Q1-Python

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1 NAFLD detection using RNA-Seq data

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2 Q1 - Python section

[1]:
```
# Import needed libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import precision_score, recall_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LassoCV
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import warnings
warnings.filterwarnings("ignore")
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
```

[2]:
```
# Load Data
normal_counts = pd.read_csv('Normal.counts.voom.csv')
meta_data = pd.read_csv('meta_data.csv')
```

[3]:
```
normal_counts.head()
```

[3]:
```
              gene  DLDR_0001  DLDR_0002  DLDR_0003  DLDR_0004  DLDR_0005  \
0  ENSG00000000003   5.965571   5.741587   5.996891   5.551919   6.430237
1  ENSG00000000005   1.612375   2.147793   0.418542   0.702492   1.215978
2  ENSG00000000419   4.133821   4.120969   4.086129   4.116240   4.393797
3  ENSG00000000457   4.111056   3.922234   3.964871   3.978350   4.018235
4  ENSG00000000460   4.150662   3.732756   3.634637   3.853979   3.614220
```

```
   DLDR_0006  DLDR_0007  DLDR_0008  DLDR_0009  …  DLDR_0183  DLDR_0184  \
0   6.234619   6.071503   6.441882   5.752712  …   6.304802   6.576246
1   0.920810   0.458163   0.927224   1.089389  …  -0.031596  -1.091275
2   4.390909   4.148242   4.554655   4.203819  …   4.176599   4.244459
3   3.864521   4.263119   3.896271   4.139546  …   4.378342   4.453838
4   3.500857   4.000565   4.016287   3.904500  …   2.974209   3.720038

   DLDR_0185  DLDR_0186  DLDR_0187  DLDR_0188  DLDR_0189  DLDR_0190  \
0   6.735760   6.344234   6.608924   6.480745   6.360397   6.367705
1  -0.942637  -0.026585  -0.757399  -1.083676   0.886550  -0.902201
2   4.342765   4.179319   4.274450   4.361634   4.093280   4.148010
3   4.685598   4.438796   4.042577   4.313540   4.205119   4.506058
4   4.640011   3.814717   2.126408   3.120196   3.336802   3.982071

   DLDR_0191  DLDR_0192
0   6.604050   6.514539
1  -0.865036  -1.588749
2   4.351489   3.859711
3   4.072137   4.341988
4   3.143138   2.741172

[5 rows x 193 columns]
```

[4]:
```
normal_counts.shape
```

[4]:
```
(17396, 193)
```

there are 192 samples with 17396 features

[5]:
```
meta_data.head()
```

[5]:
```
  Patient_ID     SEX   BMI_surg  Age         Run        Diabet  \
0  DLDR_0001  Female  35.214555   55  SRR8378590  Non Diabetic
1  DLDR_0002  Female  39.421748   47  SRR8378589      Diabetic
2  DLDR_0003    Male  48.758108   46  SRR8378432  Non Diabetic
3  DLDR_0004  Female  41.822607   36  SRR8378431  Non Diabetic
4  DLDR_0005  Female  53.582192   54  SRR8378434  Non Diabetic

  Simplified_class
0           Normal
1           Normal
2           Normal
3           Normal
4           Normal
```

[6]:
```
meta_data.shape
```

[6]:
```
(192, 7)
```

[7]:
```
print("Number of Normal samples: ", meta_data['Simplified_class'].to_list().
 ↪count("Normal"))
print("Number of Non_advanced_Fibrosis samples: ",␣
 ↪meta_data['Simplified_class'].to_list().count("Non_advanced_Fibrosis"))
print("Number of Advanced_fibrosis: ", meta_data['Simplified_class'].to_list().
 ↪count("Advanced_fibrosis"))
```

```
Number of Normal samples:  74
Number of Non_advanced_Fibrosis samples:  53
Number of Advanced_fibrosis:  65
```

Let's split our data and labels to train and test sets

[9]:
```
X_train, X_test, y_train, y_test = train_test_split(normal_counts.iloc[0:,1:].
 ↪T, meta_data['Simplified_class'], test_size=0.3, random_state = 10101)
```

