AAI_501_assignment_4.1_ajmal-jalal

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1 Classification Using Scikit-learn

In this homework you will learn how to build a basic supervised learning algorithm (classification) using the most popular Python machine learning library, scikit-learn. You will follow the 3 canonical steps for building a model:

1) Data preparation
2) Model fitting
3) Model evaluation & selection

We will use the World Happiness Report (WHR) data, bringing in some additional information that will enable us to formulate a classification problem to predict categorical labels on the dataset.

2 Data Preparation

Execute the code cell below to import some modules and read in and preprocess the WHR data. The last line in the code cell below returns the head of the basic WHR dataframe, to show you what is in that dataset.

[15]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

dfraw = pd.read_excel('WHR2018Chapter2OnlineData.xls', sheet_name='Table2.1')
cols_to_include = ['country', 'year', 'Life Ladder',
                   'Positive affect','Negative affect',
                   'Log GDP per capita', 'Social support',
                   'Healthy life expectancy at birth',
                   'Freedom to make life choices',
                   'Generosity', 'Perceptions of corruption']
renaming = {'Life Ladder': 'Happiness',
            'Log GDP per capita': 'LogGDP',
            'Social support': 'Support',
            'Healthy life expectancy at birth': 'Life',
            'Freedom to make life choices': 'Freedom',
            'Perceptions of corruption': 'Corruption',
            'Positive affect': 'Positive',
```

```
            'Negative affect': 'Negative'}
df = dfraw[cols_to_include].rename(renaming, axis=1)
key_vars = ['Happiness', 'LogGDP', 'Support', 'Life', 'Freedom', 'Generosity',␣
 ↪'Corruption', 'Positive', 'Negative']
df.head()
```

[15]:

```
       country  year  Happiness  Positive  Negative    LogGDP   Support  \
0  Afghanistan  2008   3.723590  0.517637  0.258195  7.168690  0.450662
1  Afghanistan  2009   4.401778  0.583926  0.237092  7.333790  0.552308
2  Afghanistan  2010   4.758381  0.618265  0.275324  7.386629  0.539075
3  Afghanistan  2011   3.831719  0.611387  0.267175  7.415019  0.521104
4  Afghanistan  2012   3.782938  0.710385  0.267919  7.517126  0.520637

        Life   Freedom  Generosity  Corruption
0  49.209663  0.718114    0.181819    0.881686
1  49.624432  0.678896    0.203614    0.850035
2  50.008961  0.600127    0.137630    0.706766
3  50.367298  0.495901    0.175329    0.731109
4  50.709263  0.530935    0.247159    0.775620
```

2.0.1 Step 1.

First, we will augment the core WHR dataset to bring in some additional information that is included in a different worksheet. Since this is mostly about data processing rather than machine learning, simply execute the next two code cells below. But study each line of code and the associated comments, and then examine the head of the new dataframe named `df2` to understand what has been done.

[16]:

```
# read in data from SupportingFactors worksheet into a new dataframe dfsupp
dfsupp = pd.read_excel('WHR2018Chapter2OnlineData.xls',␣
 ↪sheet_name='SupportingFactors')

# extract out region information from SupportingFactors dataframe
regions = dfsupp[['country', 'Region indicator']].rename({'Region indicator':␣
 ↪'region'}, axis=1)

# examine head of regions dataframe -- each country has an associated world␣
 ↪region
regions.head()
```

[16]:

```
       country                       region
0  Afghanistan                   South Asia
1      Albania   Central and Eastern Europe
2      Algeria  Middle East and North Africa
3       Angola           Sub-Saharan Africa
4    Argentina    Latin America and Caribbean
```

```
[18]: # compute the mean values of all the WHR data for each country, averaging over
      ↪all years in the dataset
dfmean = df.groupby('country').mean().drop('year', axis=1)

# merge the mean WHR data with the region information extracted previously
df2 = pd.merge(dfmean, regions, on='country').dropna()

