0.11618257261410789
```

[ ]:

```
print(f"zero-one-loss of {meka.weka_classifier} is {zero_one_loss(y_test,␣
↪predictions)}")
print(f"hamming loss of {meka.weka_classifier} is {hamming_loss(y_test,␣
↪predictions)}")
print(f"zero-one-loss of {meka.weka_classifier} is {subset_acc(y_test,␣
↪predictions)}")
print(f"zero-one-loss of {meka.weka_classifier} is {f1_score(y_test,␣
↪predictions, average='macro')}")
```

[ ]:

[ ]:

[ ]:

```
meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.CC", #
        weka_classifier = "weka.classifiers.trees.RandomForest", #
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)
```

```
meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Subset Accuracy Score  is %f' % subset_acc(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

```
zero-one-loss is 0.439058
hamming-loss is 0.088643
Subset Accuracy Score  is 0.560942
F1_score is 0.702144
```

[ ]:
```
meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.CC", #
        weka_classifier = "weka.classifiers.functions.SMO", #
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)

meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Subset Accuracy Score  is %f' % subset_acc(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

```
zero-one-loss is 0.380886
hamming-loss is 0.117036
Subset Accuracy Score  is 0.619114
F1_score is 0.680167
```

[ ]:
```
meka = Meka(
        meka_classifier = "meka.classifiers.multilabel.CC", #
        weka_classifier = "weka.classifiers.rules.JRip", #
        meka_classpath = meka_classpath, #obtained via download_meka
        java_command = '/usr/bin/java' # path to java executable
)

meka.fit(X_train, y_train)
predictions = meka.predict(X_test)
from sklearn.metrics import hamming_loss

print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
```

```
print('hamming-loss is %f'% hamming_loss(y_test, predictions))
print('Subset Accuracy Score  is %f' % subset_acc(y_test, predictions))
print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

[ ]: 0.19236111111111112

```
[ ]: meka = Meka(
             meka_classifier = "meka.classifiers.multilabel.CC", #
             weka_classifier = "weka.classifiers.trees.J48", #
             meka_classpath = meka_classpath, #obtained via download_meka
             java_command = '/usr/bin/java' # path to java executable
     )

     meka.fit(X_train, y_train)
     predictions = meka.predict(X_test)
     from sklearn.metrics import hamming_loss

     print('zero-one-loss is %f'% zero_one_loss(y_test, predictions))
     print('hamming-loss is %f'% hamming_loss(y_test, predictions))
     print('Subset Accuracy Score  is %f' % subset_acc(y_test, predictions))
     print('F1_score is %f' % f1_score(y_test, predictions, average='macro'))
```

[ ]: 0.20555555555555555

```
[ ]: weka_clf = ['weka.classifiers.lazy.IBk',
     'weka.classifiers.trees.RandomForest',
     'weka.classifiers.bayes.NaiveBayes',
     'weka.classifiers.rules.ZeroR', 'weka.classifiers.functions.SMO',  "weka.
      ↪classifiers.trees.J48", 'weka.classifiers.meta.AdaBoostM1', 'weka.
      ↪classifiers.rules.JRip' ,'weka.classifiers.bayes.NaiveBayesMultinomial']


     base_model_names = ["IBk", "Random Forest", "NaiveBayes", "ZeroR", "SMO", 'SVM'␣
      ↪,"J48", 'AdaBoostM1', 'JRipper', 'NaiveBayesMultinomial']

     zero_score = dict()
     cc_accuracies = dict()
     cc_f1 = dict()
     cc_hamming = dict()

     i = 0

     for clf in weka_clf:
         meka = Meka(
                 meka_classifier = "meka.classifiers.multilabel.BR", #
                 weka_classifier = clf, #
                 meka_classpath = meka_classpath, #obtained via download_meka
```

```
            java_command = '/usr/bin/java' # path to java executable
    )

    meka.fit(X_train, y_train)
    predictions = meka.predict(X_test)

    # zero-one-score
    z_one = zero_one_loss(y_test, predictions)
    zero_score[base_model_names[i]] = z_one
    # accuracy score
    accuracy = subset_acc(y_test, predictions)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = f1_score(y_test, predictions, average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # hamming loss
    hamming = hamming_loss(y_test, predictions)
    cc_hamming[base_model_names[i]] = hamming

    i+=1

print('Binary Relevance')
print('-------------------------------------------------------')
print("====================z_one Accuracy====================")
display(zero_score)
print("=================== F1 Scores====================")
display(cc_f1)
print("=================== Hamming Loss Scores====================")
display(cc_hamming)
print("=================== subset accuracy Scores====================")
display(cc_accuracies)
```

```
Binary Relevance
-------------------------------------------------------
====================z_one Accuracy====================

{'IBk': 0.8193103448275862,
 'Random Forest': 0.856551724137931,
 'NaiveBayes': 0.9131034482758621,
 'ZeroR': 0.9751724137931035,
 'SMO': 0.886896551724138,
 'SVM': 0.9641379310344828,
 'J48': 0.9255172413793104,
 'AdaBoostM1': 0.9517241379310345,
 'JRipper': 0.9089655172413793}

=================== F1 Scores====================

{'IBk': 0.4310097731530584,
```

```
 'Random Forest': 0.405075567007733,
 'NaiveBayes': 0.411853273188045,
 'ZeroR': 0.23957008933277274,
 'SMO': 0.3064896991627125,
 'SVM': 0.376515964777626,
 'J48': 0.34525243473176087,
 'AdaBoostM1': 0.3483133912119068,
 'JRipper': 0.2984405582397283}
```

```
=================== Hamming Loss Scores====================
```