[10]:
```
X_train.head()
```

[10]:
```
                 0         1         2         3         4         5     \
DLDR_0036  5.820135 -1.060061  4.388400  4.080172  2.564430  3.552685
DLDR_0081  6.546299  0.582165  3.752090  4.645175  3.840899  3.201075
DLDR_0191  6.604050 -0.865036  4.351489  4.072137  3.143138  4.037476
DLDR_0188  6.480745 -1.083676  4.361634  4.313540  3.120196  1.941859
DLDR_0130  6.550016 -1.222374  4.534941  4.370763  3.512952  2.517867

                  6         7         8         9     …     17386     17387  \
DLDR_0036  11.011379  4.682305  6.951539  4.589555  …  4.851631 -0.719024
DLDR_0081  11.433579  3.705547  7.143316  5.482169  …  5.050934  1.681701
DLDR_0191  11.782524  4.358527  8.468526  5.013154  …  5.112244 -2.002540
DLDR_0188  11.451981  4.556052  7.183779  5.066071  …  5.204366  2.086249
DLDR_0130  12.041229  4.315374  7.485927  4.655817  …  5.519093 -0.037949

              17388     17389     17390     17391     17392     17393  \
DLDR_0036 -0.719024 -1.266512 -0.323095  3.157170  0.459313  3.115198
DLDR_0081 -0.640228  0.096738  0.582165  4.041596  0.096738  2.418666
DLDR_0191 -0.076540 -1.154543 -0.624028  2.050571 -1.517113  2.084923
DLDR_0188  0.501286  0.632531 -0.431600  2.616763  1.063165  1.941859
DLDR_0130 -0.289488 -1.874450 -0.981365  2.594319  0.447478  2.556600

              17394     17395
DLDR_0036 -2.645023  0.760969
DLDR_0081 -2.225190  0.582165
DLDR_0191 -4.324468  0.067849
DLDR_0188 -2.306069  0.632531
DLDR_0130 -2.359877  0.932905
```

```
[5 rows x 17396 columns]
```

[11]:
```
X_train.shape
```

[11]:
```
(134, 17396)
```

[12]:
```
y_train.head()
```

[12]:
```
35                     Normal
80          Advanced_fibrosis
190                    Normal
187                    Normal
129    Non_advanced_Fibrosis
Name: Simplified_class, dtype: object
```

[13]:
```
y_train.shape
```

[13]:
```
(134,)
```

Labels distribution in train set:

[14]:
```
print("Number of Normal samples: ", y_train.to_list().count("Normal"))
print("Number of Non_advanced_Fibrosis samples: ", y_train.to_list().
 ↪count("Non_advanced_Fibrosis"))
print("Number of Advanced_fibrosis samples: ", y_train.to_list().
 ↪count("Advanced_fibrosis"))
```

```
Number of Normal samples:  44
Number of Non_advanced_Fibrosis samples:  38
Number of Advanced_fibrosis samples:  52
```

Now, let's save the training set data to use in the R Jupyter Notebook for feature selection

[15]:
```
X_train.T.to_csv('train_normal_counts.csv', index=False)
y_train.T.to_csv('train_meta_data.csv', index=False)
```