# set the index of df2 to be the country name
df2.set_index('country', inplace=True)

# examine head of df2 dataframe -- mean WHR values for each country, along with
      ↪associated regions
df2.head()
```

```
[18]:              Happiness  Positive  Negative    LogGDP   Support       Life  \
country
Afghanistan     3.806614  0.580873  0.301283  7.419697  0.517146  50.838271
Albania         4.988791  0.642628  0.303256  9.247059  0.723204  68.027213
Algeria         5.555004  0.616524  0.265460  9.501728  0.804633  64.984461
Angola          4.420299  0.613339  0.351173  8.713935  0.737973  51.729801
Argentina       6.406131  0.840998  0.273187  9.826051  0.906080  66.764205

              Freedom  Generosity  Corruption                        region
country
Afghanistan  0.544895    0.118428    0.826794                    South Asia
Albania      0.626155   -0.105019    0.859691    Central and Eastern Europe
Algeria      0.536398   -0.208236    0.661478  Middle East and North Africa
Angola       0.455957   -0.077940    0.867018            Sub-Saharan Africa
Argentina    0.753122   -0.154544    0.844038   Latin America and Caribbean
```

2.0.2 Step 2.

This new dataframe `df2` is what we want to use for our machine learning task. For each country in the dataset, we have a set of numerical values ('Happiness', 'Positive', 'Negative', etc., which are all listed in the variable `key_vars`) and a categorical value ('region'). We would like to know if the raw numerical data are predictive of the region. In other words, if someone gave you a set of numerical data on Happiness, etc. for an unknown country, would you be able to predict what region of the world it might be located in? This is an example of classification, where we will train a model based on the numerical data and the associated labels (regions).

In order to proceed, we first want to extract and process some data from our `df2` dataframe. We need to separate the data into two parts: * the region data that we want to be able to predict (we'll call it `y`) * the WHR numerical data that we want to use as input to our prediction (we'll call it `x`)

Again, our goal is to build a classifier that we will train on a subset of the WHR numerical data (x) and the region data (y), so that we can predict regions from data for countries that we have not trained our model on.

In the code cell below: * Extract the subset of `df2` associated with the columns in `key_vars` and assign it to the variable `x`. * Extract the subset of `df2` associated with the region column, and assign it to the variable `y`. * Print the shape of both `x` and `y`.

2.1 Graded Cell

This cell is worth 5% of the grade for this assignment.

[19]:
```
# Extracting the subset of df2 associated with the columns in key_vars and␣
↪assign it to x
x = df2[key_vars]

# Extract the subset of df2 associated with the 'region' column and assign it␣
↪to y
y = df2['region']

# Print the shape of both x and y
print("Shape of x:", x.shape)
print("Shape of y:", y.shape)
```

```
Shape of x: (152, 9)
Shape of y: (152,)
```

2.1.1 Step 3.

You should see that the shape of `x` is (152, 9) and the shape of `y` is (152,). There are 152 samples (countries), and 9 features (each of the key_vars) that we are using to make predictions.

Note that the numerical data columns in `x` represent different quantities and have different scales. A key step in machine learning is *standardization*: the transformation of features to be on the same scale (with a mean of 0 and a standard deviation of 1). Standardization can substantially increase model accuracy, performance and interpretability.

`sklearn` provides various utilities to perform standardization. We will use one here called `StandardScaler`, which will transform a data set so that each resulting column has zero mean and unit standard deviation.

Carrying out this scaling is a little complicated if we want to maintain the basic structure of our dataframe, so we have provided the relevant code in the next code cell below. (The code examples describing StandardScaler in the sklearn documentation typically just extract out the numerical values in numpy arrays. For this exercise, we'd like to keep the labels together in a dataframe.)

Please perform the following steps in the below graded cell: * Import the `StandardScaler` object * Create and fit a `StandardScaler` object to our dataframe `x` * Create a new dataframe `x_scaled` that contains the scaled (transformed) data, using the column and index labels from our unscaled dataframe `x` * Print out the mean and standard deviation of each column of `x_scaled` * Peek at the head of the new dataframe `x_scaled`

In examining the output, check that the means of each column have been scaled to nearly zero (to within a very small tolerance) and the standard deviations have been scaled to one. Some of the very small numbers might be printed out in scientific notation, where a number like `1.928282e-16` means `1.928282 * 10**(-16)`.

2.2 Graded Cell

This cell is worth 20% of the grade for this assignment.

[20]:
```python
from sklearn.preprocessing import StandardScaler