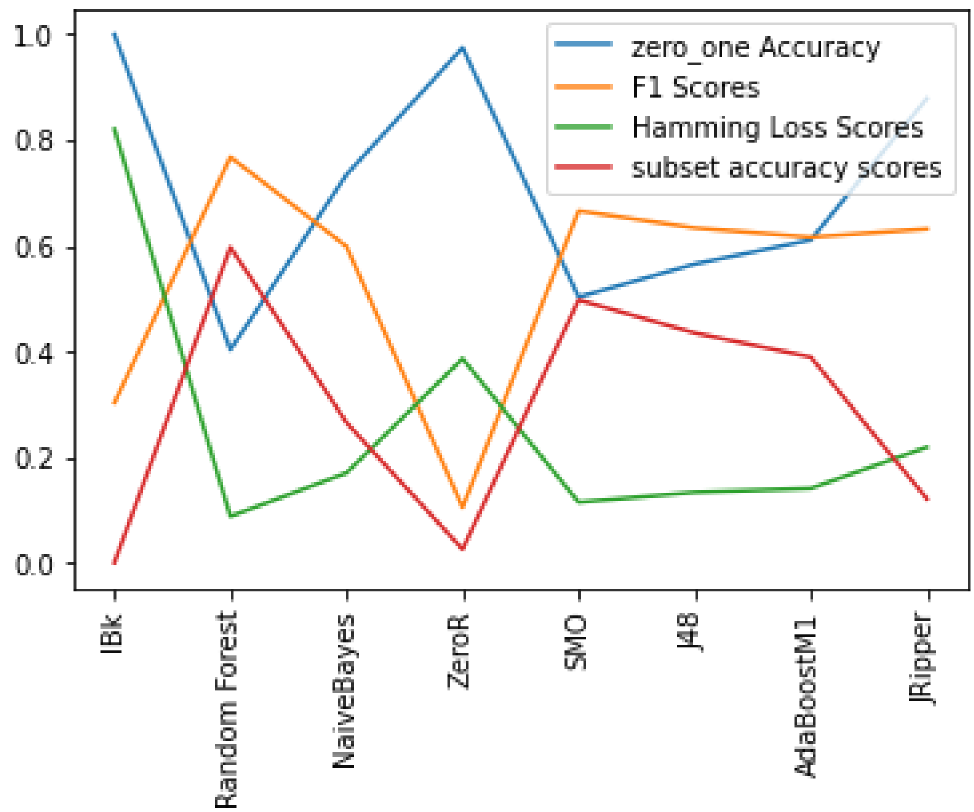
```
{'IBk': 0.25733990147783253,
 'Random Forest': 0.21448275862068966,
 'NaiveBayes': 0.30295566502463056,
 'ZeroR': 0.28502463054187194,
 'SMO': 0.21655172413793103,
 'SVM': 0.27497536945812806,
 'J48': 0.2367487684729064,
 'AdaBoostM1': 0.2530049261083744,
 'JRipper': 0.23773399014778326}
```

```
=================== subset accuracy Scores====================
```