Run R Jupyter Notebook Let's load the output of R to continue the task

[16]:
```
subset_data = pd.read_csv('subset_data.csv')
```

[17]:
```
subset_data
```

[17]:
```
     Unnamed: 0  DLDR_0036  DLDR_0081  DLDR_0191  DLDR_0188  DLDR_0130  \
0            10   4.589555   5.482169   5.013154   5.066071   4.655817
1            57  -0.719024   0.582165  -1.154543  -1.083676  -0.289488
2           265   0.587637  -2.225190  -0.076540   0.196432   0.272391
3           275   1.662405   2.529697   1.508422   1.991612   1.467942
4           278   5.529902   5.846272   5.553583   5.359267   5.774549
..          …          …          …          …          …          …
```

```
522      16863  3.811126  3.329399  2.183327  2.412750  3.323819
523      16887  3.576080  2.418666  3.355012  3.288878  3.231084
524      16892  4.007463  3.060212  2.951656  3.366357  2.649112
525      17075  6.925971  7.323632  7.411511  7.189120  7.519400
526      17187 -2.645023 -2.225190 -4.324468 -3.891031 -4.681805

     DLDR_0013  DLDR_0079  DLDR_0131  DLDR_0135  …  DLDR_0175  DLDR_0052  \
0     4.299078   4.752957   5.409514   4.993777  …   4.853565   4.567173
1    -0.006469  -1.138550  -4.060128  -2.104255  …  -2.285986  -0.110595
2     2.523150   1.424386   0.332190   0.217673  …   1.083248   0.352377
3     1.934152   2.031375   2.048397   0.528013  …   1.083248   2.556469
4     4.962662   5.201300   5.500205   5.782051  …   5.862067   5.038603
..         …          …          …          …  …        …          …
522   2.690386   3.515760   3.197260   2.112975  …   1.555316   3.901539
523   3.757011   2.435441   3.079423   2.393996  …   2.974541   3.737944
524   2.774044   3.123117   2.951099   2.974696  …   2.604785   3.934981
525   6.661844   7.087205   7.366661   7.586092  …   7.491543   6.721953
526   0.820694  -3.013019  -4.060128  -4.426183  …  -3.870949  -3.735085

     DLDR_0087  DLDR_0155  DLDR_0092  DLDR_0187  DLDR_0186  DLDR_0179  \
0     4.985158   5.234776   4.900754   4.923087   5.004500   5.058062
1    -0.385647  -3.580073   0.317259  -0.757399  -3.486017  -1.346471
2    -0.309698   0.120366   0.890444  -0.291735   0.811664  -0.246936
3     2.055951   1.374123   1.902221   1.838969   1.643266   1.272439
4     5.665231   5.781140   5.745159   5.438062   5.570169   5.558701
..         …          …          …          …          …          …
522   3.344479   1.911780   3.763838   3.667268   2.742802   2.446087
523   2.476362   2.817958   2.596331   3.203431   3.162640   2.353968
524   3.001089   2.596515   3.945549   4.002569   3.359473   3.497226
525   7.511299   7.684565   7.620817   7.419428   7.417614   7.354464
526  -4.010138  -5.165036  -2.718365  -5.149716  -5.070979  -2.568864

     DLDR_0182  DLDR_0001
0     5.002454   4.221450
1    -1.103280  -0.005377
2     0.416094   2.729099
3     1.932344   2.467558
4     5.733822   5.220121
..         …          …
522   3.857108   2.844001
523   3.445156   3.271068
524   3.563476   2.830128
525   7.633460   6.752731
526  -3.425208   1.202731

[527 rows x 135 columns]
```

[18]:
```
subset_data.shape
```

[18]:
```
(527, 135)
```

We need to extract the same features for the X test dataset as well. To do this, we must identify the indices of our selected DEGs and apply the same subsetting to the test data.

[19]:
```
selected_genes_R = subset_data.T.iloc[0,:].to_list()
```

[20]:
```
selected_genes_Python = [int(i-1) for i in selected_genes_R ]
```

[21]:
```
selected_genes_Python[:10]
```

[21]:
```
[9, 56, 264, 274, 277, 296, 309, 340, 351, 389]
```

[22]:
```
len(selected_genes_Python)
```

[22]:
```
527
```

[23]:
```
df_deg = subset_data.iloc[0:,1:].T
df_deg_test = X_test[selected_genes_Python]
```

[24]:
```
df_deg.head()
```

[24]:
```
                  0         1         2         3         4         5    \
DLDR_0036  4.589555 -0.719024  0.587637  1.662405  5.529902  7.549487
DLDR_0081  5.482169  0.582165 -2.225190  2.529697  5.846272  7.759228
DLDR_0191  5.013154 -1.154543 -0.076540  1.508422  5.553583  7.612538
DLDR_0188  5.066071 -1.083676  0.196432  1.991612  5.359267  8.070057
DLDR_0130  4.655817 -0.289488  0.272391  1.467942  5.774549  7.439405

                  6         7         8         9    …       517       518  \
DLDR_0036  0.318451  6.089009  5.898008  9.044188  …  3.104511  1.602904
DLDR_0081  0.096738  6.539682  6.101239  8.633568  …  2.819204  1.234242
DLDR_0191  1.033084  6.434588  6.098648  8.244201  …  2.275445  0.884985
DLDR_0188  0.356896  6.476384  6.118797  7.951712  …  2.708882  0.356896
DLDR_0130  0.362589  6.486240  6.239292  8.248378  …  2.969247  1.248932

                519       520       521       522       523       524  \
DLDR_0036  0.915692  7.886943  5.319606  3.811126  3.576080  4.007463
DLDR_0081 -0.640228  6.310085  3.797178  3.329399  2.418666  3.060212
DLDR_0191  0.067849  7.139567  3.909152  2.183327  3.355012  2.951656
DLDR_0188 -0.431600  7.167637  4.021858  2.412750  3.288878  3.366357
DLDR_0130 -1.222374  6.106913  3.570860  3.323819  3.231084  2.649112

                525       526
DLDR_0036  6.925971 -2.645023
DLDR_0081  7.323632 -2.225190
```

```
DLDR_0191  7.411511 -4.324468
DLDR_0188  7.189120 -3.891031
DLDR_0130  7.519400 -4.681805

[5 rows x 527 columns]
```

