





```
In [180]: #RUN THIS CELL
          import requests
          from IPython.core.display import HTML
          # Import libraries
          %matplotlib inline
          import math
          import numpy as np
          import pandas as pd
          #import seaborn as sns
          from collections import Counter
          import matplotlib.pyplot as plt
          from sklearn.utils import shuffle
          from sklearn.linear_model import Lasso
          from sklearn.preprocessing import StandardScaler
          from sklearn.metrics import mean_squared_error
          from sklearn.linear_model import LinearRegression
          from sklearn.model_selection import cross_validate
          from sklearn.model_selection import train_test_split
          from sklearn.preprocessing import PolynomialFeatures
          from sklearn.linear_model import LogisticRegression
          from sklearn.model_selection import cross_val_score
          from sklearn.metrics import accuracy_score
          from sklearn.model_selection import KFold
          from sklearn.metrics import roc_auc_score
          from sklearn.metrics import roc curve
          from sklearn.ensemble import RandomForestClassifier
          #sns.set()
          import warnings
          from sklearn.metrics import confusion_matrix
          from sklearn.tree import DecisionTreeClassifier
          from sklearn import datasets, tree
          import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          #import seaborn as sns
          from tgdm import tgdm
          import time
          from sklearn.model_selection import cross_val_score, train_test_split, GridSearc
          from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDis
          from sklearn.metrics import recall_score, precision_score, classification_report
          from sklearn import tree
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.linear_model import LogisticRegression
          from sklearn.inspection import permutation_importance
          from imblearn.over_sampling import SMOTE
          from imblearn.under sampling import RandomUnderSampler
          from sklearn.impute import SimpleImputer
          #RUN THIS CELL
          import requests
          from IPython.core.display import HTML
          # Import libraries
          %matplotlib inline
          import math
          import numpy as np
          import pandas as pd
          #import seaborn as sns
          from collections import Counter
```

```
import matplotlib.pyplot as plt
from sklearn.utils import shuffle
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean squared error
from sklearn.linear model import LinearRegression
from sklearn.model_selection import cross_validate
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.model selection import KFold
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
#sns.set()
import warnings
from sklearn.metrics import confusion matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn import datasets, tree
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#import seaborn as sns
from tadm import tadm
import time
from sklearn.model selection import cross val score, train test split, GridSearc
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDis
from sklearn.metrics import recall_score, precision_score, classification_report
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.inspection import permutation_importance
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from sklearn.impute import SimpleImputer
from sklearn.decomposition import TruncatedSVD
from sklearn.datasets import load_svmlight_file
from sklearn.datasets import dump_svmlight_file
from scipy import sparse as sps
from sklearn.preprocessing import MinMaxScaler
from scipy.linalg import circulant
from sklearn.model_selection import train_test_split
from keras.optimizers import *
import random
import math
import pandas as pd
from tensorflow.python.keras.utils.data_utils import Sequence
import warnings
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
warnings.filterwarnings("ignore")
import tensorflow.keras as k
import keras.backend as K
import numpy as np
from keras.layers import *
from keras.models import Sequential, Model
from keras.regularizers import 12
import matplotlib.pyplot as plt
from keras.optimizers import Adam, Adadelta
from keras.callbacks import ModelCheckpoint, EarlyStopping
from tensorflow.python.framework.ops import disable eager execution
```

```
from sklearn.model selection import GridSearchCV
          from sklearn.metrics import classification_report
          disable_eager_execution()
          %matplotlib inline
          %matplotlib inline
In [181]: import utils
          import scipy
          import sklearn
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.model_selection import train_test_split
          from sklearn.metrics import accuracy_score
          dictSize = 225
          (X_raw, y_raw) = utils.loadData( "train", dictSize = dictSize )
In [182]: X1=X_raw.toarray()
          y1=y_raw
          from sklearn.decomposition import TruncatedSVD
          svd = TruncatedSVD(n components=224)
          svd.fit(X1)
          X_t = svd.transform(X1)
          classes = np.unique(y1)
          classes
Out[182]: array([ 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., 34., 35., 37., 39., 40., 41., 42.,
                 43., 44., 45., 46., 47., 48., 49., 50.])
In [183]: # print (np.unique(y))
          # unique, counts = np.unique(y, return_counts=True)
          # print (unique)
          # print (counts)
In [184]: print(X_t.shape)
          print(y1.shape)
          (10000, 224)
          (10000,)
In [185]: X_train, X_test, y_train, y_test=train_test_split(X1,y1,test_size=0.2)
          # sm = SMOTE()
          # X_train_SMOTE, y_train_SMOTE = sm.fit_resample(X_train, y_train)
In [186]: dt=DecisionTreeClassifier(class_weight="balanced")
In [187]: dt.fit(X_train,y_train)
Out[187]:
                        DecisionTreeClassifier
          DecisionTreeClassifier(class_weight='balanced')
In [188]: y_pred=dt.predict(X_test)
In [189]: y_pred
Out[189]: array([15., 32., 13., ..., 4., 1., 1.])
In [190]: acc=accuracy_score(y_test, y_pred )
In [191]: acc
Out[191] · a 603
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In [192]: # npzModel = np.load( "model.npz" )
        # model = npzModel[npzModel.files[0]]
        # --- Let us predict a random subset of the 2k most popular labels no matter wha
        # shortList = model[0:2*5]
        # (i,j)=np.unique(model,return_index=True)
        # print(shortList)
        # print(model)
        # print(i)
        # print (j)
In [193]: # a=np.array([4,3])
        # b=np.array([[2,3, 6,22,2],[3,9,7,49,5]])
        # utils.validateAndCleanup(a,b,5)
In [194]: dict={'C':(0.01,0.1,1,10,100), 'solver':('newton-cg', 'lbfgs', 'liblinear', 'sag
In [197]: lr1=LogisticRegression()
        clf=GridSearchCV(lr1, dict, scoring='accuracy')
        clf.fit(X_train, y_train)
Out[197]:
                  GridSearchCV
          ▶ estimator: LogisticRegression
              ▶ LogisticRegression
In [198]: print( 'Best score: %0.3f' % clf.best_score_)
        print( 'Best parameters set:')
        best_parameters = clf.best_estimator_.get_params()
        for param_name in sorted(dict.keys()):
            print( '\t%s: %r' % (param_name, best_parameters[param_name]) )
        predictions = clf.predict(X test)
        print( classification_report(y_test, predictions) )
        #print(accuracy_score(y_test, predictions))
        Best score: 0.792
        Best parameters set:
               C: 10
               solver: 'newton-cg'
                    precision recall f1-score support
                1.0
                       0.84
                               0.73 0.78
                                                  311
                                                  532
                2.0
                        0.89
                               0.96 0.92
                        0.86
                                0.91 0.88
                                                  292
                3.0
                4.0
                        0.69
                                0.81 0.74
                                                  263
                5.0
                                                  24
                        0.88
                                 0.62
                                         0.73
                6.0
                        0.67
                                 1.00
                                         0.80
                                                    2
                                0.94
                                        0.96
                7.0