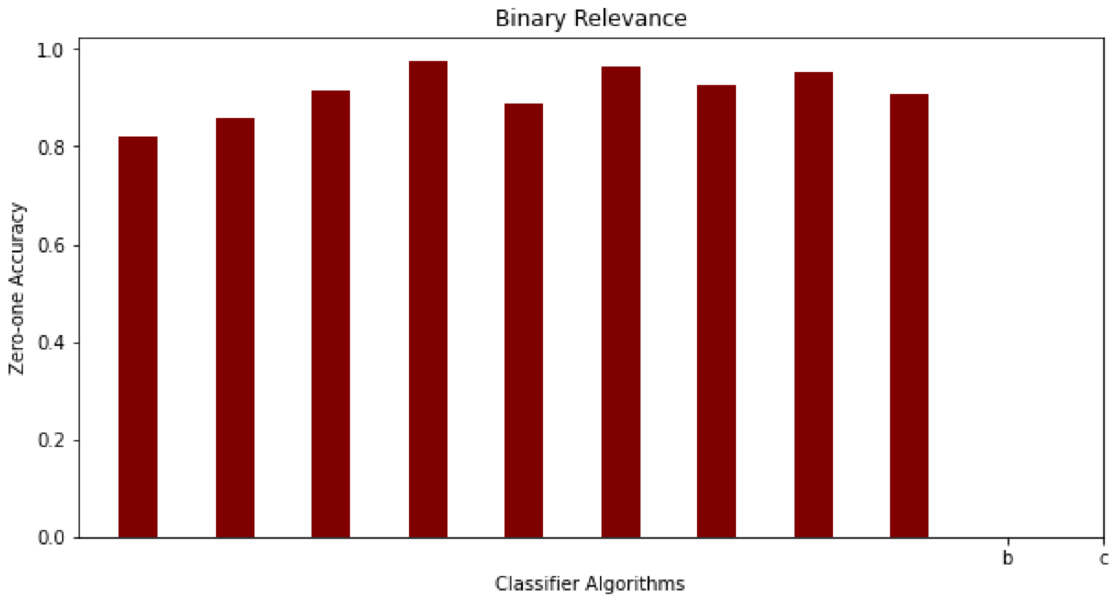
```
{'IBk': 0.18068965517241378,
 'Random Forest': 0.14344827586206896,
 'NaiveBayes': 0.08689655172413793,
 'ZeroR': 0.02482758620689655,
 'SMO': 0.11310344827586206,
 'SVM': 0.03586206896551724,
 'J48': 0.07448275862068965,
 'AdaBoostM1': 0.04827586206896552,
 'JRipper': 0.0910344827586207}
```

[ ]:
```
plt.plot(list(zero_score.keys()), list(zero_score.values()))
plt.plot(list(cc_f1.keys()), list(cc_f1.values()))
plt.plot(list(cc_hamming.keys()), list(cc_hamming.values()))
plt.plot(list(cc_accuracies.keys()), list(cc_accuracies.values()))

plt.xticks(rotation=90)
plt.legend(['zero_one Accuracy','F1 Scores', 'Hamming Loss Scores', 'subset␣
 ↪accuracy scores'])
```

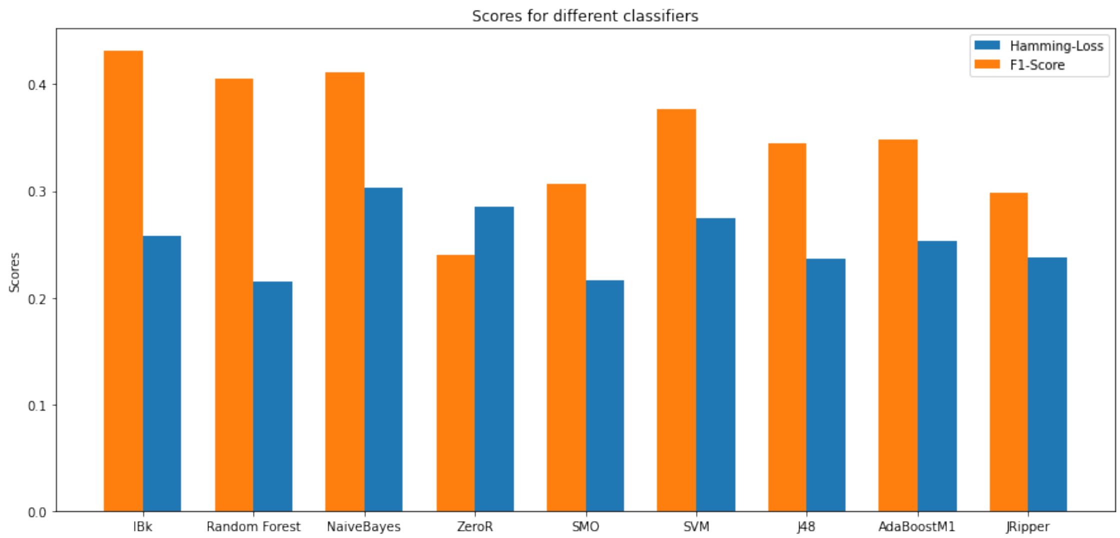
[ ]:
```
<matplotlib.legend.Legend at 0x7fe516da8f40>
```




```
[ ]: import numpy as np
     import matplotlib.pyplot as plt
     fig = plt.figure(figsize = (10, 5))
     # creating the bar plot
     plt.bar(list(zero_score.keys()), list(zero_score.values()), color ='maroon',␣
      ↪width = 0.4)
     plt.bar(list(cc_f1.keys()), list(cc_f1.values()), color ='maroon', width = 0.4)
     plt.xlabel("Classifier Algorithms")
     plt.ylabel("Zero-one Accuracy")
     plt.xticks(["b", "c"])
     plt.title("Binary Relevance")
     plt.show()
```




```
[ ]: import numpy as np

plt.figure(figsize=(15,7))
N = 9
#men_means = (20, 35, 30, 35, 27)
#women_means = (25, 32, 34, 20, 25)

ind = np.arange(N)
width = 0.35
plt.bar(ind + width, list(cc_hamming.values()), width,
    label='Hamming-Loss')
plt.bar(ind,list(cc_f1.values()) , width, label='F1-Score')


plt.ylabel('Scores')
plt.title('Scores for different classifiers')

plt.xticks(ind + width / 2, ("IBk", "Random Forest", "NaiveBayes", "ZeroR",␣
 ↪"SMO", 'SVM' ,"J48", 'AdaBoostM1', 'JRipper', 'NaiveBayesMultinomial'))
plt.legend(loc='best')
plt.show()
```