[25]:
```
df_deg_test.head()
```

[25]:
```
                  9        56       264       274       277       296    \
DLDR_0022  3.967031  0.177378  2.880522  2.254454  5.101756  7.696151
DLDR_0016  4.603126  0.002788  2.608214  1.992446  5.079298  7.453528
DLDR_0004  4.003661 -0.178864  2.418699  2.287454  5.125878  6.943351
DLDR_0165  5.286333  0.143691  0.332137  1.587791  5.827910  7.489948
DLDR_0127  5.118729 -0.818750  0.897457  1.530400  5.446251  7.622416

                309       340       351       389   …     16641     16686  \
DLDR_0022  2.077214  5.845657  5.444621  8.076772  …  2.825450  0.246091
DLDR_0016  2.274384  5.735367  5.394124  9.027927  …  2.934201  0.299770
DLDR_0004  2.538993  6.049955  5.583037  8.243201  …  2.418699  0.217065
DLDR_0165  1.225221  6.994423  6.261908  8.733452  …  2.368478  0.143691
DLDR_0127  0.897457  6.472366  5.832644  8.246698  …  2.137661  0.811301

              16715     16731     16762     16862     16886     16891  \
DLDR_0022  0.928350  7.735892  4.644785  2.335526  3.460071  3.723708
DLDR_0016  0.488215  7.956485  5.527246  2.274384  3.722128  3.226652
DLDR_0004 -0.519901  7.122512  3.978350  2.974088  3.280568  2.418699
DLDR_0165  0.389852  6.695064  3.291074  1.485611  2.862085  2.892352
DLDR_0127  1.128783  6.668899  3.631283  3.308569  2.881690  2.101816

              17074     17186
DLDR_0022  6.646771  0.246091
DLDR_0016  6.739625  0.545930
DLDR_0004  6.827647  0.999473
DLDR_0165  7.434889 -3.697611
DLDR_0127  7.391864  0.215197

[5 rows x 527 columns]
```

It's time for classification. I have used four types of classifiers throughout the project to ensure consistency. These classifiers are well-established in machine learning and are well-suited for this task. The classifiers used are: Logistic Regression, Support Vector Machine, Random Forest, and Multilayer Perceptron.

Logistic Regression

[26]:
```
# Logistic Regression
LR_model = LogisticRegression(solver='saga')
LR_model.fit(df_deg, y_train)
```

```
y_pred_LR = LR_model.predict(df_deg_test)
LR_precision = precision_score(y_test, y_pred_LR, average='macro')
LR_recall = recall_score(y_test, y_pred_LR, average='macro')
print(LR_precision)
print(LR_recall)
```

```
0.8010912698412698
0.7752136752136751
```

Support Vector Machine

[27]:
```
# Support Vector Machine
SVM_model = SVC(kernel='linear', C=1)
SVM_model.fit(df_deg, y_train)
y_pred_SVM = SVM_model.predict(df_deg_test)
SVM_precision = precision_score(y_test, y_pred_SVM, average='macro')
SVM_recall = recall_score(y_test, y_pred_SVM, average='macro')
print(SVM_precision)
print(SVM_recall)
```

```
0.8441558441558442
0.8008547008547008
```