# Creating a StandardScaler object
scaler = StandardScaler()

# Fitting the StandardScaler to the dataframe x
scaler.fit(x)

# Transforming the data and creating a new dataframe x_scaled with the same␣
↪columns and index as x
x_scaled = pd.DataFrame(scaler.transform(x), columns=x.columns, index=x.index)

# Printing out the mean of each column in x_scaled
print("Mean of each column in x_scaled:")
print(x_scaled.mean())

# Printing out the standard deviation of each column in x_scaled
print("\nStandard Deviation of each column in x_scaled:")
print(x_scaled.std())

# Peek at the first few rows of the x_scaled dataframe
print("\nHead of x_scaled:")
print(x_scaled.head())
```

```
Mean of each column in x_scaled:
Happiness     1.782200e-16
LogGDP        6.135443e-17
Support      -2.337312e-16
Life         -5.843279e-17
Freedom       6.748987e-16
Generosity    1.168656e-17
Corruption    9.349247e-17
Positive      1.811417e-16
Negative      2.337312e-16
dtype: float64

Standard Deviation of each column in x_scaled:
Happiness     1.003306
LogGDP        1.003306
Support       1.003306
Life          1.003306
Freedom       1.003306
Generosity    1.003306
Corruption    1.003306
```

```
Positive      1.003306
Negative      1.003306
dtype: float64

Head of x_scaled:
             Happiness    LogGDP   Support      Life   Freedom  Generosity  \
country
Afghanistan  -1.443128 -1.438896 -2.425953 -1.333584 -1.397623    0.735439
Albania      -0.360792  0.054466 -0.681799  0.776161 -0.776670   -0.719736
Algeria       0.157600  0.262588  0.007447  0.402698 -1.462554   -1.391919
Angola       -0.881273 -0.381215 -0.556782 -1.224159 -2.077245   -0.543385
Argentina     0.936845  0.527632  0.866136  0.621142  0.193546   -1.042257

             Corruption  Positive  Negative
country
Afghanistan    0.451854 -1.262731  0.471370
Albania        0.632648 -0.638194  0.499009
Algeria       -0.456675 -0.902184 -0.030449
Angola         0.672914 -0.934399  1.170248
Argentina      0.546624  1.367958  0.077797
```

3 Model Fitting

3.0.1 Step 4.

Now that the data has been preprocessed, we can begin with our classification analysis. Let's start by importing some additional tools from `sklearn`. Execute the code cell below to import: * the `svm` and `tree` submodules * the `train_test_split` function * the `accuracy_score` function

We'll discuss in more detail below what each of these does.

[21]:
```
from sklearn import svm, tree
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

3.0.2 Step 5.

One of the convenience functions that we imported above is called `train_test_split`. As its name suggests, this function splits a dataset into separate training and testing sets. The online documentation indicates that it splits a dataset randomly, such that approximately 25% of the data winds up in the test set and the remaining 75% in the training set. Note that the documentation is a bit confusing, since the function can take a variable number of arrays as inputs. In our case, we want to split up 2 arrays (`x_scaled` and `y`) into coordinated test and train sets, so that the function will return a total of 4 subarrays (`x_train, x_test, y_train, y_test`).

Because `train_test_split` generates random splits of the input data, each time we call the function we will get a different split. For the purposes of code development, it's useful to be able to get reproducible random numbers or random splits, as it makes debugging and model improvements much easer. This can then be relaxed once one wishes to generate statistics over many random runs. With `train_test_split`, this can be accomplished by using the `random_state` option; if specified with that state as an integer, then the same random split will be generated each time the function is called (until one changes the value of the integer). This is known as providing a seed to the pseudo-random number generator that is used by `train_test_split`.