[ ]:

[ ]:
```
weka_clf = ['weka.classifiers.lazy.IBk',
'weka.classifiers.trees.RandomForest',
'weka.classifiers.bayes.NaiveBayes',
'weka.classifiers.rules.ZeroR', 'weka.classifiers.functions.SMO', "weka.
↪classifiers.trees.J48", 'weka.classifiers.meta.AdaBoostM1']

base_model_names = ["IBk", "Random Forest", "NaiveBayes", "ZeroR", "SMO",␣
↪"J48", 'AdaBoostM1']

zero_score = dict()
cc_accuracies = dict()
cc_f1 = dict()
cc_hamming = dict()

i = 0

for clf in weka_clf:
    meka = Meka(
            meka_classifier = "meka.classifiers.multilabel.CC", #
            weka_classifier = clf, #
            meka_classpath = meka_classpath, #obtained via download_meka
            java_command = '/usr/bin/java' # path to java executable
    )

    meka.fit(X_train, y_train)
    predictions = meka.predict(X_test)
```

```python
    # zero-one-score
    z_one = zero_one_loss(y_test, predictions)
    zero_score[base_model_names[i]] = z_one
    # accuracy score
    accuracy = subset_acc(y_test, predictions)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = f1_score(y_test, predictions, average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # hamming loss
    hamming = hamming_loss(y_test, predictions)
    cc_hamming[base_model_names[i]] = hamming

    i+=1

print('Classifier Chain')
print('-------------------------------------------------------')
print("====================z_one Accuracy====================")
display(zero_score)
print("=================== F1 Scores====================")
display(cc_f1)
print("=================== Hamming Loss Scores====================")
display(cc_hamming)
print("=================== subset accuracy Scores====================")
display(cc_accuracies)
```

```
Classifier Chain
-------------------------------------------------------
====================z_one Accuracy====================

{'IBk': 0.8193103448275862,
 'Random Forest': 0.8248275862068966,
 'NaiveBayes': 0.9020689655172414,
 'ZeroR': 0.9875862068965517,
 'SMO': 0.8510344827586207,
 'J48': 0.8786206896551724,
 'AdaBoostM1': 0.886896551724138}

=================== F1 Scores====================

{'IBk': 0.4310097731530584,
 'Random Forest': 0.35099424257917733,
 'NaiveBayes': 0.4305050955408004,
 'ZeroR': 0.11906666607491435,
 'SMO': 0.3313561383771514,
 'J48': 0.3799405454730588,
 'AdaBoostM1': 0.3302755593782595}

=================== Hamming Loss Scores====================
```

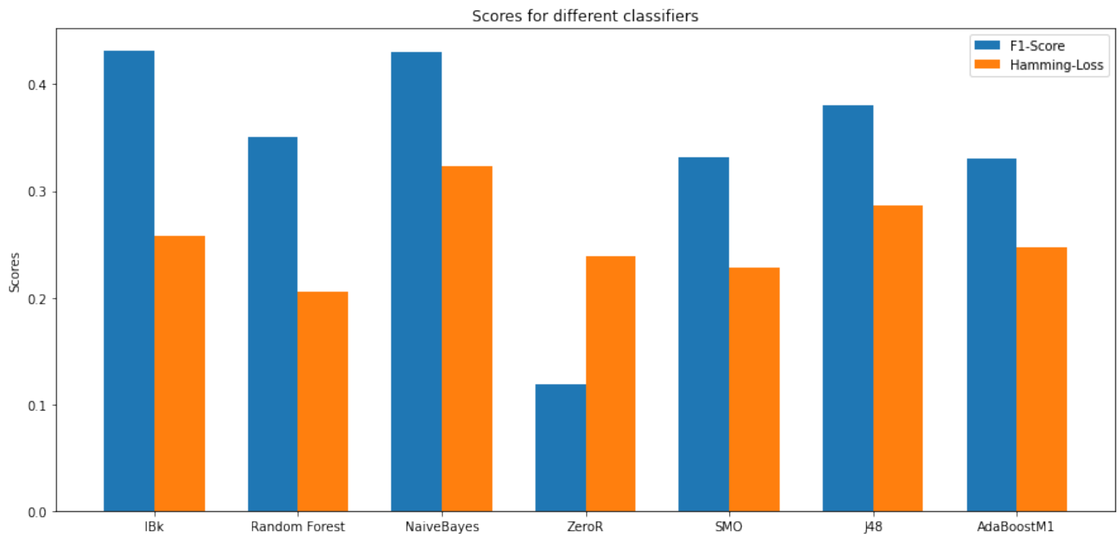
```
{'IBk': 0.25733990147783253,
 'Random Forest': 0.20532019704433496,
 'NaiveBayes': 0.32315270935960594,
 'ZeroR': 0.23881773399014777,
 'SMO': 0.2277832512315271,
 'J48': 0.2860098522167488,
 'AdaBoostM1': 0.24689655172413794}
```

```
=================== subset accuracy Scores====================
```

```
{'IBk': 0.18068965517241378,
 'Random Forest': 0.17517241379310344,
 'NaiveBayes': 0.09793103448275862,
 'ZeroR': 0.012413793103448275,
 'SMO': 0.1489655172413793,
 'J48': 0.12137931034482759,
 'AdaBoostM1': 0.11310344827586206}
```