Random Forest

[28]:
```
# Random Forest
RF_model = RandomForestClassifier(random_state = 10101)
RF_model.fit(df_deg, y_train)
y_pred_RF = RF_model.predict(df_deg_test)
RF_precision = precision_score(y_test, y_pred_RF, average='macro')
RF_recall = recall_score(y_test, y_pred_RF, average='macro')
print(RF_precision)
print(RF_recall)
```

```
0.7743589743589744
0.7606837606837606
```

Multi Layer Perceptron

[29]:
```
# Multi Layer Perceptron
MLP_model = MLPClassifier(hidden_layer_sizes=(100,), max_iter=300,␣
 ↪activation='relu', solver='adam', random_state = 10101)
MLP_model.fit(df_deg, y_train)
y_pred_MLP = MLP_model.predict(df_deg_test)
MLP_precision = precision_score(y_test, y_pred_MLP, average='macro')
MLP_recall = recall_score(y_test, y_pred_MLP, average='macro')
print(MLP_precision)
print(MLP_recall)
```

```
0.7317550505050505
0.7051282051282052
```

So far, we have obtained only a single result for each classifier, but these results are not statistically valid. To test for reproducibility, we have put the entire process into a loop to run it 100 times. Additionally, we created an R script to perform DE analysis automatically using subprocess. Let's run this cell and save the results for statistical analysis.

[30]:
```
import subprocess

# Load Data
normal_counts = pd.read_csv('Normal.counts.voom.csv')
meta_data = pd.read_csv('meta_data.csv')

n_iterations = 300
test_size = 0.3

LR_precisions = []
LR_recalls = []

SVM_precisions = []
SVM_recalls = []

RF_precisions = []
RF_recalls = []

MLP_precisions = []
MLP_recalls = []

for i in range(100):
    print('iteration',i)
    X_train, X_test, y_train, y_test = train_test_split(normal_counts.iloc[0:,1:
↪].T, meta_data['Simplified_class'], test_size=0.3, random_state = i)
    X_train.T.to_csv('train_normal_counts.csv', index=False)
    y_train.T.to_csv('train_meta_data.csv', index=False)

    r_script_path = r"q1r.R"
    rscript_path = r"C:\Program Files\R\R-4.2.1\bin\Rscript.exe"
    # Execute the R script
    try:
            subprocess.run([rscript_path, r_script_path], capture_output=True,␣
↪text=True)
    except subprocess.CalledProcessError as e:
            print(f"Error executing R script: {e}")

    #
    subset_data = pd.read_csv('subset_data.csv')
    selected_genes_R = subset_data.T.iloc[0,:].to_list()
    selected_genes_Python = [int(i-1) for i in selected_genes_R ]
    df_deg = subset_data.iloc[0:,1:].T
```

```
    df_deg_test = X_test[selected_genes_Python]


    # Logistic Regression
    LR_model = LogisticRegression(solver='saga')
    LR_model.fit(df_deg, y_train)
    y_pred_LR = LR_model.predict(df_deg_test)
    LR_precision = precision_score(y_test, y_pred_LR, average='macro')
    LR_recall = recall_score(y_test, y_pred_LR, average='macro')
    LR_precisions.append(LR_precision)
    LR_recalls.append(LR_recall)

    # Support Vector Machine
    SVM_model = SVC(kernel='linear', C=1)
    SVM_model.fit(df_deg, y_train)
    y_pred_SVM = SVM_model.predict(df_deg_test)
    SVM_precision = precision_score(y_test, y_pred_SVM, average='macro')
    SVM_recall = recall_score(y_test, y_pred_SVM, average='macro')
    SVM_precisions.append(SVM_precision)
    SVM_recalls.append(SVM_recall)

    # Random Forest
    RF_model = RandomForestClassifier(random_state = i)
    RF_model.fit(df_deg, y_train)
    y_pred_RF = RF_model.predict(df_deg_test)
    RF_precision = precision_score(y_test, y_pred_RF, average='macro')
    RF_recall = recall_score(y_test, y_pred_RF, average='macro')
    RF_precisions.append(RF_precision)
    RF_recalls.append(RF_recall)

    # Multi Layer Perceptron
    MLP_model = MLPClassifier(hidden_layer_sizes=(100,), max_iter=300,␣
↪activation='relu', solver='adam', random_state = i)
    MLP_model.fit(df_deg, y_train)
    y_pred_MLP = MLP_model.predict(df_deg_test)
    MLP_precision = precision_score(y_test, y_pred_MLP, average='macro')
    MLP_recall = recall_score(y_test, y_pred_MLP, average='macro')
    MLP_precisions.append(MLP_precision)
    MLP_recalls.append(MLP_recall)
```

```
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iteration 99
```