You may enter and execute a call to `train_test_split` that takes `x_scaled` and `y` as inputs, along with the optional parameter `random_state=0`, and returns the 4 data subsets mentioned above, to be named as `x_train`, `x_test`, `y_train`, `y_test`. The online documentation provides an example of what such a function call looks like. After the function call, print the shapes of each of the four arrays that are returned.

At first pass, it makes sense to simply apply `train_test_split()` directly to `x_scaled` and `y`; however, there is a subtle downside. Performing standardization prior to `train_test_split()` potentially leads to 'information leakage' whereby information about the testing dataset (its underlying distribution) is learned during the training phase. This is because the testing data distribution is used to scale the training dataset.

In the code cell below, please perform `train_test_split()` first before applying `StandardScaler().fit()` *only* to the training dataset. Use that fit to transform the training dataset and the testing dataset separately. Ultimately, you should end up with the variables `x_train_scale`, `x_test_scale`, `y_train` and '`y_test`.

3.1 Graded Cell

This cell is worth 5% of the grade for this assignment.

[22]:
```
# Performing train_test_split on x and y with random_state=0
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0)

# Creating and fitting StandardScaler only on the training data
scaler = StandardScaler()
scaler.fit(x_train)

# Transforming both training and testing data
x_train_scale = scaler.transform(x_train)
x_test_scale = scaler.transform(x_test)

# Printing the shapes of the resulting datasets
print("Shape of x_train_scale:", x_train_scale.shape)
print("Shape of x_test_scale:", x_test_scale.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of x_train_scale: (114, 9)
Shape of x_test_scale: (38, 9)
Shape of y_train: (114,)
Shape of y_test: (38,)
```

3.1.1 Step 6.

Having split our datasets, we want to first train a classifier on our training data so that we can apply it to the testing data. One way of assessing the performance of a classifier is to compute its accuracy on the test data. That is, what fraction of the test data are correctly predicted by the classifier? Fortunately, `sklearn` provides a built-in function named `accuracy_score` that carries out this computation. We imported it above, and you can read more about it in the documentation.

We also imported above the `svm` and `tree` submodules from sklearn. These provide support for Support Vector Machine (svm) and Decision Tree (tree) machine learning algorithms. For more information, review the Support Vector Machines (SVMs) documentation and the Decision Trees documentation. Under the hood, these are very different types of algorithms. Decision Trees try to formulate a series of yes/no questions based on the data that can distinguish the categories from one another. SVMs, on the other hand, use techniques from geometry to find cuts through the data space to separate different categories from one another. Understanding how these methods work in detail is beyond the scope of this exercise, but fortunately (despite the very different data structures and algorithms used internally) `sklearn` provides a uniform interface that lets us easily build these different sorts of classifiers and compare their performance.

We will first consider SVMs, and then revisit the problem with Decision Trees.

In the code cell below: * create a new `svm.SVC()` object and assign it to the variable `clf1` — a call to `svm.SVC()` creates a Support Vector Classifier from the svm submodule, similar to what we did in the earlier exercise on hand-written digits * call the `fit` method on `clf1` with the `x_train_scale` and `y_train` training data (i.e., training the model to associate `x_train_scale` with `y_train`) * call the `predict` method on `clf1` on the `x_test_scale` testing data and assign the result to the variable `predictions1`, in order to make predictions for those inputs * call the `accuracy_score` function on the `y` testing data and the test predictions you generated and assign the result to the variable `score1` * print the value of `score1`

The accuracy score is a fraction between 0 and 1 indicating the fraction of predictions that match the true value in the test set.

3.2 Graded Cell

This cell is worth 20% of the grade for this assignment.

[23]:
```
# Creating a Support Vector Classifier (SVM) object
clf1 = svm.SVC()

# Fitting the SVM model to the training data
clf1.fit(x_train_scale, y_train)

# Making predictions on the testing data
predictions1 = clf1.predict(x_test_scale)

# Calculating the accuracy of the predictions
score1 = accuracy_score(y_test, predictions1)

# Printing the accuracy score
```

```
print("Accuracy of SVM classifier:", score1)
```

```
Accuracy of SVM classifier: 0.7105263157894737
```

3.2.1 Step 7.

The accuracy score reported should be around 71% (0.71). This means that approximately 29% of the countries in the test set had their regions mispredicted. While that doesn't sound great, it could be that the WHR numerical data are not always completely predictive of region. One could imagine some countries that are "outliers" in a particular region, and more closely resemble other regions based on the WHR indicators.