[ ]:

```
import numpy as np

plt.figure(figsize=(15,7))
N = 7

ind = np.arange(N)
width = 0.35

plt.bar(ind, list(cc_f1.values()) , width, label='F1-Score')
plt.bar(ind + width, list(cc_hamming.values()), width,
    label='Hamming-Loss')

plt.ylabel('Scores')
plt.title('Scores for different classifiers')

plt.xticks(ind + width / 2, ("IBk", "Random Forest", "NaiveBayes", "ZeroR",␣
 ↪"SMO", "J48", 'AdaBoostM1'))
plt.legend(loc='best')
plt.show()
```



[ ]:
```
weka_clf = ['weka.classifiers.lazy.IBk',
'weka.classifiers.trees.RandomForest',
'weka.classifiers.bayes.NaiveBayes',
'weka.classifiers.rules.ZeroR', 'weka.classifiers.functions.SMO', "weka.
↪classifiers.trees.J48", 'weka.classifiers.meta.AdaBoostM1']

base_model_names = ["IBk", "Random Forest", "NaiveBayes", "ZeroR", "SMO",␣
↪"J48", 'AdaBoostM1']

zero_score = dict()
cc_accuracies = dict()
cc_f1 = dict()
cc_hamming = dict()

i = 0

for clf in weka_clf:
    meka = Meka(
            meka_classifier = "meka.classifiers.multilabel.MULAN -S CLR", #
            weka_classifier = clf, #
            meka_classpath = meka_classpath, #obtained via download_meka
            java_command = '/usr/bin/java' # path to java executable
    )

    meka.fit(X_train, y_train)
    predictions = meka.predict(X_test)

    # zero-one-score
    z_one = zero_one_loss(y_test, predictions)
```

```python
    zero_score[base_model_names[i]] = z_one
    # accuracy score
    accuracy = subset_acc(y_test, predictions)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = f1_score(y_test, predictions, average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # hamming loss
    hamming = hamming_loss(y_test, predictions)
    cc_hamming[base_model_names[i]] = hamming

    i+=1

print('Calibrated Label Ranking')
print('-------------------------------------------------------')
print("====================z_one Accuracy====================")
display(zero_score)
print("=================== F1 Scores====================")
display(cc_f1)
print("=================== Hamming Loss Scores====================")
display(cc_hamming)
print("=================== subset accuracy Scores====================")
display(cc_accuracies)
```