Last but not least, we need to report the average and confidence interval for the results of each classifier. We will also create a bar plot to visually compare the results of the classifiers.

```
[31]: LR_mean_precision = np.mean(LR_precisions)
LR_mean_recall = np.mean(LR_recalls)
LR_precision_conf_interval = np.percentile(LR_precisions, [2.5, 97.5])
LR_recall_conf_interval = np.percentile(LR_recalls, [2.5, 97.5])
print(f'Mean Precision for Logistic Regression: {LR_mean_precision}, 95% CI:␣
 ↪{LR_precision_conf_interval}')
print(f'Mean Recall for Logistic Regression: {LR_mean_recall}, 95% CI:␣
 ↪{LR_recall_conf_interval}')
print("---------------------------------------------------------------------------------------

SVM_mean_precision = np.mean(SVM_precisions)
SVM_mean_recall = np.mean(SVM_recalls)
SVM_precision_conf_interval = np.percentile(SVM_precisions, [2.5, 97.5])
SVM_recall_conf_interval = np.percentile(SVM_recalls, [2.5, 97.5])
print(f'Mean Precision for Support Vector Machine: {SVM_mean_precision}, 95% CI:
 ↪ {SVM_precision_conf_interval}')
print(f'Mean Recall for Support Vector Machine: {SVM_mean_recall}, 95% CI:␣
 ↪{SVM_recall_conf_interval}')
print("---------------------------------------------------------------------------------------

RF_mean_precision = np.mean(RF_precisions)
RF_mean_recall = np.mean(RF_recalls)
RF_precision_conf_interval = np.percentile(RF_precisions, [2.5, 97.5])
RF_recall_conf_interval = np.percentile(RF_recalls, [2.5, 97.5])
print(f'Mean Precision for Random Forest: {RF_mean_precision}, 95% CI:␣
 ↪{RF_precision_conf_interval}')
print(f'Mean Recall for Random Forest: {RF_mean_recall}, 95% CI:␣
 ↪{RF_recall_conf_interval}')
print("---------------------------------------------------------------------------------------

MLP_mean_precision = np.mean(MLP_precisions)
MLP_mean_recall = np.mean(MLP_recalls)
MLP_precision_conf_interval = np.percentile(MLP_precisions, [2.5, 97.5])
MLP_recall_conf_interval = np.percentile(MLP_recalls, [2.5, 97.5])
print(f'Mean Precision for Multi Layer Perceptron: {MLP_mean_precision}, 95% CI:
 ↪ {MLP_precision_conf_interval}')
print(f'Mean Recall for Multi Layer Perceptron: {MLP_mean_recall}, 95% CI:␣
 ↪{MLP_recall_conf_interval}')
```

```
Mean Precision for Logistic Regression: 0.7636803304888079, 95% CI: [0.64076229
0.85890152]
Mean Recall for Logistic Regression: 0.7645416569253737, 95% CI: [0.63156272
0.87401786]
--------------------------------------------------------------------------------
-----------------
Mean Precision for Support Vector Machine: 0.7743040927880918, 95% CI:
[0.66116453 0.85674319]
```

```
Mean Recall for Support Vector Machine: 0.7723320280185707, 95% CI: [0.65753472
0.86513971]
--------------------------------------------------------------------------------
-----------------
Mean Precision for Random Forest: 0.7860810773240244, 95% CI: [0.6725455
0.87525208]
Mean Recall for Random Forest: 0.7867412414621653, 95% CI: [0.65607372
0.88233974]
--------------------------------------------------------------------------------
-----------------
Mean Precision for Multi Layer Perceptron: 0.7677514303520464, 95% CI:
[0.65656233 0.85438582]
Mean Recall for Multi Layer Perceptron: 0.7618658834643532, 95% CI: [0.6144042
0.8572071]
```