In the below code cell, please loop over all the predicted and true values in the test set, and prints out the country name and predicted region when the prediction is incorrect. An output line like: `Sri Lanka : South Asia -> Sub-Saharan Africa` means that Sri Lanka is actually part of the South Asia region but was predicted to be part of Sub-Saharan Africa.

3.3 Graded Cell

This cell is worth 10% of the grade for this assignment.

[24]:
```
# Looping over all predicted and true values in the test set
for country, actual, predicted in zip(x_test.index, y_test, predictions1):
    if actual != predicted:
        print(f"{country} : {actual} -> {predicted}")
```

```
Israel : Middle East and North Africa -> Western Europe
Sri Lanka : South Asia -> Sub-Saharan Africa
Tajikistan : Commonwealth of Independent States -> Sub-Saharan Africa
Yemen : Middle East and North Africa -> Sub-Saharan Africa
Hong Kong S.A.R. of China : East Asia -> Western Europe
Philippines : Southeast Asia -> Latin America and Caribbean
Italy : Western Europe -> Central and Eastern Europe
Slovenia : Central and Eastern Europe -> Western Europe
Gabon : Sub-Saharan Africa -> Middle East and North Africa
Azerbaijan : Commonwealth of Independent States -> Middle East and North Africa
Malaysia : Southeast Asia -> Latin America and Caribbean
```

4 Model evaluation & selection

4.0.1 Step 8.

It is often not obvious what specific algorithm will work best for a particular dataset, so it is good to be able to conduct numerical experiments to see how different methods perform (even if we might not fully understand *why* one method might work better than another). Because `sklearn` provides a consistent interface to very different types of underlying algorithms, it is easy to build additional classifiers to carry out these kinds of comparisons. Here, we will build a second classifier based on Decision Trees as supported by the `tree` module. Decision Tree algorithms have an element of randomness to them, so a Decision Tree can also be constructed with a specified `random_state` such as an integer that seeds the random number generator. Most of what we will do here is very similar to the code you wrote a few cells up when you built a SVC classifier.

In the code cell below:

- Create a new `tree.DecisionTreeClassifier()` object with the optional argument `random_state=0`, and assign it to the variable `clf2` (`clf2` stands for "classifier number 2", so that we can compare with `clf1` above).
- Call the `fit` method on `clf2` with the `x_train_scale` and `y_train` training data (i.e., training the model to associate `x_train_scale` with `y_train`).
- Call the `predict` method on `clf2` on the `x_test_scale` testing data and assign the result to the variable `predictions2`, in order to make predictions for those inputs.
- Call the `accuracy_score` function on the `y_test` testing data and the test predictions you generated and assign the result to the variable `score2`.
- Print the value of `score2`.

4.1 Graded Cell

This cell is worth 10% of the grade for this assignment.

[25]:
```python
from sklearn.tree import DecisionTreeClassifier



# Creating a Decision Tree Classifier with random_state=0
clf2 = DecisionTreeClassifier(random_state=0)

# Fitting the Decision Tree model to the training data
clf2.fit(x_train_scale, y_train)

# Making predictions on the testing data using the Decision Tree model
predictions2 = clf2.predict(x_test_scale)

# Calculating the accuracy of the Decision Tree predictions
score2 = accuracy_score(y_test, predictions2)

# Printing the accuracy score of the Decision Tree classifier
print("Accuracy of Decision Tree classifier:", score2)
```

```
Accuracy of Decision Tree classifier: 0.7631578947368421
```

4.1.1 Step 9.

We ran two classifiers — `clf1` (SVM) and `clf2` (Decision Tree) — on a particular random `train_test_split` of the full dataset. We can't really reach any conclusions about the relative performance of the two methods just by considering one split. Given that `train_test_split` can produce different random splits, let's write a little code to compare the two classifiers for different splits.

In the code cell below, write some code to do the following: * Write a Python `for` loop so that you can run through the loop 20 times * Within each pass through the loop, do the following: *

Call `test_train_split` on `x` and `y` to get new random instances of `x_train`, `x_test`, `y_train`, `y_test` – in this case, you don't want to pass in a value for `random_state` since you want to get different random splits each time * Fit StandardScaler to `x_train`, and use it to transform both `x_train` and `x_test` into `x_train_scaled` and `x_train_test` * Fit each of the classifiers `clf1` and `clf2` to `x_train_scaled` and `y_train` * Run predictions on each of the classifiers `clf1` and `clf2` on the `x_test_scaled` and `y_test` testing data * Compute the accuracy_score of each of the two classifiers on the test data and the test predictions you generated * Print the score of each classifier, as well as their difference (hint: `print(score1, score2, score1-score2)` to get just one line of output per iteration of the loop)

Execute the code you have written. You should see it run through the loop 20 times, for different random data splits. While the overall performance varies from run to run, you should probably see that the SVC classifier (`clf1`) generally performs a little bit better than the DecisionTree classifier (`clf2`).

4.2 Graded Cell

This cell is worth 10% of the grade for this assignment.

[26]:
```
# Since clf1 and clf2 are simple classifier objects, re-instantiating them␣
↪inside the loop ensures independence

for i in range(20):
    # Splitting the data without specifying random_state for different splits␣
↪each time
    x_train, x_test, y_train, y_test = train_test_split(x, y)

    # Initializing and fitting StandardScaler on the training data
    scaler = StandardScaler()
    scaler.fit(x_train)

    # Transforming both training and testing data
    x_train_scaled = scaler.transform(x_train)
    x_test_scaled = scaler.transform(x_test)

    # Initializing classifiers
    clf1 = svm.SVC()
    clf2 = tree.DecisionTreeClassifier(random_state=0)

    # Fitting the classifiers on the scaled training data
    clf1.fit(x_train_scaled, y_train)
    clf2.fit(x_train_scaled, y_train)

    # Making predictions on the scaled testing data
    predictions1 = clf1.predict(x_test_scaled)
    predictions2 = clf2.predict(x_test_scaled)

    # Calculating accuracy scores
```

```
    score1 = accuracy_score(y_test, predictions1)
    score2 = accuracy_score(y_test, predictions2)

    # Printing the accuracy scores and their difference
    print(f"Iteration {i+1}: SVM Accuracy = {score1:.2f}, Decision Tree␣
↪Accuracy = {score2:.2f}, Difference = {score1 - score2:.2f}")
```

```
Iteration 1: SVM Accuracy = 0.53, Decision Tree Accuracy = 0.45, Difference =
0.08
Iteration 2: SVM Accuracy = 0.82, Decision Tree Accuracy = 0.63, Difference =
0.18
Iteration 3: SVM Accuracy = 0.71, Decision Tree Accuracy = 0.55, Difference =
0.16
Iteration 4: SVM Accuracy = 0.61, Decision Tree Accuracy = 0.58, Difference =
0.03
Iteration 5: SVM Accuracy = 0.53, Decision Tree Accuracy = 0.53, Difference =
0.00
Iteration 6: SVM Accuracy = 0.71, Decision Tree Accuracy = 0.61, Difference =
0.11
Iteration 7: SVM Accuracy = 0.68, Decision Tree Accuracy = 0.61, Difference =
0.08
Iteration 8: SVM Accuracy = 0.71, Decision Tree Accuracy = 0.61, Difference =
0.11
Iteration 9: SVM Accuracy = 0.53, Decision Tree Accuracy = 0.63, Difference =
-0.11
Iteration 10: SVM Accuracy = 0.76, Decision Tree Accuracy = 0.74, Difference =
0.03
Iteration 11: SVM Accuracy = 0.68, Decision Tree Accuracy = 0.63, Difference =
0.05
Iteration 12: SVM Accuracy = 0.68, Decision Tree Accuracy = 0.66, Difference =
0.03
Iteration 13: SVM Accuracy = 0.84, Decision Tree Accuracy = 0.66, Difference =
0.18
Iteration 14: SVM Accuracy = 0.71, Decision Tree Accuracy = 0.55, Difference =
0.16
Iteration 15: SVM Accuracy = 0.63, Decision Tree Accuracy = 0.61, Difference =
0.03
Iteration 16: SVM Accuracy = 0.66, Decision Tree Accuracy = 0.53, Difference =
0.13
Iteration 17: SVM Accuracy = 0.61, Decision Tree Accuracy = 0.42, Difference =
0.18
Iteration 18: SVM Accuracy = 0.61, Decision Tree Accuracy = 0.50, Difference =
0.11
Iteration 19: SVM Accuracy = 0.71, Decision Tree Accuracy = 0.74, Difference =
-0.03
Iteration 20: SVM Accuracy = 0.61, Decision Tree Accuracy = 0.53, Difference =
0.08
```

4.2.1 Step 10.

In the last code cell, you printed out the scores of the two classifiers for a small number of random splits, and examined the numerical output. Perhaps you'd rather generate a visual summary of the relative performance of the two classifiers, for a larger number of runs.

In the code cell below, copy and paste the code you wrote above and modify it to do the following:

- prior to entering the `for` loop, initialize two empty lists named `all_scores1` and `all_scores2` that will be used to collect the scores of each classifier each time through the loop
- run through the loop 1000 times instead of 20 as before
- append the scores (`score1` and `score2`) to each of the lists used to contain all the scores
- remove the print statement so that you don't get 1000 annoying print statements when you run the code
- once the loop is finished, use the `plt.hist` function to plot histograms for `all_scores1` and `all_scores2` together in the same plot
  - you can accomplish this by making two successive calls to the histogram function within the same code cell
  - you might want to add options to change the number of bins for the histograms
  - you should change the alpha value (opacity) of the histogram plots so that you can see both distributions, since at full opacity, the second one plotted will obscure the first one
  - you should use the `label` option to label the datasets
- After making your two calls to `plt.hist`, you should call `plt.legend` to produce a legend on the plot that will identify the two datasets based on the label options that you added to your `plt.hist` calls

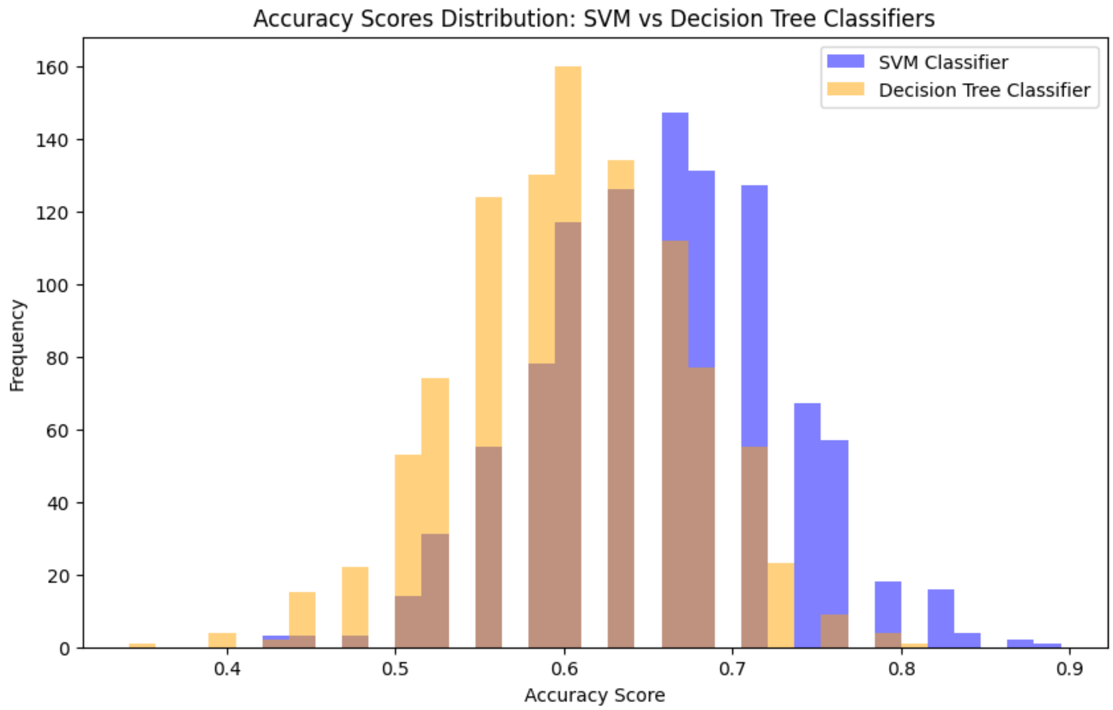
4.3 Graded Cell

This cell is worth 20% of the grade for this assignment.

[27]:
```python
import matplotlib.pyplot as plt

# Initializing empty lists to collect accuracy scores
all_scores1 = []
all_scores2 = []

# Running the loop 1000 times for different random splits
for i in range(1000):
    # Splitting the data without specifying random_state for different splits␣
 ↪each time
    x_train, x_test, y_train, y_test = train_test_split(x, y)

    # Initializing and fitting StandardScaler on the training data
    scaler = StandardScaler()
    scaler.fit(x_train)

    # Transforming both training and testing data
    x_train_scaled = scaler.transform(x_train)
    x_test_scaled = scaler.transform(x_test)
```

```
    # Initializing classifiers
    clf1 = svm.SVC()
    clf2 = tree.DecisionTreeClassifier(random_state=0)

    # Fitting the classifiers on the scaled training data
    clf1.fit(x_train_scaled, y_train)
    clf2.fit(x_train_scaled, y_train)

    # Making predictions on the scaled testing data
    predictions1 = clf1.predict(x_test_scaled)
    predictions2 = clf2.predict(x_test_scaled)

    # Calculating accuracy scores
    score1 = accuracy_score(y_test, predictions1)
    score2 = accuracy_score(y_test, predictions2)

    # Appending the scores to the respective lists
    all_scores1.append(score1)
    all_scores2.append(score2)

# Plotting the histograms of accuracy scores for both classifiers
plt.figure(figsize=(10, 6))

# Histogram for SVM classifier
plt.hist(all_scores1, bins=30, alpha=0.5, label='SVM Classifier', color='blue')

# Histogram for Decision Tree classifier
plt.hist(all_scores2, bins=30, alpha=0.5, label='Decision Tree Classifier',␣
 ↪color='orange')

# Adding title and labels
plt.title('Accuracy Scores Distribution: SVM vs Decision Tree Classifiers')
plt.xlabel('Accuracy Score')
plt.ylabel('Frequency')

# Adding legend to identify the classifiers
plt.legend()

# Display the plot
plt.show()

# Not part of the assignment, but interesting to see the average accuracy over␣
 ↪1000 runs
average_score1 = np.mean(all_scores1)
average_score2 = np.mean(all_scores2)
```

```
print(f"Average Accuracy of SVM Classifier over 1000 runs: {average_score1:.
 ↪2f}")
print(f"Average Accuracy of Decision Tree Classifier over 1000 runs:␣
 ↪{average_score2:.2f}")
```




```
Average Accuracy of SVM Classifier over 1000 runs: 0.66
Average Accuracy of Decision Tree Classifier over 1000 runs: 0.60
```

4.3.1 Just scratching the surface...

This is just the start of what you can do with scikit-learn. It is clear from the documentation that there are many different methods and algorithms for classification that are supported by the package, as well as different ways of optimizing and assessing the performance of different algorithms. If you are motivated to explore further, feel free to continue below by opening more code cells and using the scikit-learn documentation to guide some further exploration.

5 What to Submit?

Please run your Jupyter Notebook first to generate outputs for each code cell and then export the report as a HTML file by clicking the following links (File -> Download as -> HTML (.html)). Please zip both the Jupyter Notebook and the HTML file and submit your ZIP file.