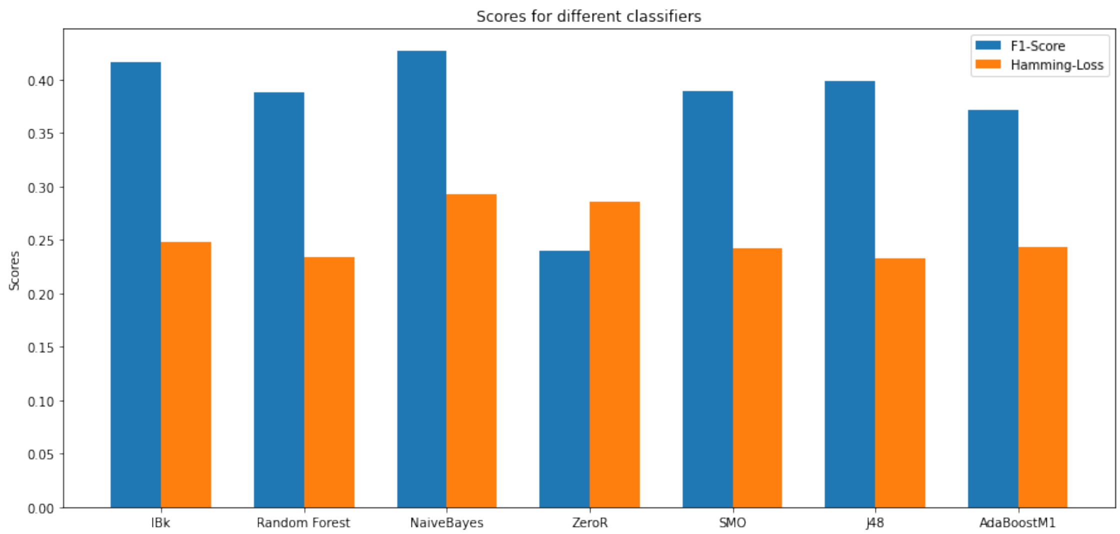
```
Calibrated Label Ranking
-------------------------------------------------------
====================z_one Accuracy====================

{'IBk': 0.863448275862069,
 'Random Forest': 0.9737931034482759,
 'NaiveBayes': 0.9213793103448276,
 'ZeroR': 0.9751724137931035,
 'SMO': 0.9682758620689655,
 'J48': 0.9131034482758621,
 'AdaBoostM1': 0.9613793103448276}

=================== F1 Scores====================

{'IBk': 0.41615823437977145,
 'Random Forest': 0.388416405621293,
 'NaiveBayes': 0.4261700374157796,
 'ZeroR': 0.23957008933277274,
 'SMO': 0.38861046489491874,
 'J48': 0.3989213322672234,
 'AdaBoostM1': 0.371152303028441}

=================== Hamming Loss Scores====================

{'IBk': 0.2482758620689655,
 'Random Forest': 0.2334975369458128,
```

```
 'NaiveBayes': 0.29211822660098524,
 'ZeroR': 0.28502463054187194,
 'SMO': 0.24226600985221675,
 'J48': 0.23290640394088669,
 'AdaBoostM1': 0.24354679802955664}
```

```
=================== subset accuracy Scores====================
```

```
{'IBk': 0.13655172413793104,
 'Random Forest': 0.02620689655172414,
 'NaiveBayes': 0.07862068965517241,
 'ZeroR': 0.02482758620689655,
 'SMO': 0.031724137931034485,
 'J48': 0.08689655172413793,
 'AdaBoostM1': 0.03862068965517241 6}
```

[ ]:
```
import numpy as np

plt.figure(figsize=(15,7))
N = 7

ind = np.arange(N)
width = 0.35

plt.bar(ind, list(cc_f1.values()) , width, label='F1-Score')
plt.bar(ind + width, list(cc_hamming.values()), width,
    label='Hamming-Loss')

plt.ylabel('Scores')
plt.title('Scores for different classifiers')

plt.xticks(ind + width / 2, ("IBk", "Random Forest", "NaiveBayes", "ZeroR",␣
 ↪"SMO", "J48", 'AdaBoostM1'))
plt.legend(loc='best')
plt.show()
```



[ ]:
```
weka_clf = ['weka.classifiers.lazy.IBk',
'weka.classifiers.trees.RandomForest',
'weka.classifiers.bayes.NaiveBayes',
'weka.classifiers.rules.ZeroR', 'weka.classifiers.functions.SMO', "weka.
↪classifiers.trees.J48", 'weka.classifiers.meta.AdaBoostM1']

base_model_names = ["IBk", "Random Forest", "NaiveBayes", "ZeroR", "SMO",␣
↪"J48", 'AdaBoostM1']

zero_score = dict()
cc_accuracies = dict()
cc_f1 = dict()
cc_hamming = dict()

i = 0

for clf in weka_clf:
    meka = Meka(
            meka_classifier = "meka.classifiers.multilabel.LC", #
            weka_classifier = clf, #
            meka_classpath = meka_classpath, #obtained via download_meka
            java_command = '/usr/bin/java' # path to java executable
    )

    meka.fit(X_train, y_train)
    predictions = meka.predict(X_test)

    # zero-one-score
    z_one = zero_one_loss(y_test, predictions)
```

```python
    zero_score[base_model_names[i]] = z_one
    # accuracy score
    accuracy = subset_acc(y_test, predictions)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = f1_score(y_test, predictions, average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # hamming loss
    hamming = hamming_loss(y_test, predictions)
    cc_hamming[base_model_names[i]] = hamming

    i+=1

print('Label Combination / Label Powerset')
print('-------------------------------------------------------')
print("====================z_one Accuracy====================")
display(zero_score)
print("=================== F1 Scores====================")
display(cc_f1)
print("=================== Hamming Loss Scores====================")
display(cc_hamming)
print("=================== subset accuracy Scores====================")
display(cc_accuracies)
```

```
Label Combination / Label Powerset
-------------------------------------------------------
====================z_one Accuracy====================

{'IBk': 0.8193103448275862,
 'Random Forest': 0.766896551724138,
 'NaiveBayes': 0.8455172413793104,
 'ZeroR': 0.9117241379310345,
 'SMO': 0.7655172413793103,
 'J48': 0.8703448275862069,
 'AdaBoostM1': 0.8937931034482759}

=================== F1 Scores====================

{'IBk': 0.4310097731530584,
 'Random Forest': 0.3853306424840523,
 'NaiveBayes': 0.4287226179942739,
 'ZeroR': 0.18920342773214388,
 'SMO': 0.39986280690689274,
 'J48': 0.3633448147857615,
 'AdaBoostM1': 0.25362650646319}

=================== Hamming Loss Scores====================

{'IBk': 0.25733990147783253,
 'Random Forest': 0.218128078817734,
```