[32]:
```
model_results = {
    'RandomForest': {
        'mean_precision': RF_mean_precision,
        'precision_ci': RF_precision_conf_interval,
        'mean_recall': RF_mean_recall,
        'recall_ci': RF_precision_conf_interval
    },
    'SVM': {
        'mean_precision': SVM_mean_precision,
        'precision_ci': SVM_precision_conf_interval,
        'mean_recall': SVM_mean_recall,
        'recall_ci': SVM_precision_conf_interval
    },
        'LogisticRegression': {
        'mean_precision': LR_mean_precision,
        'precision_ci': LR_precision_conf_interval,
        'mean_recall': LR_mean_recall,
        'recall_ci': LR_precision_conf_interval
    },
    'MLP': {
        'mean_precision': MLP_mean_precision,
        'precision_ci': MLP_precision_conf_interval,
        'mean_recall': MLP_mean_recall,
        'recall_ci': MLP_precision_conf_interval
    }
}
```

[33]:
```
models = list(model_results.keys())
mean_precisions = [model_results[model]['mean_precision'] for model in models]
precision_cis = [model_results[model]['precision_ci'] for model in models]
mean_recalls = [model_results[model]['mean_recall'] for model in models]
recall_cis = [model_results[model]['recall_ci'] for model in models]
```

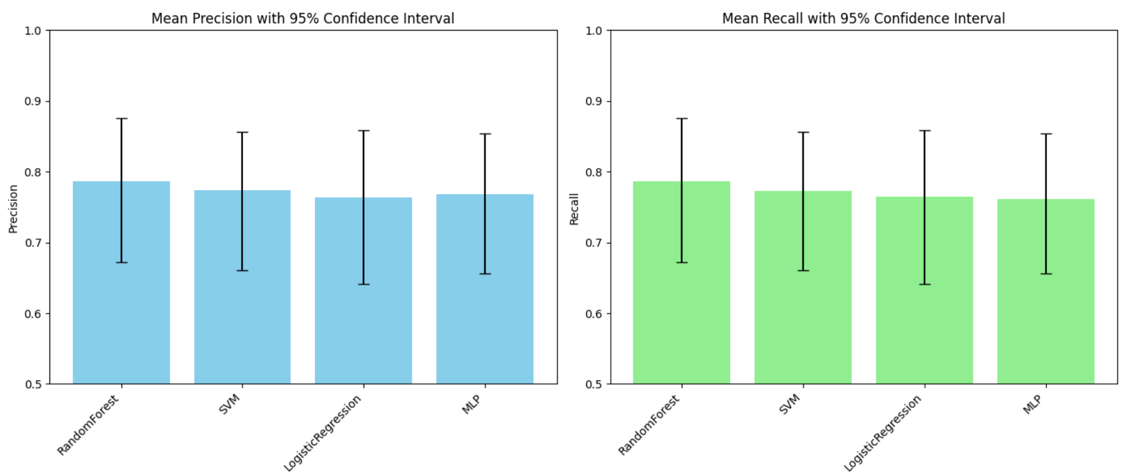
```
precision_errors = np.array([[mean - ci[0], ci[1] - mean] for mean, ci in␣
 ↪zip(mean_precisions, precision_cis)]).T
recall_errors = np.array([[mean - ci[0], ci[1] - mean] for mean, ci in␣
 ↪zip(mean_recalls, recall_cis)]).T
```

[34]:
```
fig, ax = plt.subplots(1, 2, figsize=(14, 6))

# Plot precision
ax[0].bar(models, mean_precisions, yerr=precision_errors, capsize=5,␣
 ↪color='skyblue')
ax[0].set_title('Mean Precision with 95% Confidence Interval')
ax[0].set_ylabel('Precision')
ax[0].set_ylim([0.5, 1])
ax[0].set_xticklabels(models, rotation=45, ha="right")

# Plot recall
ax[1].bar(models, mean_recalls, yerr=recall_errors, capsize=5,␣
 ↪color='lightgreen')
ax[1].set_title('Mean Recall with 95% Confidence Interval')
ax[1].set_ylabel('Recall')
ax[1].set_ylim([0.5, 1])
ax[1].set_xticklabels(models, rotation=45, ha="right")

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



Here are the final results: as you can see, the performance of the classifiers is very similar, with none of them significantly outperforming the others. However, Random Forest exhibits slightly higher precision and recall compared to the other models.