                        0.98
                                                   52
                                        0.88
                               0.82
                        0.95
                                                   51
                8.0
                                0.87
                                        0.88
                9.0
                       0.88
                                                   70
               10.0
                       0.75
                                0.73
                                        0.74
                                                   52
               11.0
                       0.78
                               0.85
                                        0.82
               12.0
                       0.00
                               0.00
                                        0.00
               13.0
                       0.60
                               0.60 0.60
                                                   30
                       0.00
                               0.00
               14.0
                                       0.00
                                                    2
               15.0
                        0.55
                                0.42
                                        0.48
                                                    26
               16.0
                                 0.46
                        0.60
                                         0.52
                                                    26
               17.0
                        0.50
                                 0.50
                                         0.50
                                                    6
               18.0
                        0.00
                                 0.00
                                          0.00
                                                    4
               19.0
                        1.00
                                 0.64
                                         0.78
                                                    14
                                0.40
               20.0
                        0.40
                                         0.40
                                                   10
                                0.50
                                        0.50
               21.0
                        0.50
                                                    8
               22.0
                       0.00
                                0.00
                                        0.00
                                                    5
               23.0
                       0.93
                               0.82
                                        0.87
                                                   17
               24.0
                       0.79
                               0.85 0.81
                                                   13
               25.0
                       0.53 0.62 0.57
                                                   13
```

```
0.94
                28.0
                        0.89
                                 1.00
                                                      8
                29.0
                        0.80
                                 0.80
                                          0.80
                                                      5
                30.0
                        1.00
                                 0.60
                                          0.75
                                 0.50
                31.0
                        0.33
                                          0.40
                32.0
                        1.00
                                 1.00
                                          1.00
                34.0
                        0.67
                                 1.00 0.80
                                                       4
                35.0
                                          1.00
                        1.00
                                 1.00
                                                       9
                37.0
                        0.50
                                          0.25
                                 0.17
                                                       6
                                          0.22
                39.0
                         0.17
                                  0.33
                                                       3
                40.0
                         1.00
                                  0.50
                                           0.67
                                                       2
                41.0
                          0.40
                                  0.67
                                           0.50
                42.0
                         0.67
                                  0.29
                                           0.40
                                  1.00
                                          0.73
                43.0
                         0.57
                                                       4
                44.0
                                          0.62
                         0.80
                                 0.50
                45.0
                        0.80
                                 0.67
                                          0.73
                46.0
                        0.67
                                 0.67
                                          0.67
                47.0
                        0.00
                                 0.00 0.00
                48.0
                        0.25 0.20 0.22
                49.0
                        0.50 0.67 0.57
                50.0
                        0.00
                                 0.00
                                          0.00
            accuracy
                                           0.81
                                                    2000
                       0.61 0.60
0.80 0.81
            macro avg
                                                     2000
                                           0.59
         weighted avg
                                           0.80
                                                    2000
In [204]: predic = clf.predict(X test)
         y_pred = clf.best_estimator_.predict(X_test)
         predic3 = clf.best_estimator_
         print(predic)
         print(y_pred)
         print(predic3)
         y_pred=[2000,5]
         [15. 32. 13. ... 7. 1. 1.]
         [15. 32. 13. ... 7. 1. 1.]
         LogisticRegression(C=10, solver='newton-cg')
In [205]: preck = utils.getPrecAtK( y_test, y_pred, 5 )
         # The macro precision code takes a bit longer to execute due to the for loop ove
         mpreck = utils.getMPrecAtK( y_test,y_pred, 5 )
         # According to our definitions, both prec@k and mprec@k should go up as k goes u
         # method, prec@i > prec@j if i > j and mprec@i > mprec@j if i > j. See the assig
         # to convince yourself why this must be the case.
         print( "prec@1: %0.3f" % preck[0], "prec@3: %0.3f" % preck[2], "prec@5: %0.3f" %
         # Dont be surprised if mprec is small -- it is hard to do well on rare error cla
         print( "mprec@1: %0.3e" % mpreck[0], "mprec@3: %0.3e" % mpreck[2], "mprec@5: %0.
         AttributeError
                                             Traceback (most recent call last)
         Cell In [205], line 1
         ----> 1 preck = utils.getPrecAtK( y_test, y_pred, 5 )
              2 # The macro precision code takes a bit longer to execute due to the for
         loop over labels
              3 mpreck = utils.getMPrecAtK( y_test,y_pred, 5 )
         File ~\OneDrive - IIT Kanpur\Desktop\Lecture Notes\Intro to ML\Assignments\Assn
         2\Madhav\utils.py:62, in getPrecAtK(yGold, yPred, k)
             60 def getPrecAtK( yGold, yPred, k ):
                      n = len(yGold)
             61
         ---> 62
                       (yGoldNew, yPredNew) = validateAndCleanup( yGold, yPred, k )
             64
                      # Use some fancy indexing (yes, this is the formal term for the
         technique)
             65
                      # to find out where all did we predict the correct error class
             66
                       # Python indexing with arrays creates copies of data so we are
         safe
                       # The -1 step is required since predicted labels are indexed 1
             67
         ... 50 whereas Python expects zero based indices
```

wins = vGoldNew[nn arange/ n)[nn newaxis] vPredNew astvne

26.0

0.67

0.91

0.77

11

```
(int) - 1 ]
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        2\Madhav\utils.py:45, in validateAndCleanup(yGold, yPred, k)
             42 n = len(yGold)
             44 # Make sure the prediction matrix is in correct shape
        ---> 45 assert yPred.shape[0] == n, "Mismatch in number of test data points and
        number of predictions"
             46 assert yPred.shape[1] == k, "Mismatch in number of predictions received
        and number expected"
             48 # Penalize duplicates in yPred by replacing them with predictions of th
        e dummy error class 0
             49 # Since error classes are numbered from 1 to 50, the 0 error class is a
        safe dummy choice
        AttributeError: 'list' object has no attribute 'shape'
In [ ]:
In [ ]:
In [ ]:
In [ ]:
In [ ]: from sklearn.decomposition import TruncatedSVD
        from sklearn.svm import SVC
        from sklearn.cluster import KMeans
        #svd = TruncatedSVD(n_components=224)
        #svd.fit(X1)
        \#X_t = svd.transform(X1)
        X_train, X_test, y_train, y_test=train_test_split(X_t,y1,test_size=0.2)
        #kms = KMeans()
        #kms.fit(X_train)
        #y train = kms.labels
        #print(y_train)
        #y_test = kms.predict(X_test)
        lr=LogisticRegression(class_weight="balanced", solver='liblinear')
        lr.fit(X train, y train)
        y_pred2=lr.predict(X_test)
        acc2=accuracy_score(y_test,y_pred2)
        proba=lr.predict_proba(X_test)
        ind = np.argsort(proba)[:,-1:-6:-1]
        print (acc2)
        print (ind.shape)
        yPred = lr.classes [ind]
In [ ]: X_train.shape
In [ ]: |y_train[:].shape
In [ ]: preck = utils.getPrecAtK( y_test, yPred, 5 )
        # The macro precision code takes a bit longer to execute due to the for loop ove
        mpreck = utils.getMPrecAtK( y_test,yPred, 5 )
        # According to our definitions, both prec@k and mprec@k should go up as k goes {f u}_i
        # method, prec@i > prec@j if i > j and mprec@i > mprec@j if i > j. See the assig
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        print( "prec@1: %0.3f" % preck[0], "prec@3: %0.3f" % preck[2], "prec@5: %0.3f" %
        # Dont be surprised if mprec is small -- it is hard to do well on rare error cla
        print( "mprec@1: %0.3e" % mpreck[0], "mprec@3: %0.3e" % mpreck[2], "mprec@5: %0.
```

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