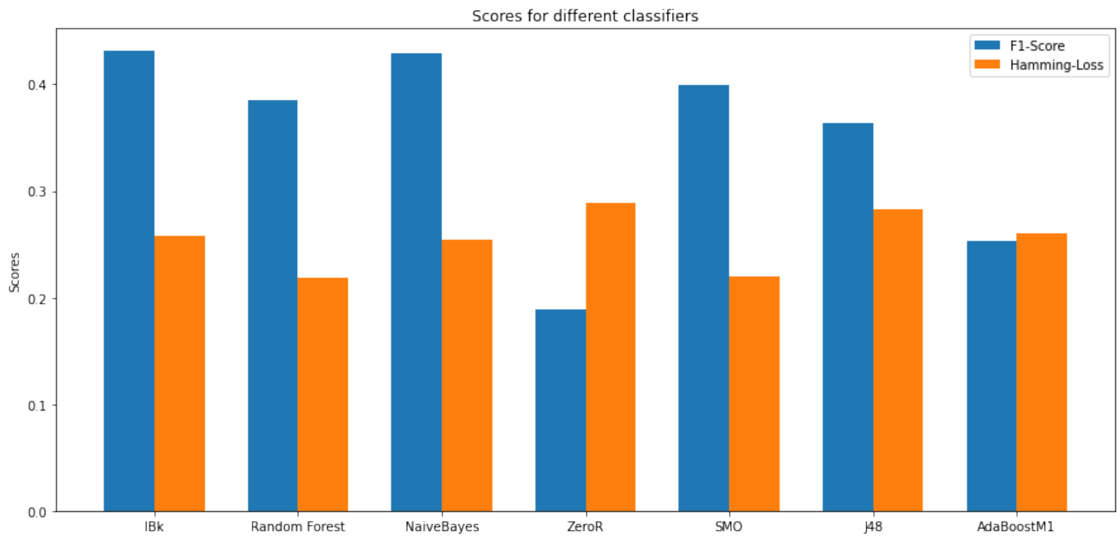
```
 'NaiveBayes': 0.2545812807881773,
 'ZeroR': 0.28866995073891627,
 'SMO': 0.21960591133004925,
 'J48': 0.2830541871921182,
 'AdaBoostM1': 0.26068965517241377}
```

```
=================== subset accuracy Scores====================
```

```
{'IBk': 0.18068965517241378,
 'Random Forest': 0.23310344827586207,
 'NaiveBayes': 0.15448275862068966,
 'ZeroR': 0.08827586206896551,
 'SMO': 0.23448275862068965,
 'J48': 0.1296551724137931,
 'AdaBoostM1': 0.10620689655172413}
```

[ ]:

```
import numpy as np

plt.figure(figsize=(15,7))
N = 7

ind = np.arange(N)
width = 0.35

plt.bar(ind, list(cc_f1.values()) , width, label='F1-Score')
plt.bar(ind + width, list(cc_hamming.values()), width,
    label='Hamming-Loss')

plt.ylabel('Scores')
plt.title('Scores for different classifiers')

plt.xticks(ind + width / 2, ("IBk", "Random Forest", "NaiveBayes", "ZeroR",␣
 ↪"SMO", "J48", 'AdaBoostM1'))
plt.legend(loc='best')
plt.show()
```



[ ]:
```
weka_clf = ['weka.classifiers.lazy.IBk',
'weka.classifiers.trees.RandomForest',
'weka.classifiers.bayes.NaiveBayes',
'weka.classifiers.rules.ZeroR', 'weka.classifiers.functions.SMO', "weka.
↪classifiers.trees.J48", 'weka.classifiers.meta.AdaBoostM1']

base_model_names = ["IBk", "Random Forest", "NaiveBayes", "ZeroR", "SMO",␣
↪"J48", 'AdaBoostM1']

zero_score = dict()
cc_accuracies = dict()
cc_f1 = dict()
cc_hamming = dict()

i = 0
for clf in weka_clf:
    meka = Meka(
            meka_classifier = "meka.classifiers.multilabel.PS -P 1 -N 1", #
            weka_classifier = clf, #
            meka_classpath = meka_classpath, #obtained via download_meka
            java_command = '/usr/bin/java' # path to java executable
    )

    meka.fit(X_train, y_train)
    predictions = meka.predict(X_test)

    # zero-one-score
    z_one = zero_one_loss(y_test, predictions)
    zero_score[base_model_names[i]] = z_one
```

```
    # accuracy score
    accuracy = subset_acc(y_test, predictions)
    cc_accuracies[base_model_names[i]] = accuracy
    # F1 score
    cc_f1_score = f1_score(y_test, predictions, average='macro')
    cc_f1[base_model_names[i]] = cc_f1_score
    # hamming loss
    hamming = hamming_loss(y_test, predictions)
    cc_hamming[base_model_names[i]] = hamming

    i+=1

print('Pruned Sets (Pruned Label Powerset)')
print('-------------------------------------------------------')
print("====================z_one Accuracy====================")
display(zero_score)
print("=================== F1 Scores====================")
display(cc_f1)
print("=================== Hamming Loss Scores====================")
display(cc_hamming)
print("=================== subset accuracy Scores====================")
display(cc_accuracies)
```

```
Pruned Sets (Pruned Label Powerset)
-------------------------------------------------------
====================z_one Accuracy====================

{'IBk': 0.816551724137931,
 'Random Forest': 0.7475862068965518,
 'NaiveBayes': 0.8427586206896551,
 'ZeroR': 0.9117241379310345,
 'SMO': 0.7586206896551724,
 'J48': 0.9062068965517242,
 'AdaBoostM1': 0.8937931034482759}

=================== F1 Scores====================

{'IBk': 0.4293935803022561,
 'Random Forest': 0.38400393323258203,
 'NaiveBayes': 0.4328279872919357,
 'ZeroR': 0.18920342773214388,
 'SMO': 0.40780071288782604,
 'J48': 0.3603727864216838,
 'AdaBoostM1': 0.25362650646319}

=================== Hamming Loss Scores====================

{'IBk': 0.2553694581280788,
 'Random Forest': 0.21832512315270935,
 'NaiveBayes': 0.2553694581280788,
```

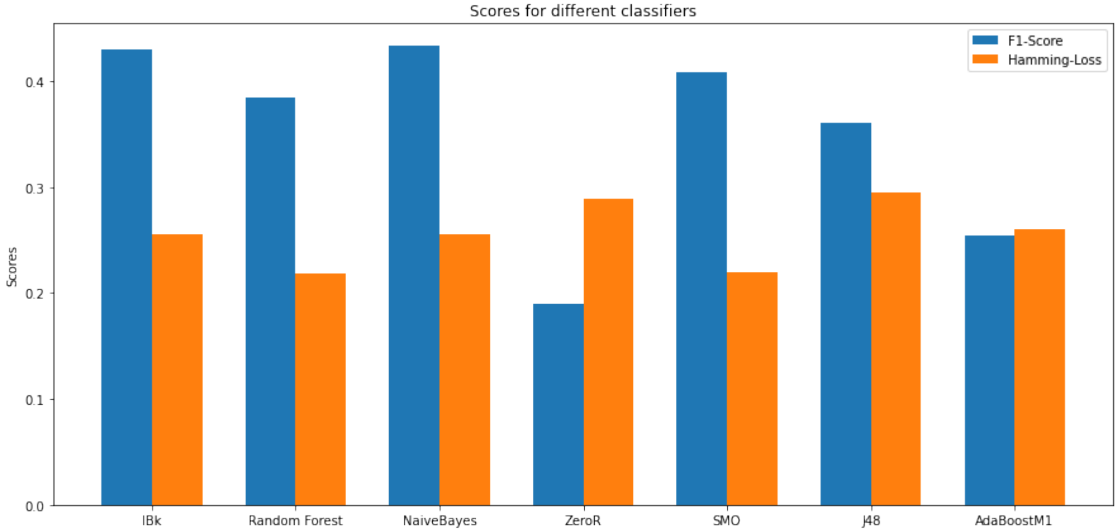
```
 'ZeroR': 0.28866995073891627,
 'SMO': 0.21911330049261082,
 'J48': 0.2952709359605911,
 'AdaBoostM1': 0.26068965517241377}
```

```
=================== subset accuracy Scores====================
```

```
{'IBk': 0.18344827586206897,
 'Random Forest': 0.2524137931034483,
 'NaiveBayes': 0.15724137931034482,
 'ZeroR': 0.08827586206896551,
 'SMO': 0.2413793103448276,
 'J48': 0.09379310344827586,
 'AdaBoostM1': 0.10620689655172413}
```

[ ]:

```
import numpy as np

plt.figure(figsize=(15,7))
N = 7

ind = np.arange(N)
width = 0.35

plt.bar(ind, list(cc_f1.values()) , width, label='F1-Score')
plt.bar(ind + width, list(cc_hamming.values()), width,
    label='Hamming-Loss')

plt.ylabel('Scores')
plt.title('Scores for different classifiers')

plt.xticks(ind + width / 2, ("IBk", "Random Forest", "NaiveBayes", "ZeroR",␣
 ↪"SMO", "J48", 'AdaBoostM1'))
plt.legend(loc='best')
plt.show()
```


Scores for different classifiers
F1-Score
Hamming-Loss
Scores
0.0
0.1
0.2
0.3
0.4
IBk
Random Forest
NaiveBayes
ZeroR
SMO
J48
AdaBoostM1

[ ]: