Project 3 - Classify your own data

For this project we're going to explore some of the new topics since the last project including Decision Trees and Un-supervised learning. The final part of the project will ask you to perform your own data science project to classify a new dataset.

Submission Details

Project is due June 14th at 11:59 am (Wednesday Afternoon). To submit the project, please save the notebook as a pdf file and submit the assignment via Gradescope. In addition, make sure that all figures are legible and sufficiently large. For best pdf results, we recommend downloading Latex (https://www.latex-project.org/) and print the notebook using Latex.

Loading Essentials and Helper Functions

In [1]:
```
#Here are a set of libraries we imported to complete this assignment.
#Feel free to use these or equivalent libraries for your implementation
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # this is used for the plot the graph
import matplotlib
import os
import time
#Sklearn classes
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV, KFold
from sklearn import metrics
from sklearn.metrics import confusion_matrix,silhouette_score
import sklearn.metrics.cluster as smc
from sklearn.cluster import KMeans
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.preprocessing import StandardScaler, OneHotEncoder ,LabelEncoder, MinMaxScaler
from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn import datasets
from sklearn.decomposition import PCA
from sklearn.neural_network import MLPClassifier
from sklearn.datasets import make_blobs

from matplotlib import pyplot
import itertools

%matplotlib inline

#Sets random seed
import random
random.seed(42)
```

In [2]:
```
#Helper functions
def draw_confusion_matrix(y, yhat, classes):
    '''
        Draws a confusion matrix for the given target and predictions
        Adapted from scikit-learn and discussion example.
    '''
    plt.cla()
    plt.clf()
    matrix = confusion_matrix(y, yhat)
    plt.imshow(matrix, interpolation='nearest', cmap=plt.cm.YlOrBr)
    plt.title("Confusion Matrix")
    plt.colorbar()
    num_classes = len(classes)
    plt.xticks(np.arange(num_classes), classes, rotation=0)
    plt.yticks(np.arange(num_classes), classes)
    plt.tick_params(top=True, bottom=False, labeltop=True, labelbottom=False)
    fmt = 'd'
    thresh = matrix.max() / 2.
    for i, j in itertools.product(range(matrix.shape[0]), range(matrix.shape[1])):
        plt.text(j, i, format(matrix[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if matrix[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.gca().xaxis.set_label_position('top')
    plt.tight_layout()
    plt.show()

def heatmap(data, row_labels, col_labels, figsize = (20,12), cmap = "YlGn",
            cbar_kw={}, cbarlabel="", valfmt="{x:.2f}",
            textcolors=("black", "white"), threshold=None):
    """
    Create a heatmap from a numpy array and two lists of labels.

    Taken from matplotlib example.

    Parameters
    ----------
    data
        A 2D numpy array of shape (M, N).
    row_labels
        A list or array of length M with the labels for the rows.
    col_labels
        A list or array of length N with the labels for the columns.
    ax
        A `matplotlib.axes.Axes` instance to which the heatmap is plotted.  If
        not provided, use current axes or create a new one.  Optional.
    cmap
        A string that specifies the colormap to use. Look at matplotlib docs for information.
        Optional.
    cbar_kw
        A dictionary with arguments to `matplotlib.Figure.colorbar`.  Optional.
    cbarlabel
        The label for the colorbar.  Optional.
    valfmt
        The format of the annotations inside the heatmap.  This should either
        use the string format method, e.g. "$ {x:.2f}", or be a
        `matplotlib.ticker.Formatter`.  Optional.
    textcolors
        A pair of colors.  The first is used for values below a threshold,
        the second for those above.  Optional.
    threshold
        Value in data units according to which the colors from textcolors are
        applied.  If None (the default) uses the middle of the colormap as
    """

    plt.figure(figsize = figsize)
    ax = plt.gca()

    # Plot the heatmap
    im = ax.imshow(data,cmap=cmap)

    # Create colorbar
    cbar = ax.figure.colorbar(im, ax=ax, **cbar_kw)
    cbar.ax.set_ylabel(cbarlabel, rotation=-90, va="bottom")

    # Show all ticks and label them with the respective list entries.
    ax.set_xticks(np.arange(data.shape[1]), labels=col_labels)
    ax.set_yticks(np.arange(data.shape[0]), labels=row_labels)

    # Let the horizontal axes labeling appear on top.
    ax.tick_params(top=True, bottom=False,
                   labeltop=True, labelbottom=False)

    # Rotate the tick labels and set their alignment.
```

```
    plt.setp(ax.get_xticklabels(), rotation=-30, ha="right",
             rotation_mode="anchor")

    # Turn spines off and create white grid.
    ax.spines[:].set_visible(False)

    ax.set_xticks(np.arange(data.shape[1]+1)-.5, minor=True)
    ax.set_yticks(np.arange(data.shape[0]+1)-.5, minor=True)
    ax.grid(which="minor", color="w", linestyle='-', linewidth=3)
    ax.tick_params(which="minor", bottom=False, left=False)


    # Normalize the threshold to the images color range.
    if threshold is not None:
        threshold = im.norm(threshold)
    else:
        threshold = im.norm(data.max())/2.

    # Set default alignment to center, but allow it to be
    # overwritten by textkw.
    kw = dict(horizontalalignment="center",
              verticalalignment="center")

    # Get the formatter in case a string is supplied
    if isinstance(valfmt, str):
        valfmt = matplotlib.ticker.StrMethodFormatter(valfmt)

    # Loop over the data and create a `Text` for each "pixel".
    # Change the text's color depending on the data.
    texts = []
    for i in range(data.shape[0]):
        for j in range(data.shape[1]):
            kw.update(color=textcolors[int(im.norm(data[i, j]) > threshold)])
            text = im.axes.text(j, i, valfmt(data[i, j], None), **kw)
            texts.append(text)


def make_meshgrid(x, y, h=0.02):
    """Create a mesh of points to plot in

    Parameters
    ----------
    x: data to base x-axis meshgrid on
    y: data to base y-axis meshgrid on
    h: stepsize for meshgrid, optional

    Returns
    -------
    xx, yy : ndarray
    """
    x_min, x_max = x.min() - 1, x.max() + 1
    y_min, y_max = y.min() - 1, y.max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    return xx, yy


def plot_contours(clf, xx, yy, **params):
    """Plot the decision boundaries for a classifier.

    Parameters
    ----------
    ax: matplotlib axes object
    clf: a classifier
    xx: meshgrid ndarray
    yy: meshgrid ndarray
    params: dictionary of params to pass to contourf, optional
    """
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    out = plt.contourf(xx, yy, Z, **params)
    return out

def draw_contour(x,y,clf, class_labels = ["Negative", "Positive"]):
    """
    Draws a contour line for the predictor

    Assumption that x has only two features. This functions only plots the first two columns of x.

    """

    X0, X1 = x[:, 0], x[:, 1]
    xx0, xx1 = make_meshgrid(X0,X1)

    plt.figure(figsize = (10,6))
    plot_contours(clf, xx0, xx1, cmap="PiYG", alpha=0.8)
    scatter=plt.scatter(X0, X1, c=y, cmap="PiYG", s=30, edgecolors="k")
```

```
    plt.legend(handles=scatter.legend_elements()[0], labels=class_labels)

    plt.xlim(xx0.min(), xx0.max())
    plt.ylim(xx1.min(), xx1.max())
```

Example Project using new techniques

Since project 2, we have learned about a few new models for supervised learning(Decision Trees and Neural Networks) and un-supervised learning (Clustering and PCA). In this example portion, we will go over how to implement these techniques using the Sci-kit learn library.

Load and Process Example Project Data

For our example dataset, we will use the Breast Cancer Wisconsin Dataset (https://www.kaggle.com/datasets/uciml/breast-cancer-wisconsin-data) to determine whether a mass found in a body is benign or malignant. Since this dataset was used as an example in project 2, you should be fairly familiar with it.

Feature Information:

Column 1: ID number

Column 2: Diagnosis (M = malignant, B = benign)

Ten real-valued features are computed for each cell nucleus:

1. radius (mean of distances from center to points on the perimeter)
2. texture (standard deviation of gray-scale values)
3. perimeter
4. area
5. smoothness (local variation in radius lengths)
6. compactness (perimeter^2 / area - 1.0)
7. concavity (severity of concave portions of the contour)
8. concave points (number of concave portions of the contour)
9. symmetry
10. fractal dimension ("coastline approximation" - 1)

Due to the statistical nature of the test, we are not able to get exact measurements of the previous values. Instead, the dataset contains the mean and standard error of the real-valued features.

Columns 3-12 present the mean of the measured values

Columns 13-22 present the standard error of the measured values

In [3]:
```
#Preprocess Data

#Load Data
data = pd.read_csv('datasets/breast_cancer_data.csv')

#Drop id column
data = data.drop(["id"],axis= 1)

#Transform target feature into numerical
le = LabelEncoder()
data['diagnosis'] = le.fit_transform(data['diagnosis'])

#Split target and data
y = data["diagnosis"]
x = data.drop(["diagnosis"],axis = 1)

#Train test split
train_raw, test_raw, target, target_test = train_test_split(x,y, test_size=0.2, stratify= y, random_state=0)

#Standardize data
#Since all features are real-valued, we only have one pipeline
pipeline = Pipeline([
    ('scaler', StandardScaler())
])

#Transform raw data
train = pipeline.fit_transform(train_raw)
test = pipeline.transform(test_raw)

#Names of Features after Pipeline
feature_names = list(pipeline.get_feature_names_out(list(x.columns)))
```

In [4]:
```
target.value_counts()
```

Out[4]:
```
0    285
1    170
Name: diagnosis, dtype: int64
```

In [5]:
```
#Baseline accuracy of using the majority class
ct = target_test.value_counts()
print("Counts of each class in target_test: ")
print(ct)
print("Baseline Accuraccy of using Majority Class: ", np.max(ct)/np.sum(ct))
```

```
Counts of each class in target_test:
0    72
1    42
Name: diagnosis, dtype: int64
Baseline Accuraccy of using Majority Class:  0.631578947368421
```

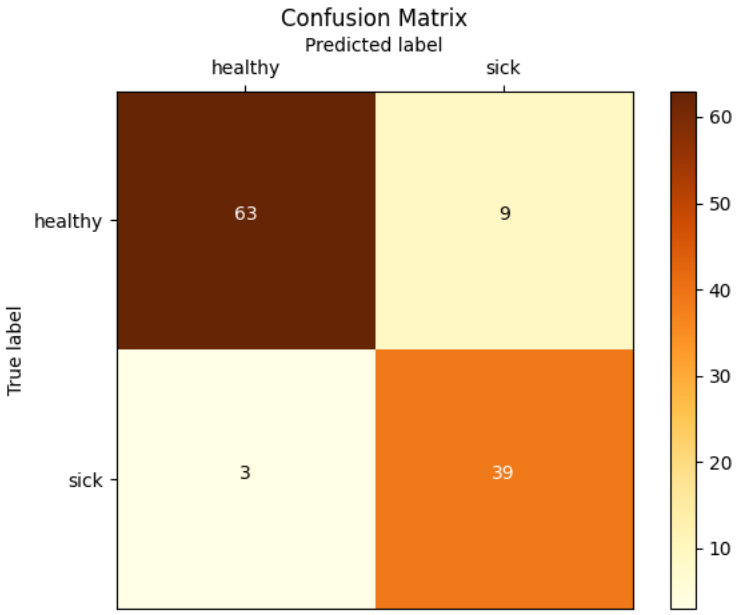
Supervised Learning: Decision Tree

Classification with Decision Tree

In [6]:
```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier(criterion="gini", random_state = 0)
clf.fit(train, target)
predicted = clf.predict(test)
```

In [7]:
```
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['healthy', 'sick'])
```

```
Accuracy:    0.894737
Confusion Matrix:
 [[63  9]
 [ 3 39]]
```



Parameters for Decision Tree Classifier

In Sci-kit Learn, the following are just some of the parameters we can pass into the Decision Tree Classifier:

- criterion: {'gini', 'entropy', 'log_loss'} default="gini"
  - The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "log_loss" and "entropy" both for the Shannon information gain
- splitter: {"best", "random"}, default="best"
  - The strategy used to choose the split at each node. "best" aims to find the best feature split amongst all features. "random" only looks for the best split amongst a random subset of features.
- max_depth: int, default = 2 {'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'}, default='lbfgs'

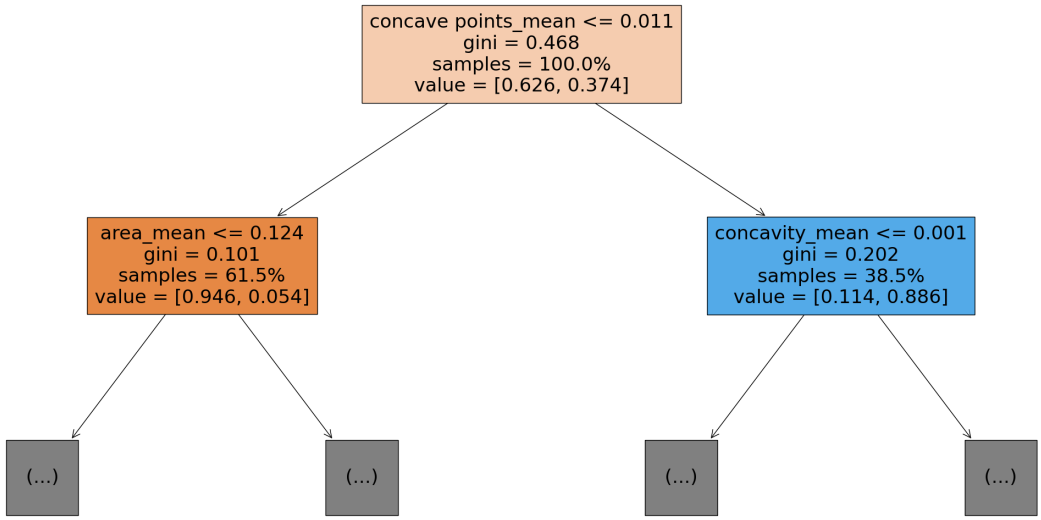
    - The maximum depth of the tree.
- min_samples_split: int or float, default=2
    - The minimum number of samples required to split an internal node. If int, then consider min_samples_split as the minimum number. If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

Visualizing Decision Trees

Scikit-learn allows us to visualize the decision tree to see what features it choose to split and what the result is. Note that if the condition in the node is true, you traverse the left edge of the node. Otherwise, you traverse the right edge.

In [8]:
```
plt.figure(figsize = (30,15))
#Note that we have to pass the feature names into the plotting function to get the actual names
#We pass the column names through the pipeline in case any feature augmentation was made
#For example, a categorical feature will be split into multiple features with one hot encoding
#and this way assigns a name to each column based on the feature value and the original feature name
tree.plot_tree(clf,max_depth=1, proportion=True,feature_names=feature_names, filled=True)
```

Out[8]:
```
[Text(0.5, 0.8333333333333334, 'concave points_mean <= 0.011\ngini = 0.468\nsamples = 100.0%\nvalue = [0.626, 0.37
4]'),
 Text(0.25, 0.5, 'area_mean <= 0.124\ngini = 0.101\nsamples = 61.5%\nvalue = [0.946, 0.054]'),
 Text(0.125, 0.16666666666666666, '\n  (...)  \n'),
 Text(0.375, 0.16666666666666666, '\n  (...)  \n'),
 Text(0.75, 0.5, 'concavity_mean <= 0.001\ngini = 0.202\nsamples = 38.5%\nvalue = [0.114, 0.886]'),
 Text(0.625, 0.16666666666666666, '\n  (...)  \n'),
 Text(0.875, 0.16666666666666666, '\n  (...)  \n')]
```



We can even look at the tree in a textual format.

In [9]:
```
from sklearn.tree import export_text
r = export_text(clf, feature_names=feature_names)
print(r)
```

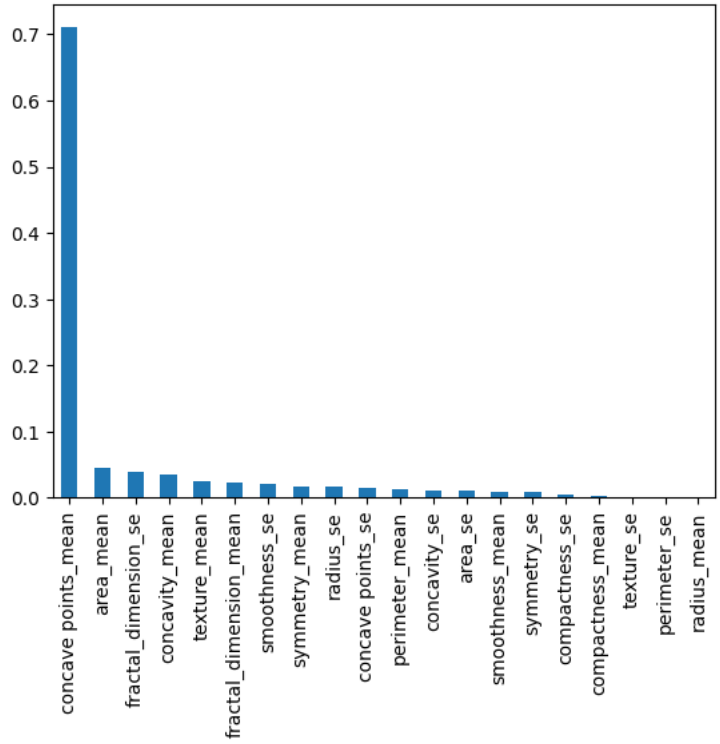
```
|--- concave points_mean <= 0.01
|   |--- area_mean <= 0.12
|   |   |--- area_se <= 0.04
|   |   |   |--- compactness_mean <= 0.59
|   |   |   |   |--- fractal_dimension_se <= -0.83
|   |   |   |   |   |--- fractal_dimension_se <= -0.84
|   |   |   |   |   |   |--- smoothness_se <= -1.22
|   |   |   |   |   |   |   |--- compactness_se <= -0.98
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- compactness_se >  -0.98
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- smoothness_se >  -1.22
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- fractal_dimension_se >  -0.84
|   |   |   |   |   |   |--- class: 1
|   |   |   |   |--- fractal_dimension_se >  -0.83
|   |   |   |   |   |--- class: 0
|   |   |   |--- compactness_mean >  0.59
|   |   |   |   |--- symmetry_se <= 0.20
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- symmetry_se >  0.20
|   |   |   |   |   |--- class: 0
|   |   |--- area_se >  0.04
|   |   |   |--- symmetry_mean <= -0.57
|   |   |   |   |--- class: 1
|   |   |   |--- symmetry_mean >  -0.57
|   |   |   |   |--- class: 0
|   |--- area_mean >  0.12
|   |   |--- texture_mean <= -0.72
|   |   |   |--- class: 0
|   |   |--- texture_mean >  -0.72
|   |   |   |--- smoothness_mean <= -1.52
|   |   |   |   |--- class: 0
|   |   |   |--- smoothness_mean >  -1.52
|   |   |   |   |--- class: 1
|--- concave points_mean >  0.01
|   |--- concavity_mean <= 0.00
|   |   |--- fractal_dimension_mean <= -0.83
|   |   |   |--- class: 1
|   |   |--- fractal_dimension_mean >  -0.83
|   |   |   |--- concave points_mean <= 0.11
|   |   |   |   |--- concavity_se <= -0.35
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- concavity_se >  -0.35
|   |   |   |   |   |--- class: 0
|   |   |   |--- concave points_mean >  0.11
|   |   |   |   |--- class: 0
|   |--- concavity_mean >  0.00
|   |   |--- fractal_dimension_se <= 2.39
|   |   |   |--- smoothness_se <= 1.87
|   |   |   |   |--- radius_se <= -0.77
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- radius_se >  -0.77
|   |   |   |   |   |--- concave points_se <= 2.59
|   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- concave points_se >  2.59
|   |   |   |   |   |   |--- radius_se <= 0.61
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- radius_se >  0.61
|   |   |   |   |   |   |   |--- class: 1
|   |   |   |--- smoothness_se >  1.87
|   |   |   |   |--- concave points_se <= 1.03
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- concave points_se >  1.03
|   |   |   |   |   |--- class: 0
|   |   |--- fractal_dimension_se >  2.39
|   |   |   |--- perimeter_mean <= 0.59
|   |   |   |   |--- class: 0
|   |   |   |--- perimeter_mean >  0.59
|   |   |   |   |--- class: 1
```

Feature Importance in Decision Trees

Decision Trees can also assign importance to features by measuring the average decrease in impurity (i.e. information gain) for each feature. The features with higher decreases are treated as more important.

In [10]:
```
imp_pd = pd.Series(data = clf.feature_importances_ ,index = feature_names)
imp_pd= imp_pd.sort_values(ascending=False)
imp_pd.plot.bar()
```

Out[10]: <AxesSubplot: >

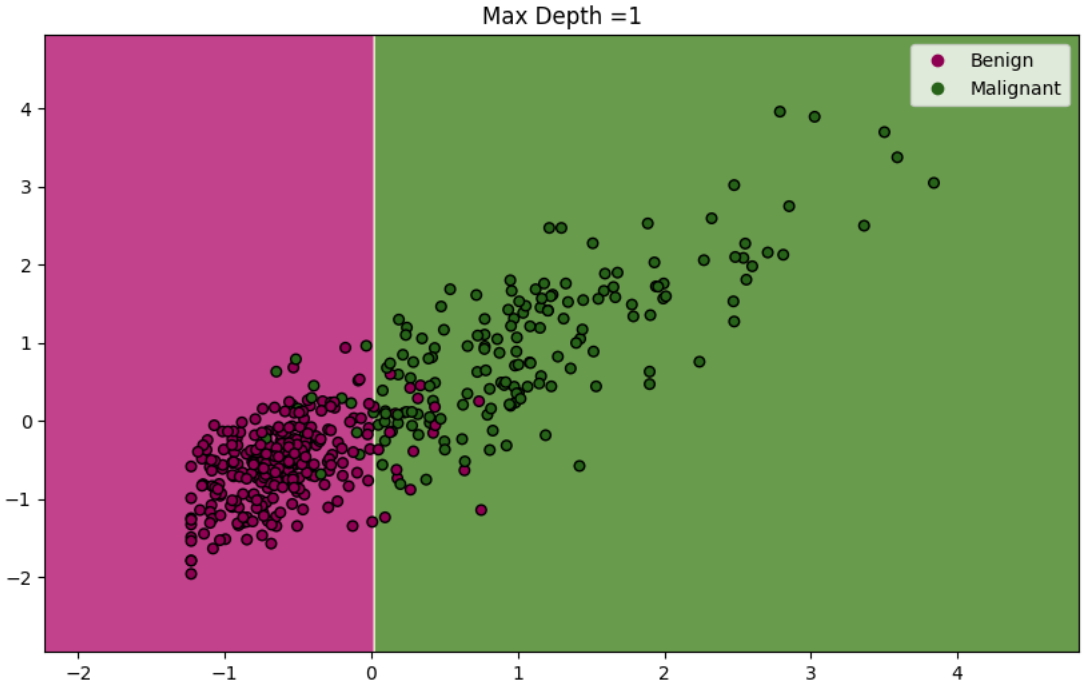


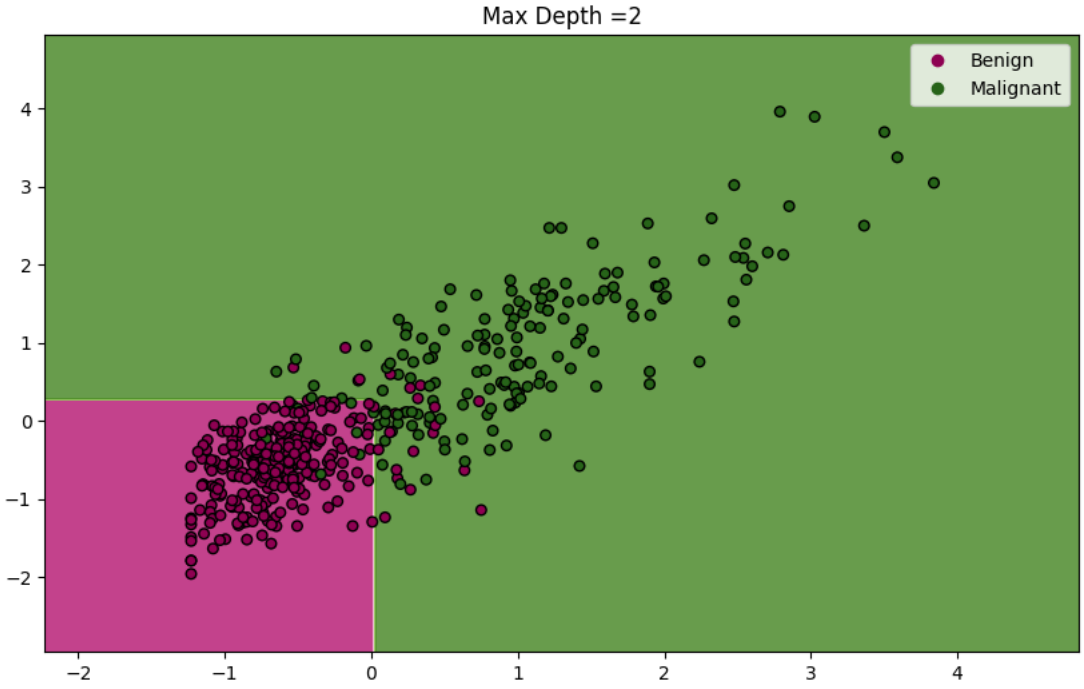
We can clearly see that "concave points_mean" has the largest importance due to it providing the most reduction in the impurity.

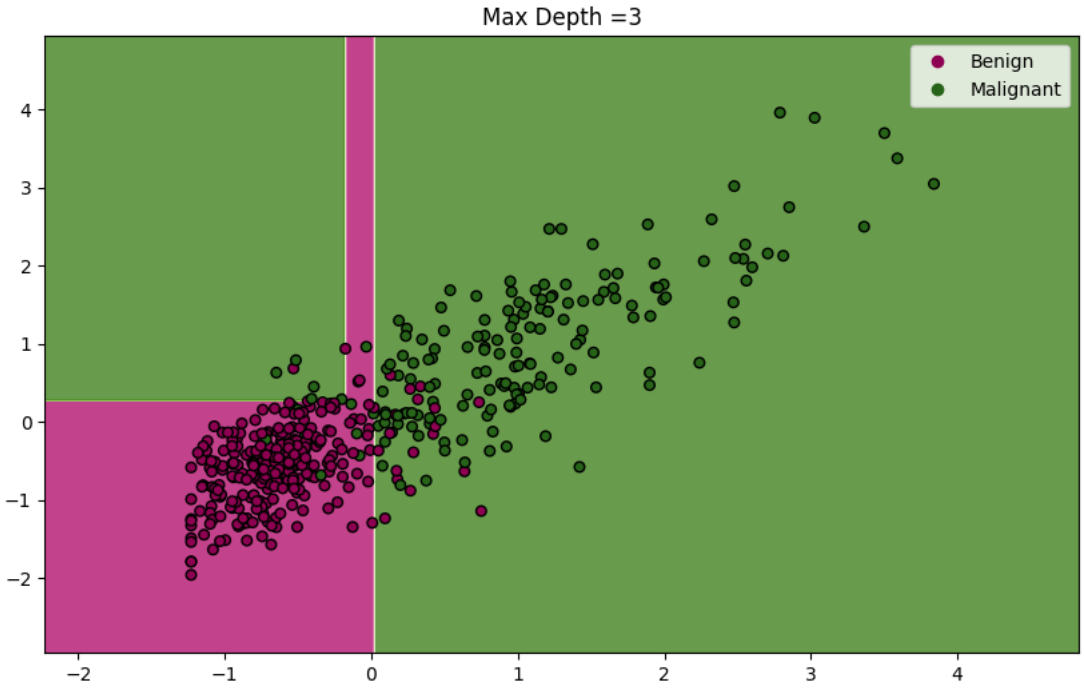
Visualizing decision boundaries for Decision Trees

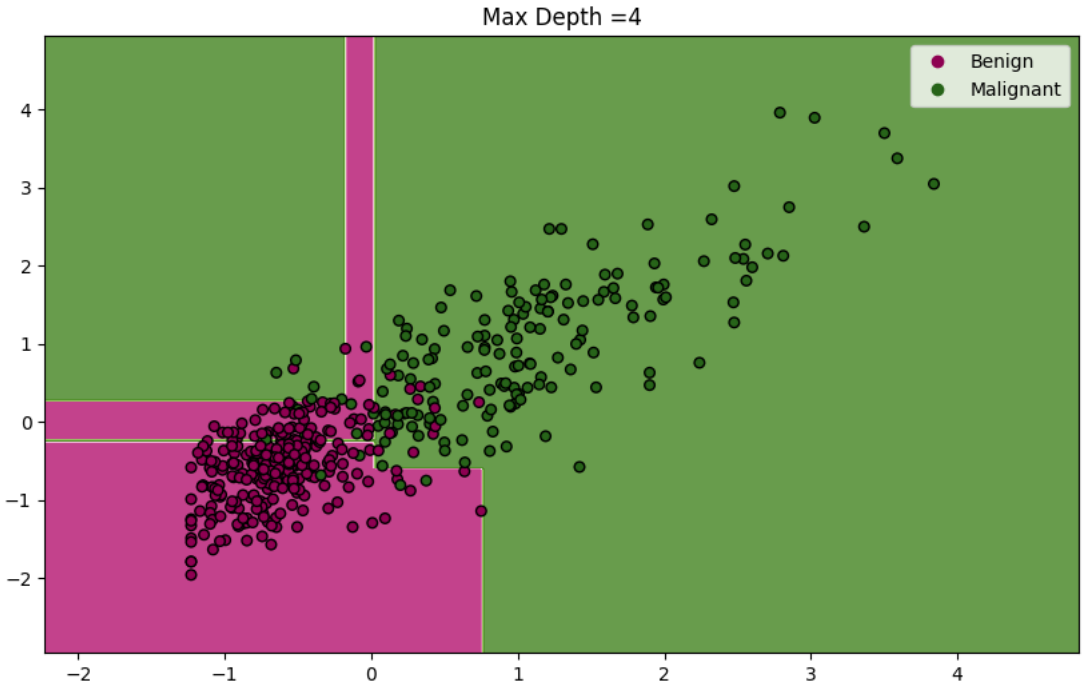
Similar to project 2, lets see what decision boundaries that a Decision Tree creates. We use the two most correlated features to the target labels: concave_points_mean and perimeter_mean.

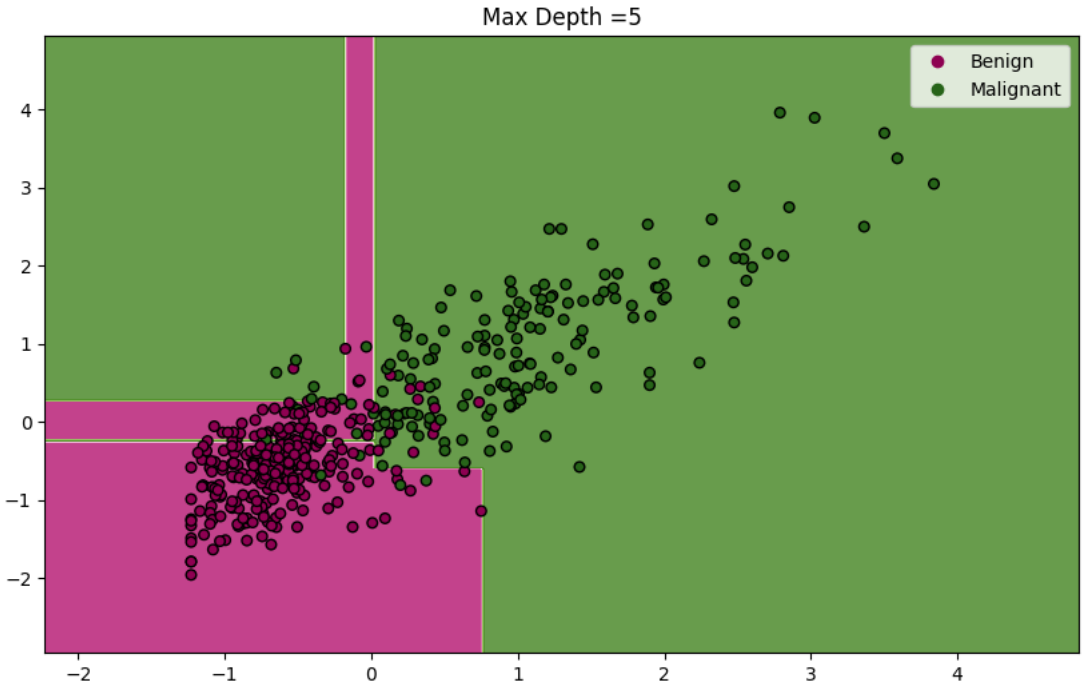
In [11]:
```
#Extract first two feature and use the standardscaler
train_2 = StandardScaler().fit_transform(train_raw[['concave points_mean','perimeter_mean']])

depth  = [1,2,3,4,5,10,15]
for d in depth:
    dt = DecisionTreeClassifier(max_depth = d, min_samples_split=7)
    dt.fit(train_2, target)
    draw_contour(train_2,target,dt,class_labels = ['Benign', 'Malignant'])

    plt.title(f"Max Depth ={d}")
```

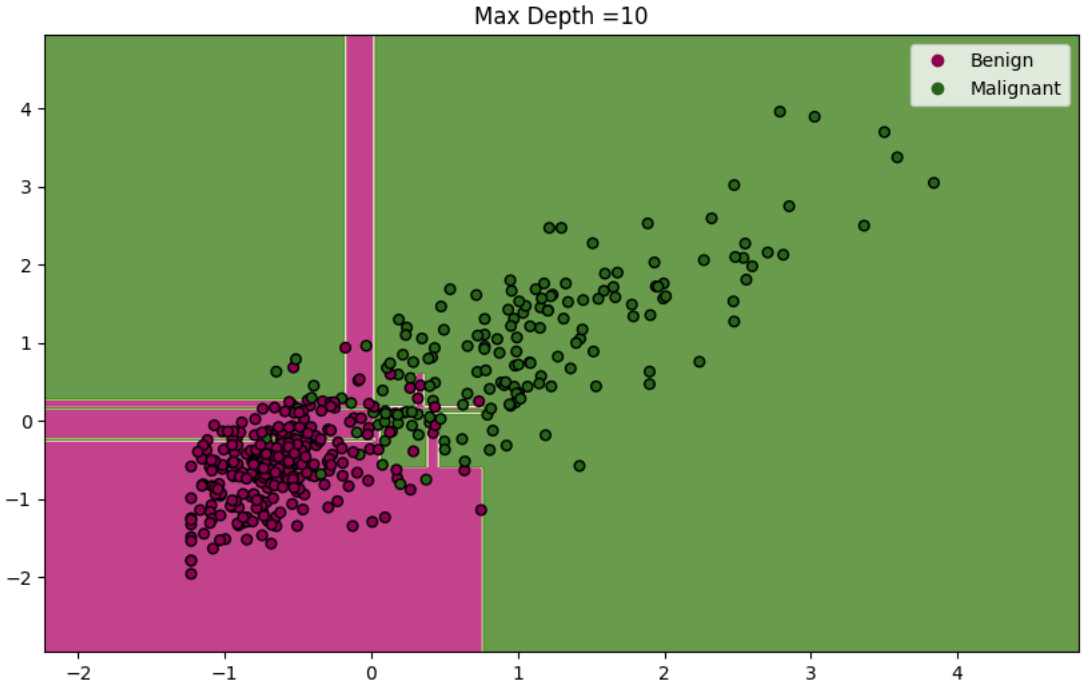


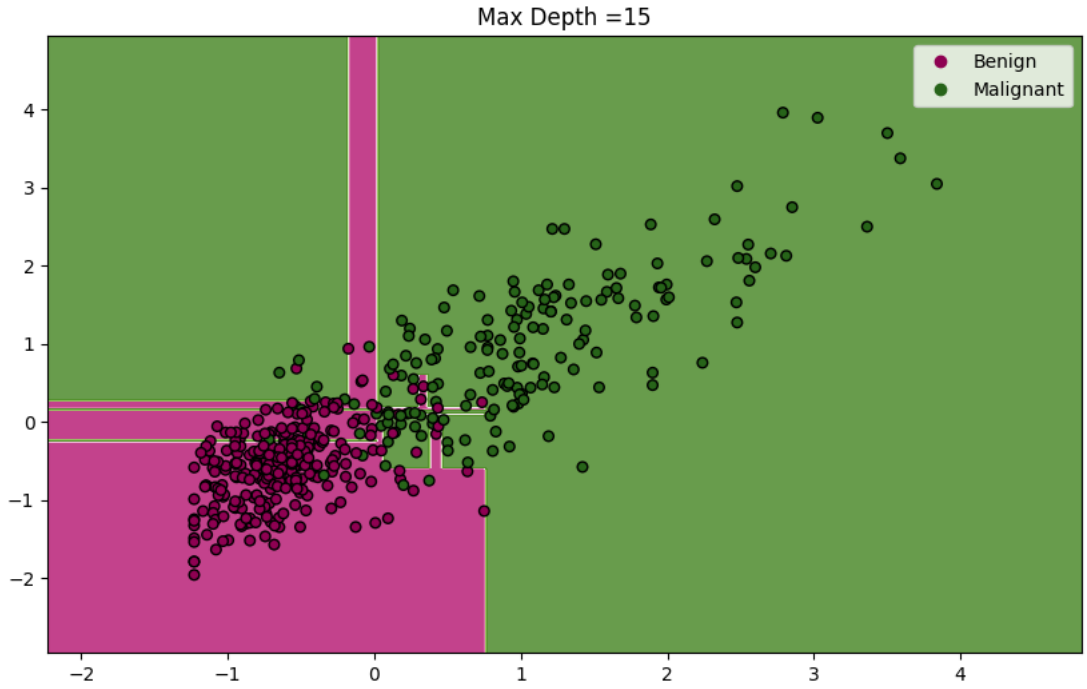



Max Depth =3
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4


Max Depth =4
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4


Max Depth =5
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4

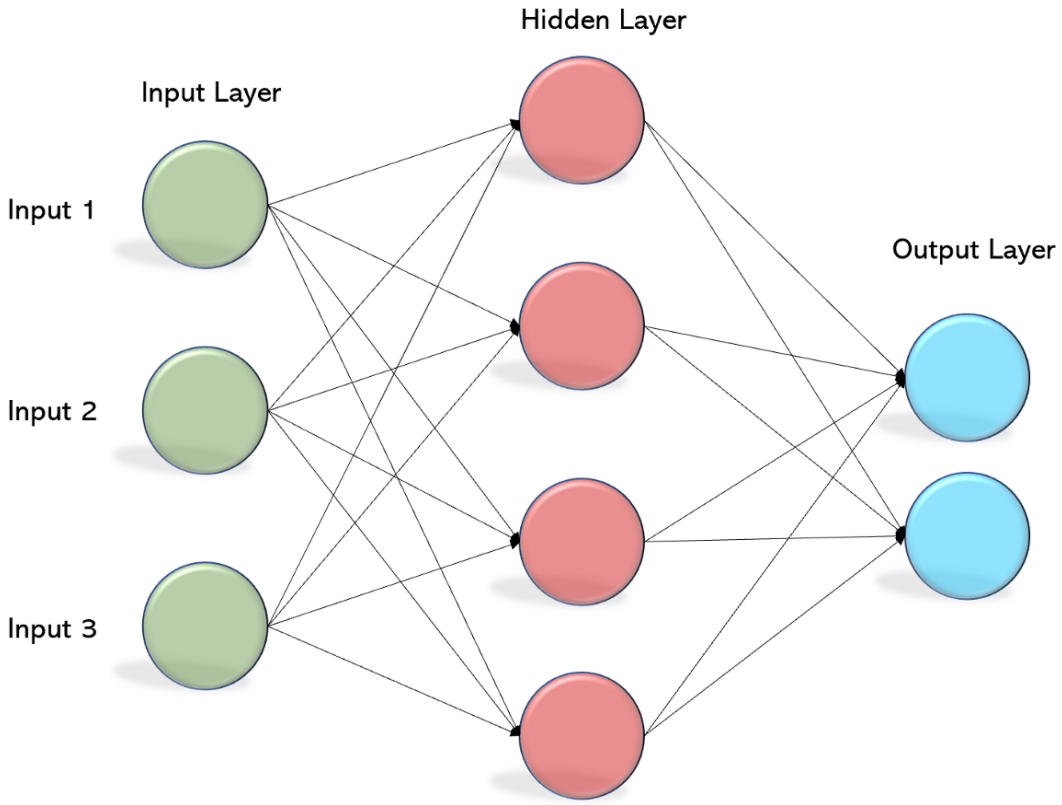

Max Depth =10
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4



We can see that the model gets more and more complex with increasing depth until it converges somewhere in between depth 10 and 15.

Supervised Learning: Multi-Layer Perceptron (MLP)

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. Neural networks are very powerful tools that are used a in a variety of applications including image and speech processing. In class, we have discussed one of the earliest types of neural networks known as a Multi-Layer Perceptron.



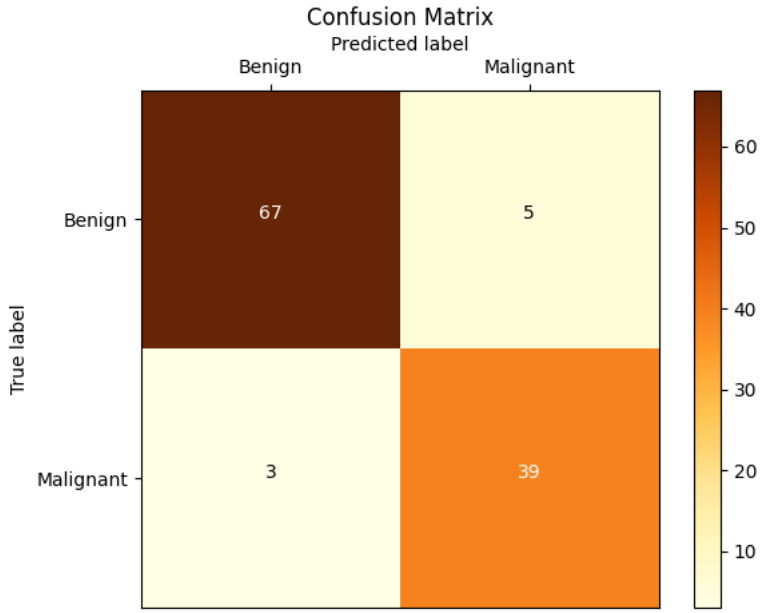
Using MLP for classification

In [12]:
```
from sklearn.neural_network import MLPClassifier
clf = MLPClassifier(hidden_layer_sizes=(100,), max_iter = 400)
clf.fit(train, target)
predicted = clf.predict(test)
```

```
/home/josh/.local/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:702: ConvergenceWa
rning: Stochastic Optimizer: Maximum iterations (400) reached and the optimization hasn't converged yet.
  warnings.warn(
```

In [13]:
```
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['Benign', 'Malignant'])
```

```
Accuracy:    0.929825
Confusion Matrix:
 [[67  5]
 [ 3 39]]
```



Parameters for MLP Classifier

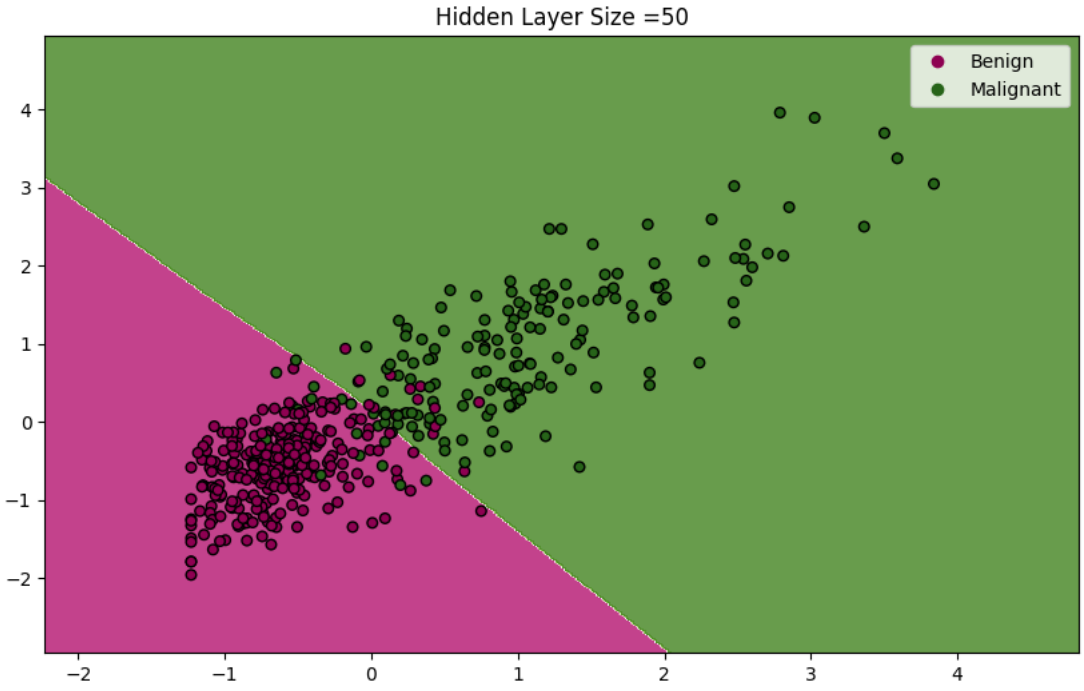
In Sci-kit Learn, the following are just some of the parameters we can pass into MLP Classifier:

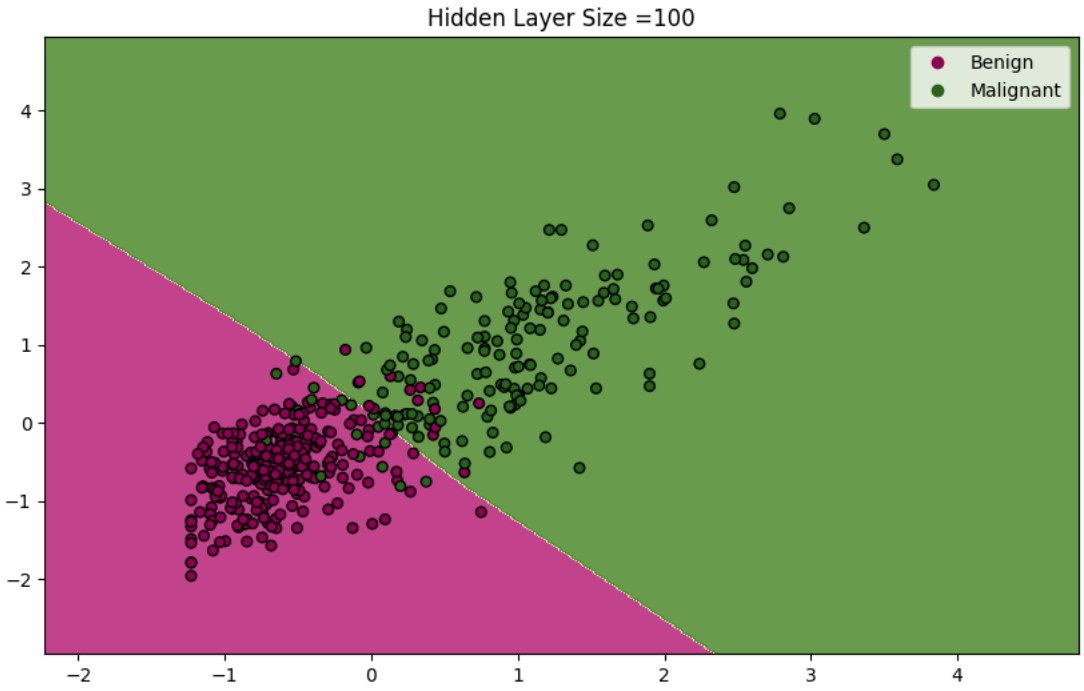
- hidden_layer_sizes: tuple, length = n_layers - 2, default=(100,)
  - The ith element represents the number of neurons in the ith hidden layer.
- activation: {'identity', 'logistic', 'tanh', 'relu'}, default='relu'
  - Activation function for the hidden layer.
- alpha: float, default = 0.0001
  - Strength of the L2 regularization term. The L2 regularization term is divided by the sample size when added to the loss.
- max_iter: int, default=200
  - Maximum number of iterations taken for the solvers to converge.

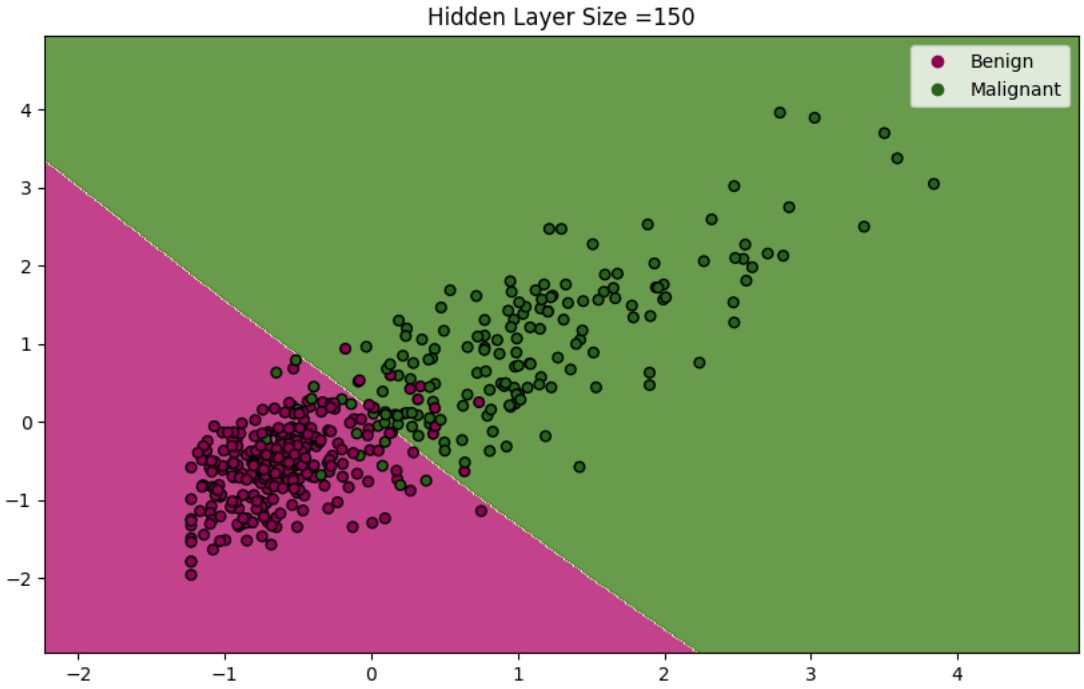
Visualizing decision boundaries for MLP

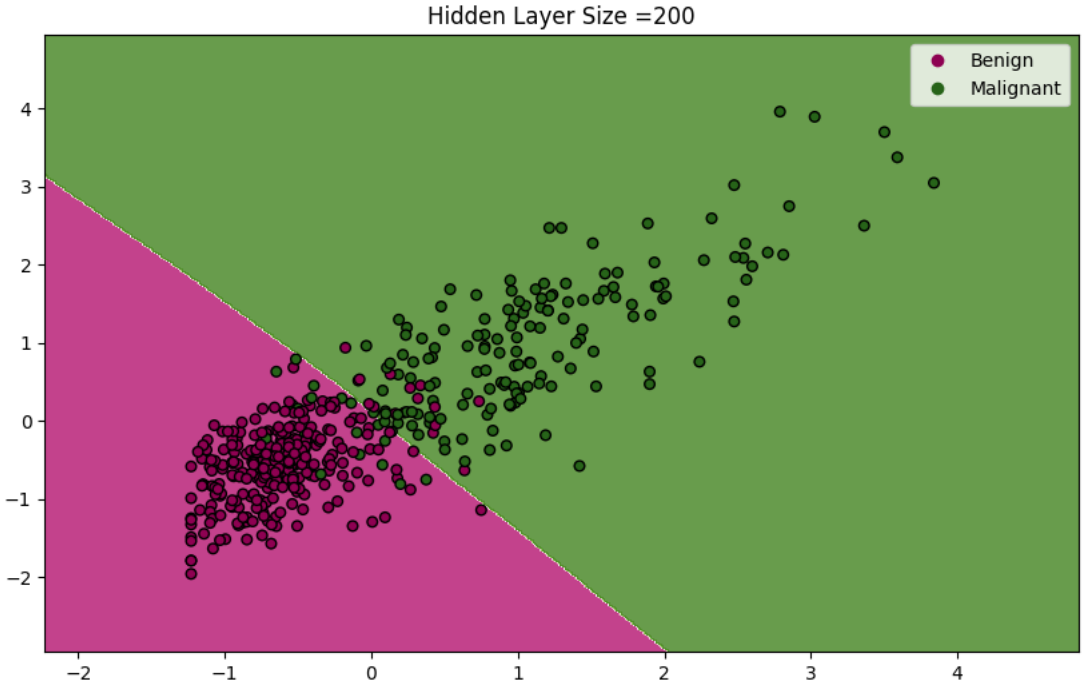
Now, lets see how the decision boundaries change as a function of both the activation function and the number of hidden layers.

In [14]:
```
#Example of using the default Relu activation while altering the number of hidden layers
train_2 = StandardScaler().fit_transform(train_raw[['concave points_mean','perimeter_mean']])

layers  = [50,100,150,200]
for l in layers:
    mlp = MLPClassifier(hidden_layer_sizes=(l,), max_iter = 400)
    mlp.fit(train_2, target)
    draw_contour(train_2,target,mlp,class_labels = ['Benign', 'Malignant'])

    plt.title(f"Hidden Layer Size ={l}")
```

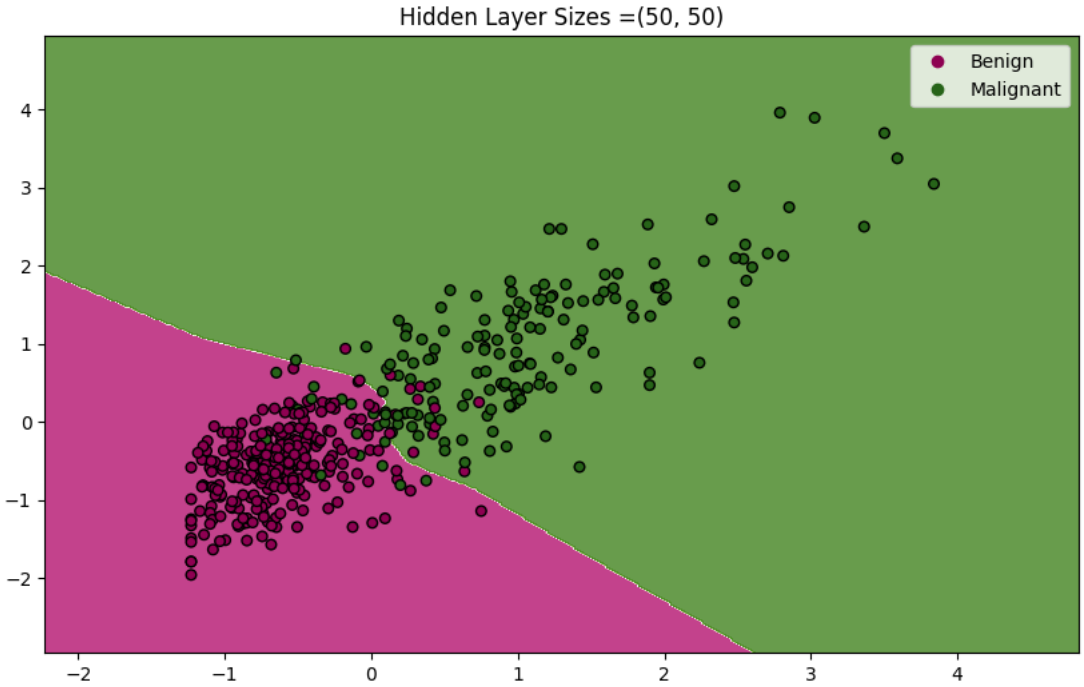


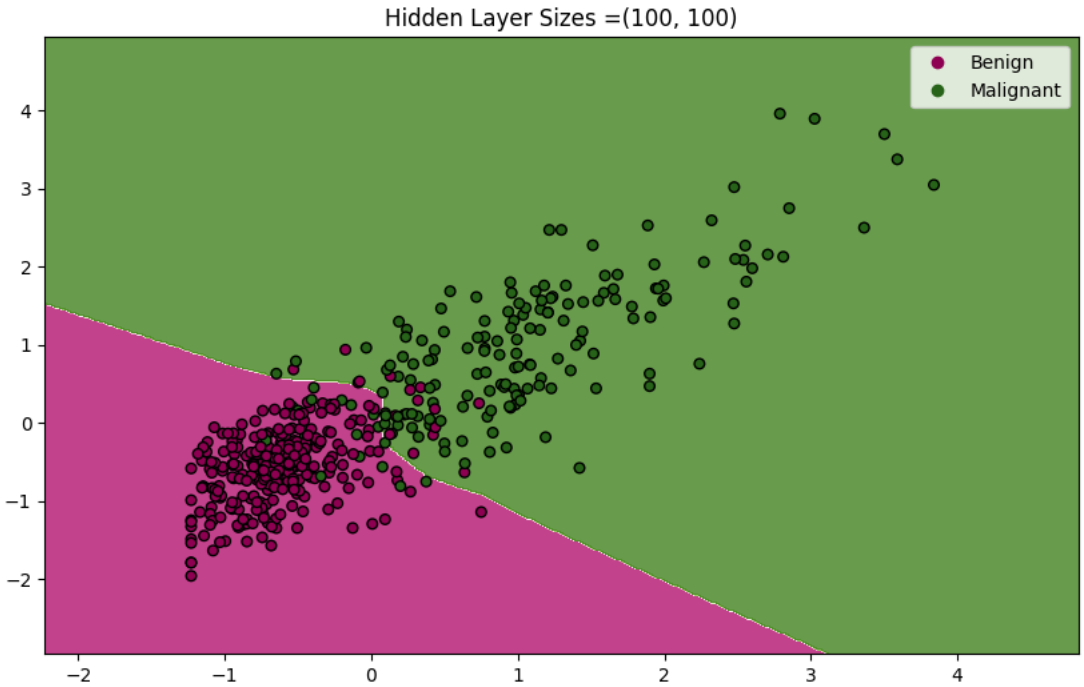


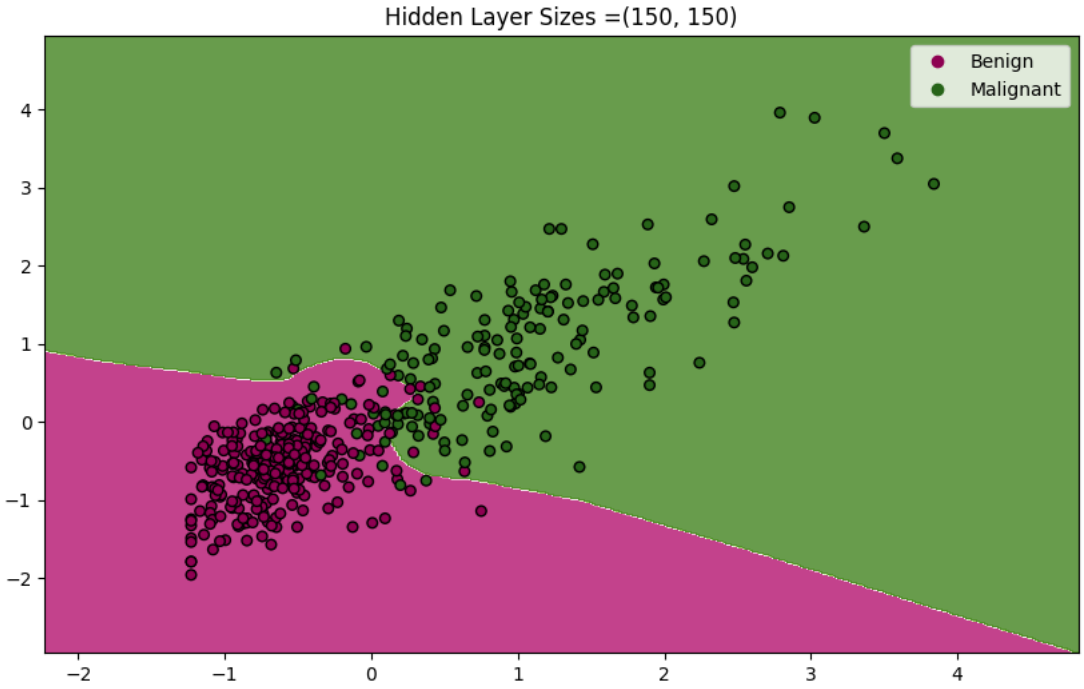

Hidden Layer Size =150
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4

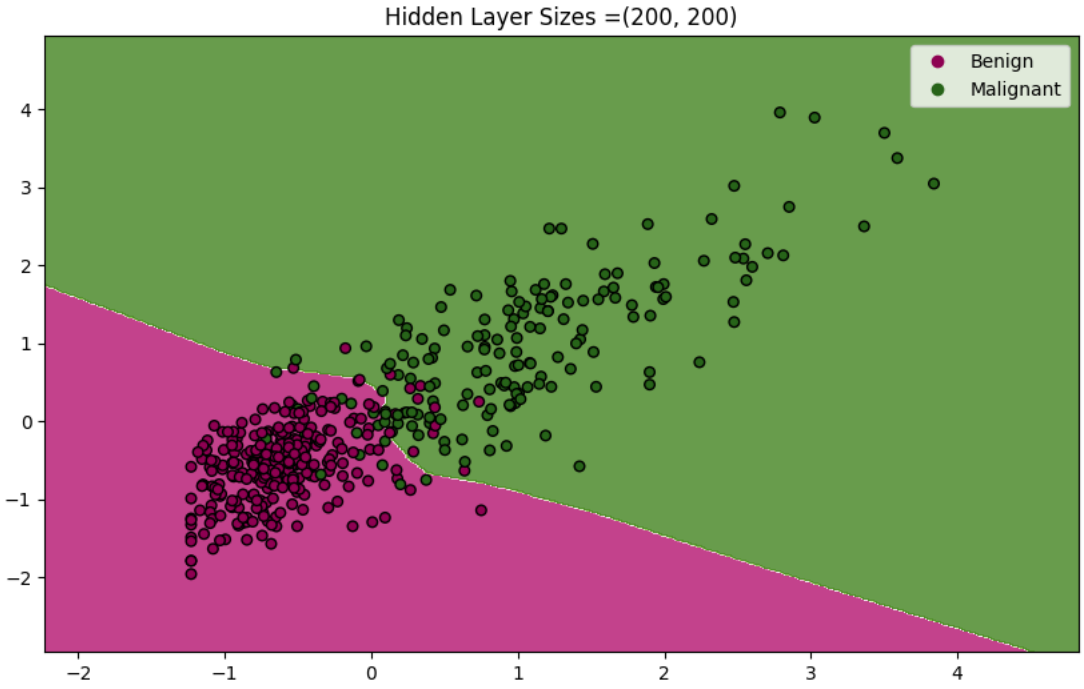

Hidden Layer Size =200
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4

In [15]:
```
#Example of using the default Relu activation
#while altering the number of hidden layers with 2 groups of hidden layers
train_2 = StandardScaler().fit_transform(train_raw[['concave points_mean','perimeter_mean']])

layers  = [50,100,150,200]
for l in layers:
    mlp = MLPClassifier(hidden_layer_sizes=(l,l), max_iter = 400)
    mlp.fit(train_2, target)
    draw_contour(train_2,target,mlp,class_labels = ['Benign', 'Malignant'])

    plt.title(f"Hidden Layer Sizes ={(l,l)}")
```

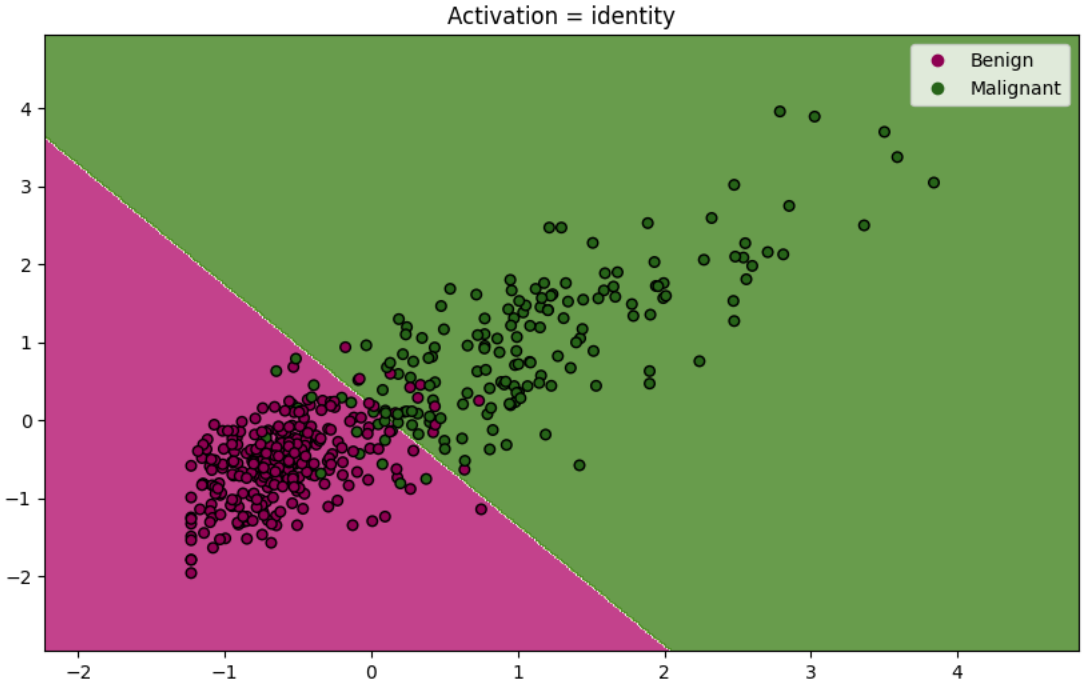


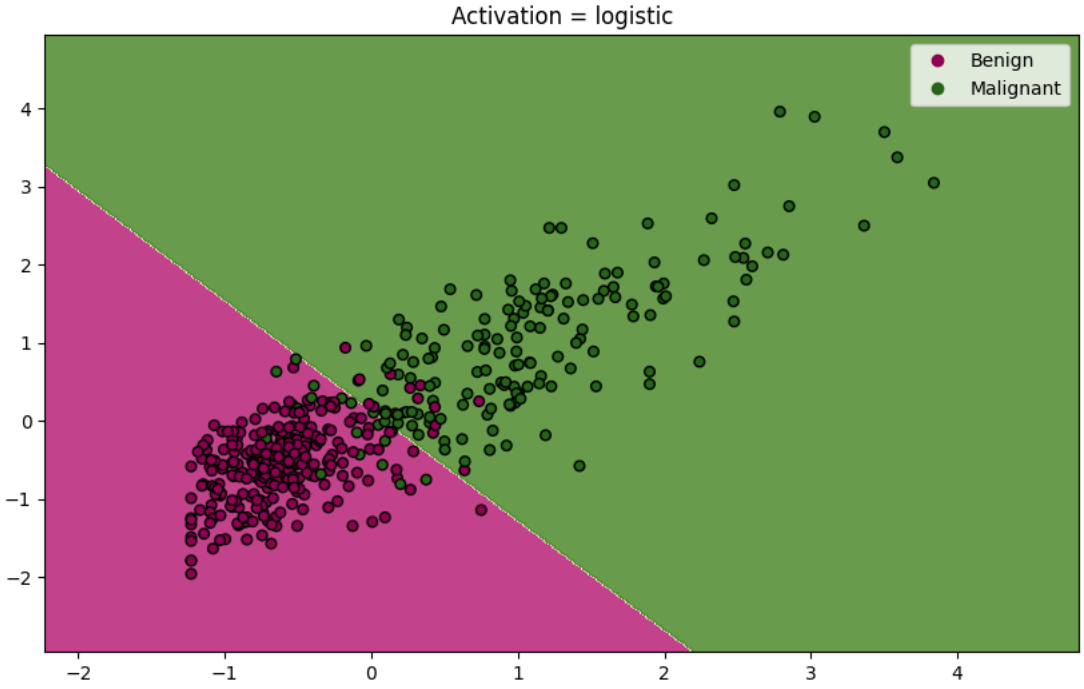


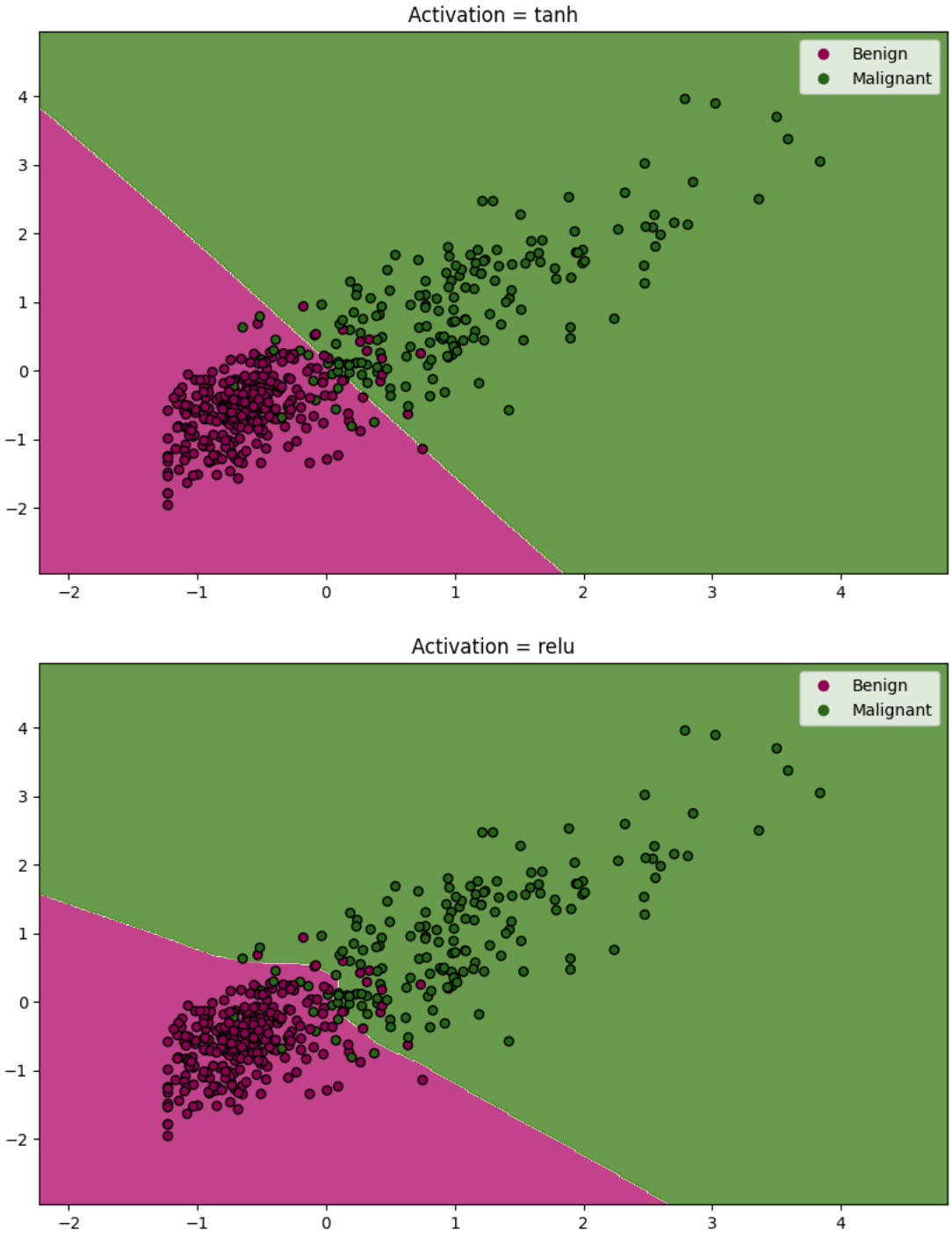

Hidden Layer Sizes =(150, 150)
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4


Hidden Layer Sizes =(200, 200)
Benign
Malignant
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4

In [16]:
```
#Example of using 2 hidden layers of 100 units each with varying activations
train_2 = StandardScaler().fit_transform(train_raw[['concave points_mean','perimeter_mean']])

acts  = ['identity', 'logistic', 'tanh', 'relu']
for act in acts:
    mlp = MLPClassifier(hidden_layer_sizes=(100,100), activation = act, max_iter = 400)
    mlp.fit(train_2, target)
    draw_contour(train_2,target,mlp,class_labels = ['Benign', 'Malignant'])

    plt.title(f"Activation = {act}")
```







Unsupervised learning: PCA

As shown in lecture, PCA is a valuable dimensionality reduction tool that can extract a small subset of valuable features. In this section, we shall demonstrate how PCA can extract important visual features from pictures of subjects faces. We shall use the AT&T Database of Faces (https://www.kaggle.com/datasets/kasikrit/att-database-of-faces). This dataset contains 40 different subjects with 10 samples per subject which means we a dataset of 400 samples.

We extract the images from the scikit-learn dataset library (https://scikit-learn.org/stable/modules/generated/sklearn.datasets.fetch_olivetti_faces.html#sklearn.datasets.fetch_olivetti_faces). The library imports the images (faces.data), the flatten array of images (faces.images), and which subject eacj image belongs to (faces.target). Each image is a 64 by 64 image with pixels converted to floating point values in [0,1].

Eigenfaces

The following codes downloads and loads the face data.

In [17]:
```
#Import faces from scikit library
faces = datasets.fetch_olivetti_faces()
print("Flattened Face Data shape:", faces.data.shape)
print("Face Image Data Shape:", faces.images.shape)
print("Shape of target data:", faces.target.shape)
```

```
Flattened Face Data shape: (400, 4096)
Face Image Data Shape: (400, 64, 64)
Shape of target data: (400,)
```

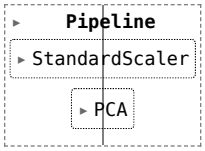
In [18]:
```
#Extract image shape for future use
im_shape = faces.images[0].shape
```

In [19]:
```
#Prints some example faces
faceimages = faces.images[np.random.choice(len(faces.images),size= 16, replace = False)] # take random 16 images

fig, axes = plt.subplots(4,4,sharex=True,sharey=True,figsize=(8,10))
for i in range(16):
    axes[i%4][i//4].imshow(faceimages[i], cmap="gray")
plt.show()
```

Now, let us see what features we can extract from these face images.

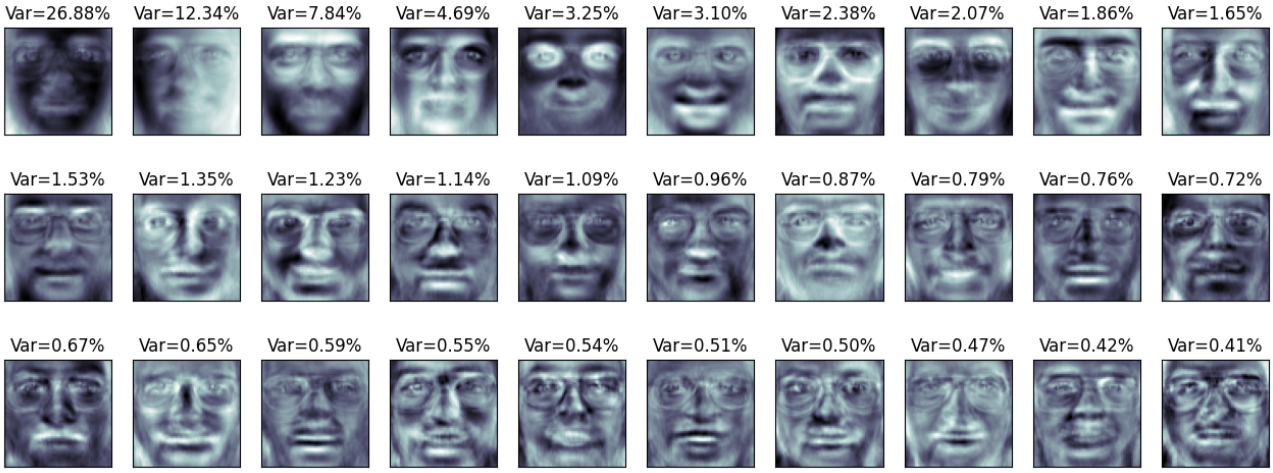
In [20]:
```
#Perform PCA
from sklearn.decomposition import PCA

pca = PCA()
pca_pipe = Pipeline([("scaler",StandardScaler()), #Scikit learn PCA does not standardize so we need to add
                     ("pca",pca)])
pca_pipe.fit(faces.data)
```

Out[20]:



The following plots the top 30 PCA components with how much variance does this feature explain.

In [21]:
```
fig = plt.figure(figsize=(16, 6))
for i in range(30):
    ax = fig.add_subplot(3, 10, i + 1, xticks=[], yticks=[])
    ax.imshow(pca.components_[i].reshape(im_shape),
              cmap=plt.cm.bone)
    ax.set_title(f"Var={pca.explained_variance_ratio_[i]:.2%}")
```



Amazing! We can see that the model has learned to focus on many features that we as humans also look at when trying to identify a face such as the nose,eyes, eyebrows, etc.

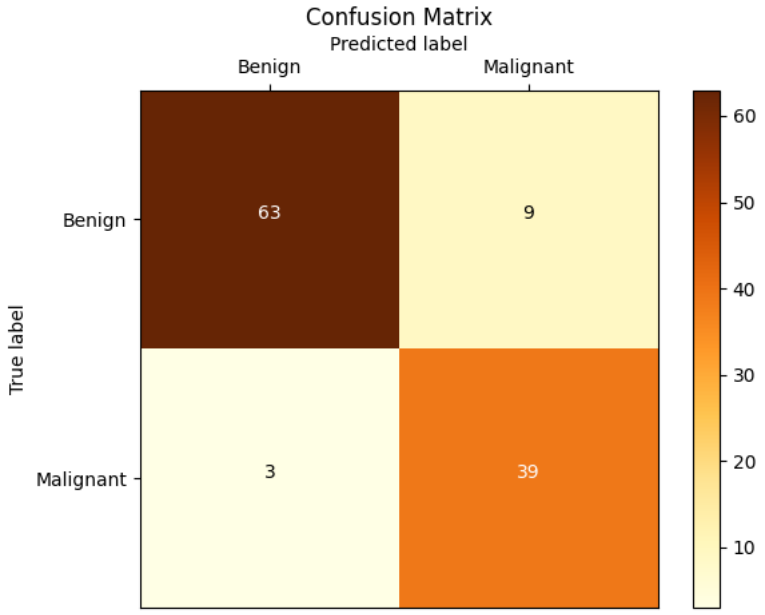
With this feature extraction, we can perform much more powerful learning.

Feature Extraction for Classification

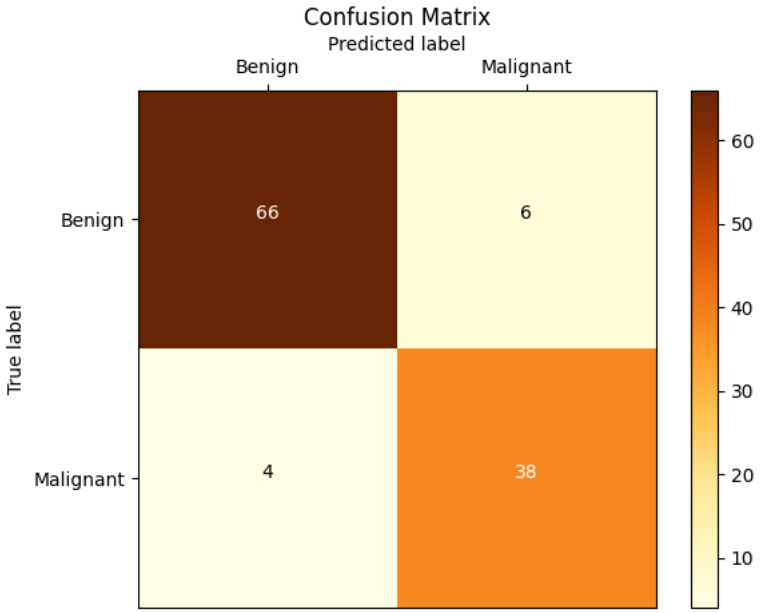
Lets see if we can use PCA to improve the accuracy of the decision tree classifier.

In [22]:
```
#Without PCA
clf = DecisionTreeClassifier(random_state=0)
clf.fit(train, target)
predicted = clf.predict(test)

print("Accuracy without PCA")
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['Benign', 'Malignant'])

#With PCA
pca = PCA(n_components = 0.9) #Take components that explain at lest 90% variance

train_new = pca.fit_transform(train)
test_new = pca.transform(test)

clf_pca = DecisionTreeClassifier(random_state=0)
clf_pca.fit(train_new, target)
predicted = clf_pca.predict(test_new)

print("Accuracy with PCA")
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['Benign', 'Malignant'])
```

```
Accuracy without PCA
Accuracy:    0.894737
Confusion Matrix:
 [[63  9]
 [ 3 39]]
```




```
Accuracy with PCA
Accuracy:    0.912281
Confusion Matrix:
 [[66  6]
 [ 4 38]]
```



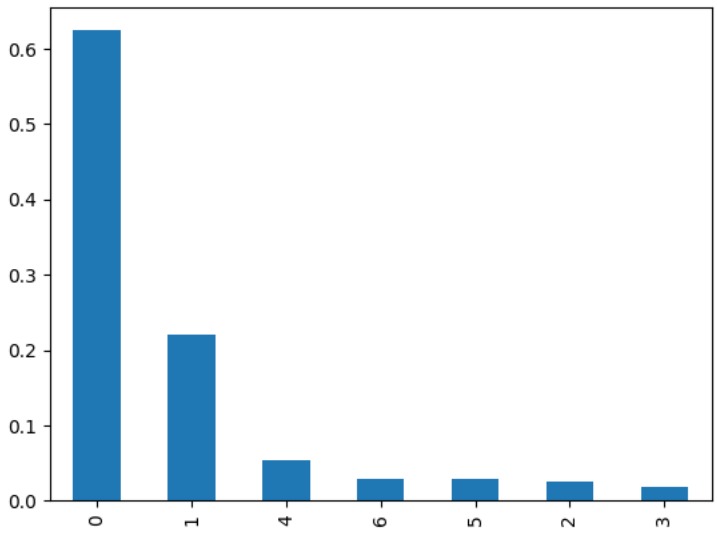
In [23]:
```
print("Number of Features without PCA: ", train.shape[1])
print("Number of Features with PCA: ", train_new.shape[1])
```

```
Number of Features without PCA:  20
Number of Features with PCA:  7
```

Clearly, we get a much better accuracy for the model while using fewer features. But does the features the PCA thought were important the same features that the decision tree used. Lets look at the feature importance of the tree. The following plot numbers the first principal component as 0, the second as 1, and so forth.

In [24]:
```
feature_names_new = list(range(train_new.shape[1]))
imp_pd = pd.Series(data = clf_pca.feature_importances_ ,index = feature_names_new)
imp_pd= imp_pd.sort_values(ascending=False)
imp_pd.plot.bar()
```

Out[24]: <AxesSubplot: >



Amazingly, the first and second components were the most important features in the decision tree. Thus, we can claim that PCA has significantly improved the performance of our model.

Unsupervised learning: Clustering

Clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups. One major algorithm we learned in class is the K-Means algorithm.

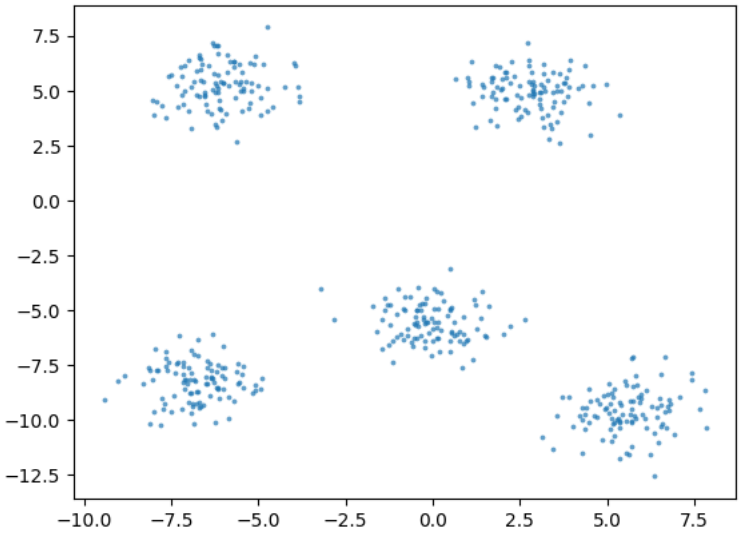
Evaluating K-Means performance

While there are many ways to evaluate the performance measure of clustering algorithsm (https://scikit-learn.org/stable/modules/clustering.html#clustering-performance-evaluation), we will focus on the inertia score of the K-Means model. Inertia is another term for the sum of squared distances of samples to their closest cluster center.

Let us look at how the Inertia changes as a function of the number of clusters for an artificial dataset.

In [25]:
```
#Artifical Dataset
X, y = make_blobs(
    n_samples=500,
    n_features=2,
    centers=5,
    cluster_std=1,
    center_box=(-10.0, 10.0),
    shuffle=True,
    random_state=10,
)  # For reproducibility

plt.scatter(X[:, 0], X[:, 1], marker=".", s=30, lw=0, alpha=0.7,edgecolor="k")
```

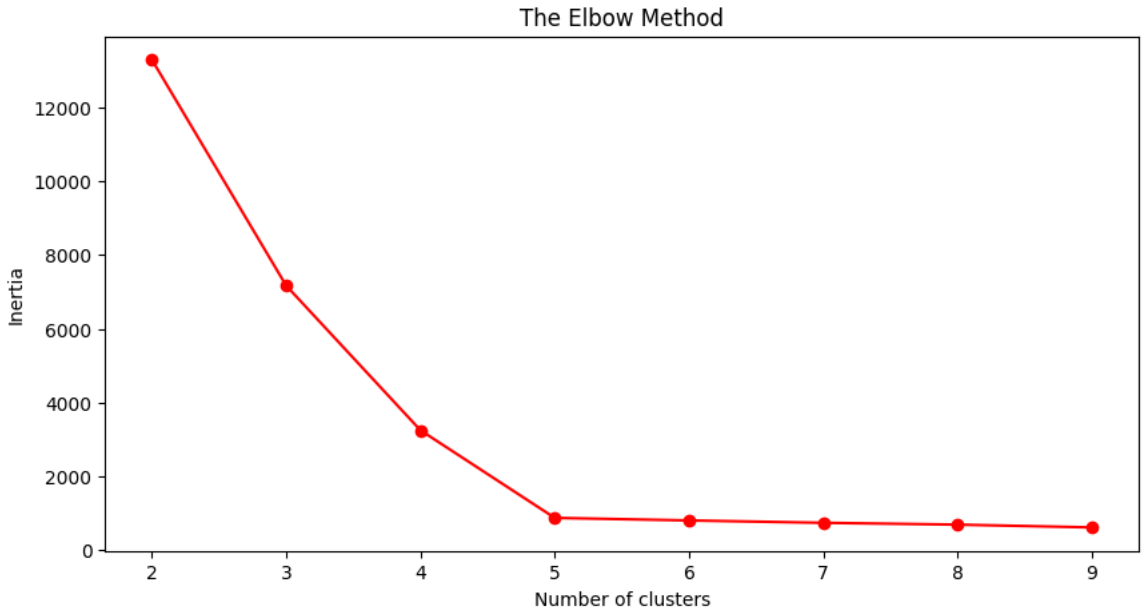
Out[25]:
```
<matplotlib.collections.PathCollection at 0x7f7e05e43c10>
```



In [26]:
```
ks = list(range(2,10))
inertia = []
for k in ks:
    kmeans = KMeans(n_clusters = k, init = 'k-means++', random_state = 0)
    kmeans.fit(X)
    # inertia method returns wcss for that model
    inertia.append(kmeans.inertia_)
    print(f"Inertia for K = {k}: {kmeans.inertia_}")
```

```
Inertia for K = 2: 13293.997460961542
Inertia for K = 3: 7169.578996856776
Inertia for K = 4: 3247.867404069585
Inertia for K = 5: 872.8554968701874
Inertia for K = 6: 803.8466864258223
Inertia for K = 7: 739.5236191503769
Inertia for K = 8: 690.2530283275601
Inertia for K = 9: 614.5138307338651
```

In [27]:
```
plt.figure(figsize=(10,5))
plt.plot(ks, inertia,marker='o',color='red')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
```



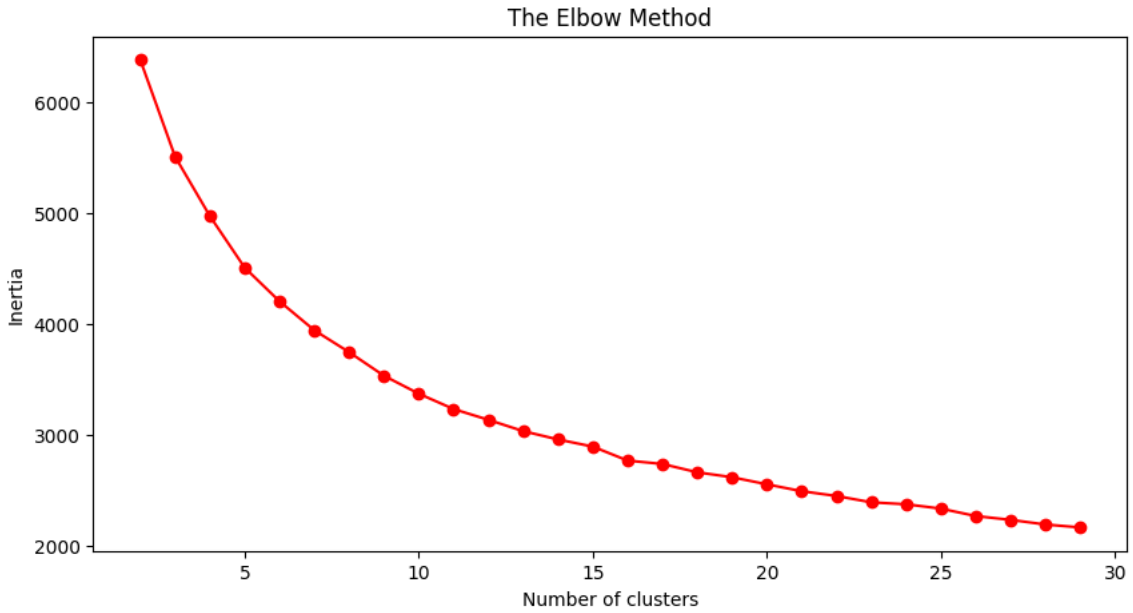
From the plot, we can see that when the number of clusters of K-means is the correct number of clusters, Inertia starts decreasing at a much slower rate. This creates a kind of elbow shape in the graph. For K-means clustering, the elbow method selects the number of clusters where the elbow shape is formed. In this case, we see that this method would produce the correct number of clusters.

Lets try it on the cancer dataset.

In [28]:
```
ks = list(range(2,30))
inertia = []
for k in ks:
    kmeans = KMeans(n_clusters = k, init = 'k-means++', random_state = 0)
    kmeans.fit(train)
    # inertia method returns wcss for that model
    inertia.append(kmeans.inertia_)
    print(f"Inertia for K = {k}: {kmeans.inertia_}")
```

```
Inertia for K = 2: 6381.278325955918
Inertia for K = 3: 5508.62144659371
Inertia for K = 4: 4972.2317219731185
Inertia for K = 5: 4507.2671373660705
Inertia for K = 6: 4203.777246823877
Inertia for K = 7: 3942.659550896413
Inertia for K = 8: 3745.112422829267
Inertia for K = 9: 3532.722515602207
Inertia for K = 10: 3371.0334670278367
Inertia for K = 11: 3232.472758070738
Inertia for K = 12: 3135.1944201924525
Inertia for K = 13: 3033.383842778647
Inertia for K = 14: 2958.320003636036
Inertia for K = 15: 2893.7987635119043
Inertia for K = 16: 2767.804761705545
Inertia for K = 17: 2737.4747101790626
Inertia for K = 18: 2662.1203080706646
Inertia for K = 19: 2617.9089069400507
Inertia for K = 20: 2553.961378449724
Inertia for K = 21: 2491.9133737078337
Inertia for K = 22: 2448.777623600996
Inertia for K = 23: 2391.644588540416
Inertia for K = 24: 2374.1345787190166
Inertia for K = 25: 2334.7940109810725
Inertia for K = 26: 2267.993521706617
Inertia for K = 27: 2233.5854532391295
Inertia for K = 28: 2191.7394026935694
Inertia for K = 29: 2165.2542076413133
```

In [29]:
```
plt.figure(figsize=(10,5))
plt.plot(ks, inertia,marker='o',color='red')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
```



Here we see that the elbow is not as cleanly defined. This may be due to the dataset not being a good fit for K-means. Regardless, we can still apply the elbow method by noting that the slow down happens around 7~14.

Kmeans on Eigenfaces

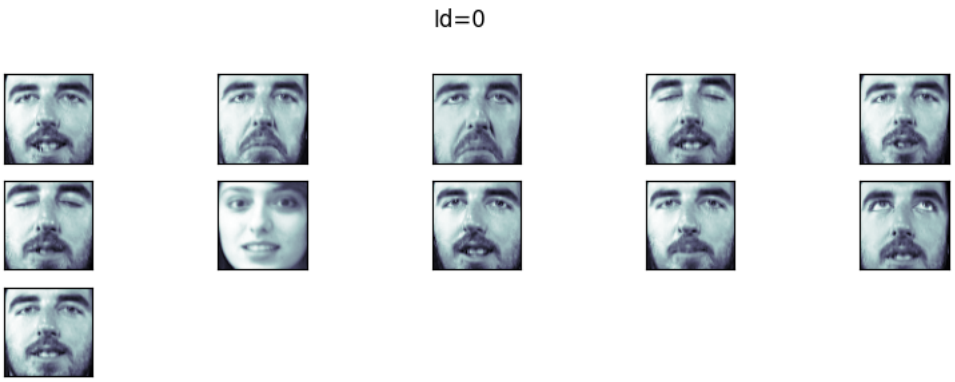
Now, lets see how K-means performs in clustering the face data with PCA.

In [30]:
```
from sklearn.cluster import KMeans

n_clusters = 10 #We know there are 10 subjects
km = KMeans(n_clusters  = n_clusters,random_state=0)

pipe= Pipeline([("scaler",StandardScaler()), #First standardize
                ("pca",PCA()), #Transform using pca
          ("kmeans", km )]) #Then apply k means
```

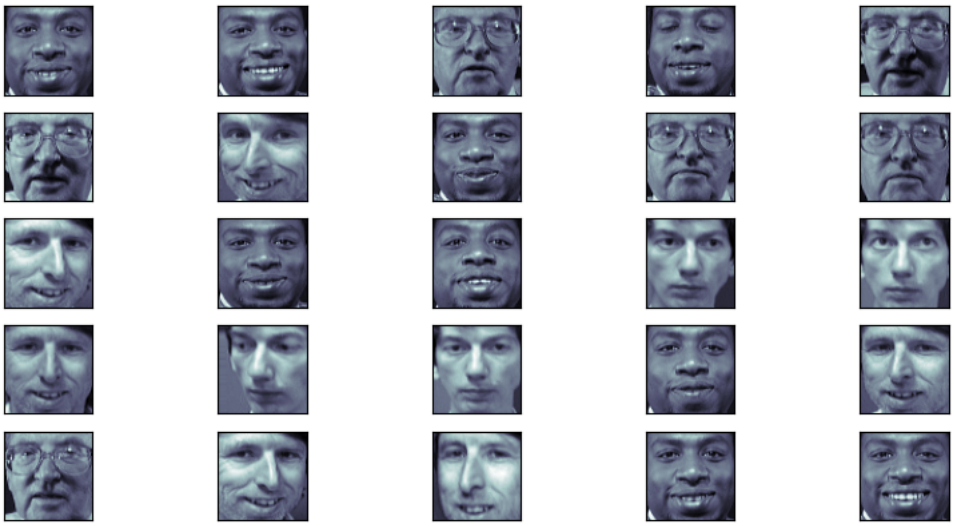
In [31]:
```
clusters = pipe.fit_predict(faces.data)
print(clusters)
```

```
[3 6 3 4 6 4 3 3 3 6 5 5 5 5 5 5 5 5 5 5 1 1 5 1 4 1 4 4 6 6 5 5 5 3 6 4 3
 5 5 6 4 1 1 4 4 4 4 4 4 3 3 3 3 3 3 3 3 3 3 3 7 7 3 4 7 3 7 7 3 7 0 6 3 6
 3 3 6 3 3 6 1 1 1 4 4 4 4 4 1 6 6 6 6 6 6 6 6 4 3 0 0 0 0 0 0 0 0 0 0 4
 1 1 1 1 4 1 6 6 4 5 5 4 4 5 5 4 4 5 4 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5
 5 5 8 3 3 3 3 8 6 8 3 3 4 4 1 1 4 4 4 4 4 4 3 6 4 6 3 3 3 3 3 3 7 7 7 7 7
 7 7 7 7 7 9 9 9 4 4 4 4 4 4 4 9 9 9 9 9 9 9 4 8 9 4 2 2 2 2 2 2 2 2 2 3 6
 1 4 1 4 1 6 4 4 8 8 8 8 5 8 8 8 8 8 6 5 6 5 5 5 6 4 5 6 1 1 1 1 1 1 3 1 1
 5 5 5 5 5 5 5 5 5 5 5 5 1 5 5 5 5 5 5 1 4 2 2 2 9 4 4 9 8 2 2 9 9 9 9 9 9
 9 9 9 9 9 9 9 9 9 9 9 9 9 9 7 7 7 7 7 7 5 7 7 7 9 9 9 9 9 9 9 9 9 9 2 2 2
 2 2 2 2 2 2 2 9 9 9 9 4 6 6 1 4 4 3 8 8 8 7 8 8 8 8 8 1 1 1 1 1 1 1 1 1 1
 4 1 1 6 1 4 6 6 4 1 2 2 2 2 2 2 2 2 2 6 4 3 4 3 1 4 1 4 4]
```

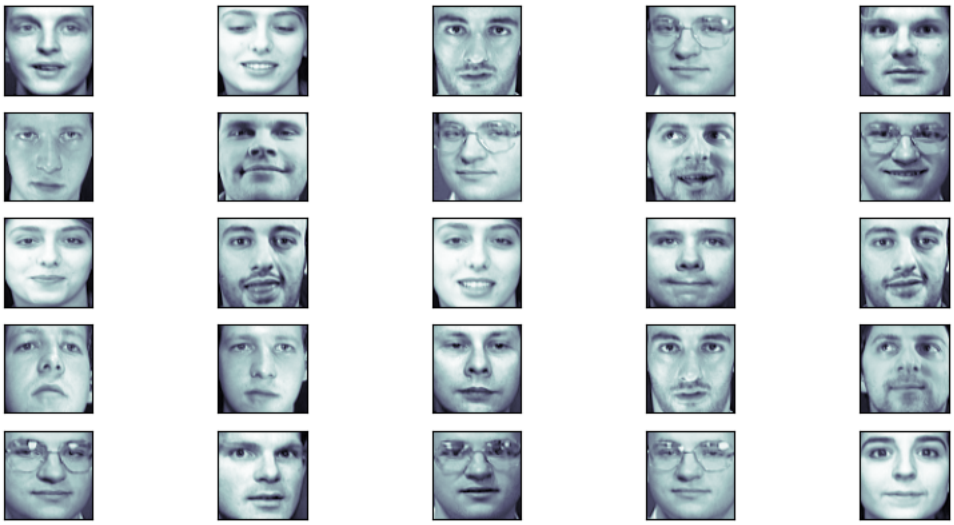
In [32]:
```
for labelID in range(n_clusters):
    # find all indexes into the `data` array that belong to the
    # current label ID, then randomly sample a maximum of 25 indexes
    # from the set
    idxs = np.where(clusters == labelID)[0]
    idxs = np.random.choice(idxs, size=min(25, len(idxs)),
        replace=False)

    # Extract the sampled indexes
    id_face = faces.images[idxs]

    #Plots sampled faces
    fig = plt.figure(figsize=(10,5))
    for i in range(min(25,len(idxs))):
        ax = fig.add_subplot(5, 5, i + 1, xticks=[], yticks=[])
        ax.imshow(id_face[i],
                  cmap=plt.cm.bone)
    fig.suptitle(f"Id={labelID}")
```



Id=2

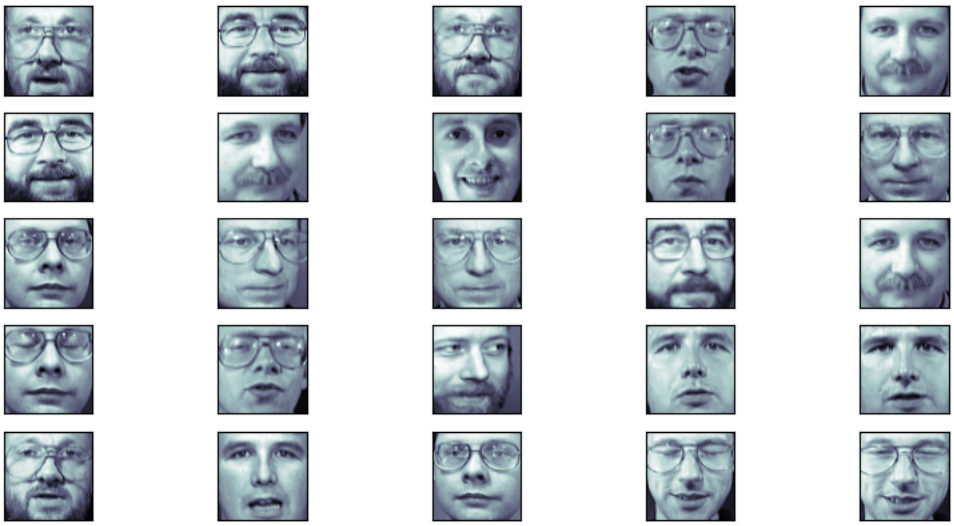


Id=3



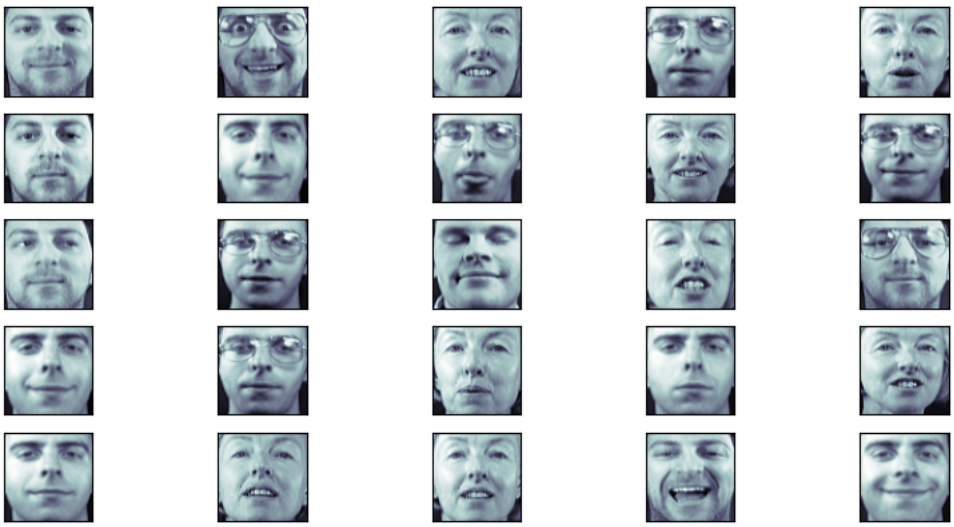
Id=4

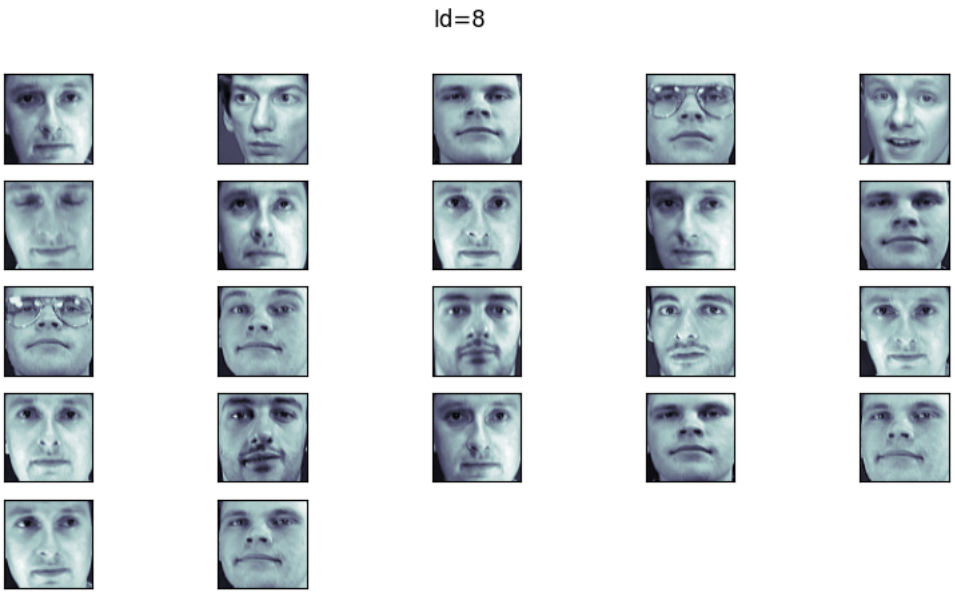
Id=5

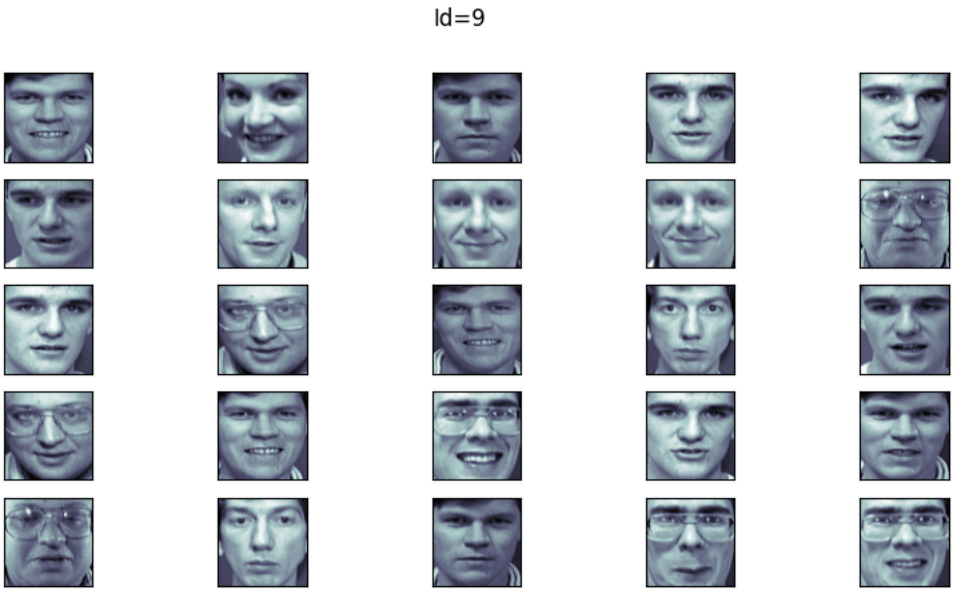


Id=6

Id=7







While the algorithm isn't perfect, we can see that K-means with PCA is picking up on some facial similarity or similar expressions.

(100 pts) Todo: Use new methods to classify heart disease

To compare how these new models perform with the other models discussed in the course, we will apply these new models on the heart disease dataset that was used in project 2.

Background: The Dataset (Recap)

For this exercise we will be using a subset of the UCI Heart Disease dataset, leveraging the fourteen most commonly used attributes. All identifying information about the patient has been scrubbed. You will be asked to classify whether a **patient is suffering from heart disease** based on a host of potential medical factors.

The dataset includes 14 columns. The information provided by each column is as follows:

- **age:** Age in years
- **sex:** (1 = male; 0 = female)
- **cp:** Chest pain type (0 = asymptomatic; 1 = atypical angina; 2 = non-anginal pain; 3 = typical angina)
- **trestbps:** Resting blood pressure (in mm Hg on admission to the hospital)
- **chol:** cholesterol in mg/dl
- **fbs** Fasting blood sugar > 120 mg/dl (1 = true; 0 = false)
- **restecg:** Resting electrocardiographic results (0= showing probable or definite left ventricular hypertrophy by Estes' criteria; 1 = normal; 2 = having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV))

- **thalach:** Maximum heart rate achieved
- **exang:** Exercise induced angina (1 = yes; 0 = no)
- **oldpeak:** Depression induced by exercise relative to rest
- **slope:** The slope of the peak exercise ST segment (0 = downsloping; 1 = flat; 2 = upsloping)
- **ca:** Number of major vessels (0-3) colored by flourosopy
- **thal:** 1 = normal; 2 = fixed defect; 7 = reversable defect
- **sick:** Indicates the presence of Heart disease (True = Disease; False = No disease)

Preprocess Data

This part is done for you since you would have already completed it in project 2. Use the train, target, test, and target_test for all future parts. We also provide the column names for each transformed column for future use.

In [33]:
```
#Preprocess Data

#Load Data
data = pd.read_csv('datasets/heartdisease.csv')

#Transform target feature into numerical
le = LabelEncoder()
data['target'] = le.fit_transform(data['sick'])
data = data.drop(["sick"], axis =1)

#Split target and data
y = data["target"]
x = data.drop(["target"],axis = 1)

#Train test split
#40% in test data as was in project 2
train_raw, test_raw, target, target_test = train_test_split(x,y, test_size=0.4, stratify= y, random_state=0)

#Feature Transformation
#This is the only change from project 2 since we replaced standard scaler to minmax
#This was done to ensure that the numerical features were still of the same scale
#as the one hot encoded features
num_pipeline = Pipeline([
    ('minmax', MinMaxScaler())
])

heart_num = train_raw.drop(['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca','thal'], axis=1)
numerical_features = list(heart_num)
categorical_features = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca','thal']

full_pipeline = ColumnTransformer([
    ("num", num_pipeline, numerical_features),
    ("cat", OneHotEncoder(categories='auto'), categorical_features),
])

#Transform raw data
train = full_pipeline.fit_transform(train_raw)
test = full_pipeline.transform(test_raw) #Note that there is no fit calls

#Extracts features names for each transformed column
feature_names = full_pipeline.get_feature_names_out(list(x.columns))
```

In [34]:
```
print("Column names after transformation by pipeline: ", feature_names)
```

```
Column names after transformation by pipeline:  ['num__age' 'num__trestbps' 'num__chol' 'num__thalach' 'num__oldpe
ak'
 'cat__sex_0' 'cat__sex_1' 'cat__cp_0' 'cat__cp_1' 'cat__cp_2' 'cat__cp_3'
 'cat__fbs_0' 'cat__fbs_1' 'cat__restecg_0' 'cat__restecg_1'
 'cat__restecg_2' 'cat__exang_0' 'cat__exang_1' 'cat__slope_0'
 'cat__slope_1' 'cat__slope_2' 'cat__ca_0' 'cat__ca_1' 'cat__ca_2'
 'cat__ca_3' 'cat__ca_4' 'cat__thal_0' 'cat__thal_1' 'cat__thal_2'
 'cat__thal_3']
```

The following shows the baseline accuracy of simply classifying every sample as the majority class.

In [35]:
```
#Baseline accuracy of using the majority class
ct = target_test.value_counts()
print("Counts of each class in target_test: ")
print(ct)
print("Baseline Accuraccy of using Majority Class: ", np.max(ct)/np.sum(ct))
```

```
Counts of each class in target_test:
0    66
1    56
Name: target, dtype: int64
Baseline Accuraccy of using Majority Class:  0.5409836065573771
```

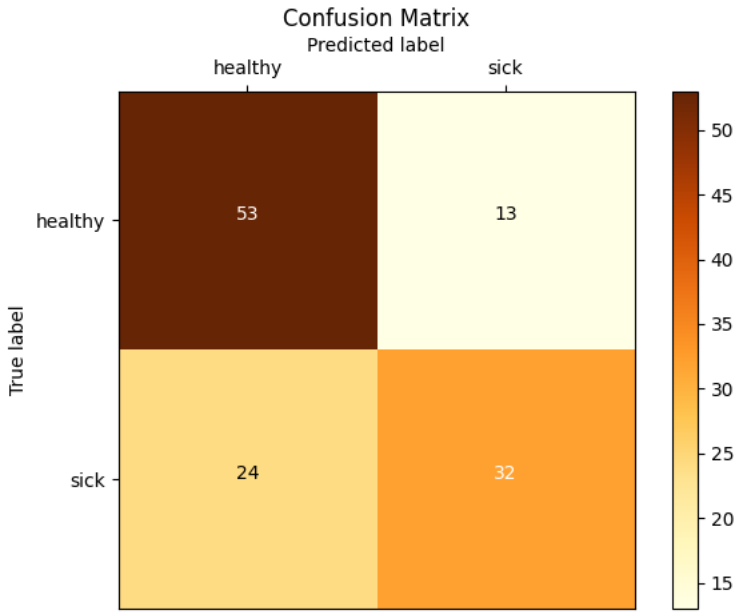
(25 pts) Decision Trees

[5 pts] Apply Decision Tree on Train Data

Apply the decision tree on the **train data** with default parameters of the DecisionTreeClassifier. **Report the accuracy and print the confusion matrix**. Make sure to use random_state = 0 so that your results match ours.

In [36]:
```
clf = DecisionTreeClassifier(criterion="gini", random_state = 0)
clf.fit(train, target)
predicted = clf.predict(test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['healthy', 'sick'])
```

```
Accuracy:    0.696721
Confusion Matrix:
 [[53 13]
 [24 32]]
```

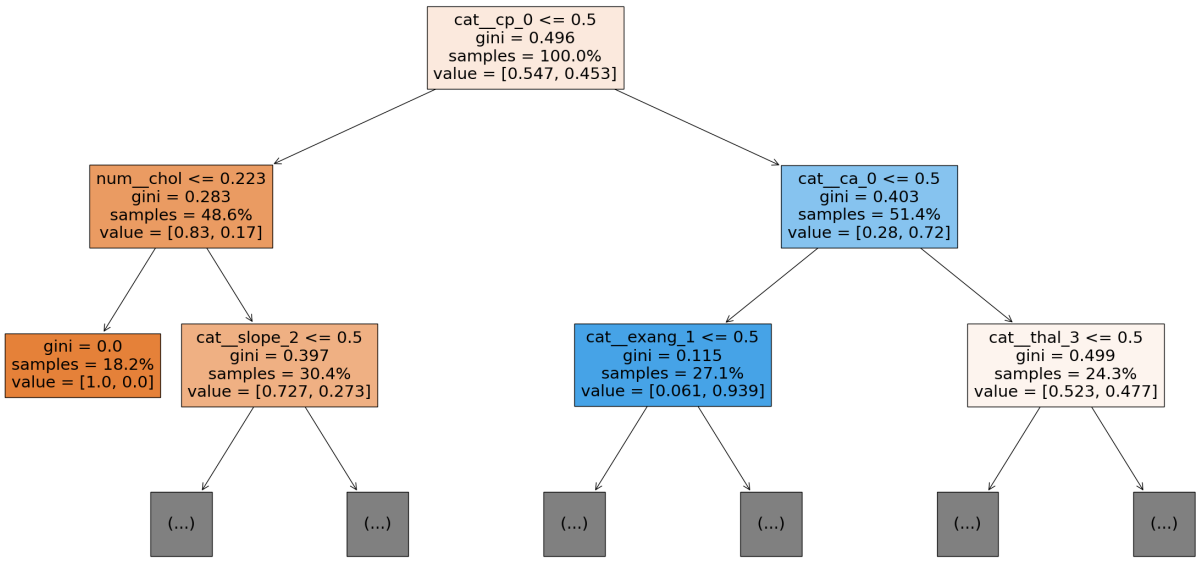


[5 pts] Visualize the Decision Tree

Visualize the first two layers of the decision tree that you trained.

In [37]:
```
plt.figure(figsize = (30,15))
tree.plot_tree(clf,max_depth=2, proportion=True,feature_names=feature_names, filled=True)
```

Out[37]:
```
[Text(0.4230769230769231, 0.875, 'cat__cp_0 <= 0.5\ngini = 0.496\nsamples = 100.0%\nvalue = [0.547, 0.453]'),
 Text(0.15384615384615385, 0.625, 'num__chol <= 0.223\ngini = 0.283\nsamples = 48.6%\nvalue = [0.83, 0.17]'),
 Text(0.07692307692307693, 0.375, 'gini = 0.0\nsamples = 18.2%\nvalue = [1.0, 0.0]'),
 Text(0.23076923076923078, 0.375, 'cat__slope_2 <= 0.5\ngini = 0.397\nsamples = 30.4%\nvalue = [0.727, 0.273]'),
 Text(0.15384615384615385, 0.125, '\n  (...)  \n'),
 Text(0.3076923076923077, 0.125, '\n  (...)  \n'),
 Text(0.6923076923076923, 0.625, 'cat__ca_0 <= 0.5\ngini = 0.403\nsamples = 51.4%\nvalue = [0.28, 0.72]'),
 Text(0.5384615384615384, 0.375, 'cat__exang_1 <= 0.5\ngini = 0.115\nsamples = 27.1%\nvalue = [0.061, 0.939]'),
 Text(0.46153846153846156, 0.125, '\n  (...)  \n'),
 Text(0.6153846153846154, 0.125, '\n  (...)  \n'),
 Text(0.8461538461538461, 0.375, 'cat__thal_3 <= 0.5\ngini = 0.499\nsamples = 24.3%\nvalue = [0.523, 0.477]'),
 Text(0.7692307692307693, 0.125, '\n  (...)  \n'),
 Text(0.9230769230769231, 0.125, '\n  (...)  \n')]
```



What is the gini index improvement of the first split?

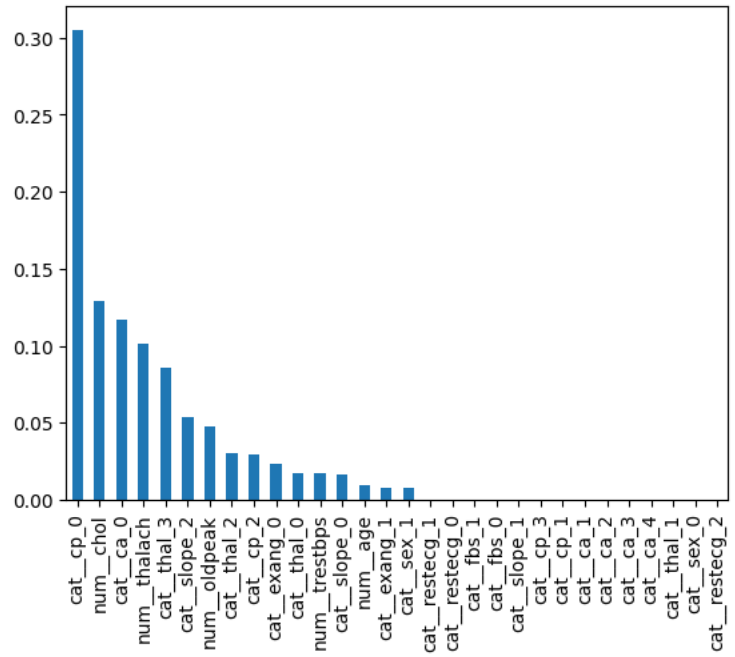
Response: Gini Improvement = G(Parent) - (p_1*G(c_1)* + *p_2*G(c_2)) => .496 - ((.486*.283) + (.514 * .403)) => .151

[5 pts] Plot the importance of each feature for the Decision Tree

In [38]:
```
imp_pd = pd.Series(data = clf.feature_importances_ ,index = feature_names)
imp_pd= imp_pd.sort_values(ascending=False)
print(imp_pd)
imp_pd.plot.bar()
```

```
cat__cp_0         0.304932
num__chol         0.129301
cat__ca_0         0.116845
num__thalach      0.101678
cat__thal_3       0.086105
cat__slope_2      0.053376
num__oldpeak      0.048016
cat__thal_2       0.030665
cat__cp_2         0.029861
cat__exang_0      0.023225
cat__thal_0       0.017625
num__trestbps     0.017518
cat__slope_0      0.016157
num__age          0.009555
cat__exang_1      0.007709
cat__sex_1        0.007432
cat__restecg_1    0.000000
cat__restecg_0    0.000000
cat__fbs_1        0.000000
cat__fbs_0        0.000000
cat__slope_1      0.000000
cat__cp_3         0.000000
cat__cp_1         0.000000
cat__ca_1         0.000000
cat__ca_2         0.000000
cat__ca_3         0.000000
cat__ca_4         0.000000
cat__thal_1       0.000000
cat__sex_0        0.000000
cat__restecg_2    0.000000
dtype: float64
```

Out[38]: <AxesSubplot: >



How many features have non-zero importance for the Decision Tree? If we remove the features with zero importance, will it change the decision tree for the same sampled dataset?

Response: 16 features have non-zero importance. These features are: cat__cp_0, num__chol, cat__ca_0, num__thalach, cat__thal_3, cat__slope_2, num__oldpeak, cat__thal_2, cat__cp_2, cat__exang_0, cat__thal_0, num__trestbps, cat__slope_0, num__age, cat__exang_1, cat__sex_1, cat__restecg_1. We can drop the features with zero importance without changing the decision tree as none of them are splitting features within the first two levels.

[10 pts] Optimize Decision Tree

While the default Decision Tree performs fairly well on the data, lets see if we can improve performance by optimizing the parameters.

Run a GridSearchCV with 3-Fold Cross Validation for the Decision Tree. Find the best model parameters amongst the following:

- max_depth = [1,2,3,4,5,10,15]
- min_samples_split = [2,4,6,8]
- criterion = ["gini", "entropy"]

After using GridSearchCV, print the best model parameters and the best score.

In [39]:
```
parameters = [
    {"max_depth": [1,2,3,4,5,10,15],
    "min_samples_split": [2,4,6,8],
    "criterion": ["gini","entropy"]}
]

k = 3
kf = KFold(n_splits=k, random_state=None)

clf = DecisionTreeClassifier(criterion="gini", random_state = 0)
grid = GridSearchCV(clf, parameters, cv = kf, scoring = "accuracy")
grid.fit(train,target)
#Put results into Dataframe
res= pd.DataFrame(grid.cv_results_)
res
```

4	0.000605	0.000077	gini	5	8	{'criterion': 'gini', 'max_depth': 5, 'min_sam...	0.754098	0.683333	0.783333	0.
4	0.000567	0.000067	gini	10	2	{'criterion': 'gini', 'max_depth': 10, 'min_sa...	0.737705	0.716667	0.800000	0.
3	0.000565	0.000023	gini	10	4	{'criterion': 'gini', 'max_depth': 10, 'min_sa...	0.737705	0.683333	0.733333	0.
4	0.000739	0.000293	gini	10	6	{'criterion': 'gini', 'max_depth': 10, 'min_sa...	0.737705	0.650000	0.733333	0.

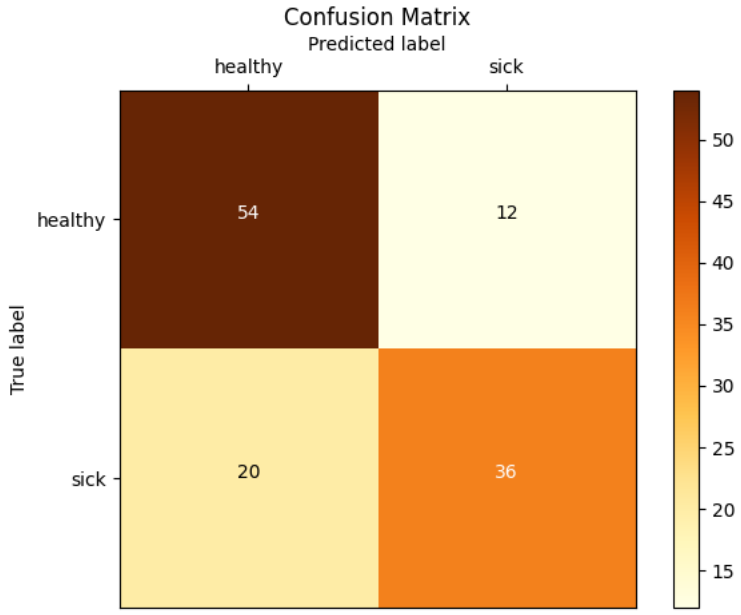
In [40]:
```
ram_criterion", "param_max_depth", "param_min_samples_split","mean_test_score"]].sort_values(by=['rank_test_score'])
```

6	42	gini	2	6	0.734973
7	42	gini	2	8	0.734973
14	46	gini	4	6	0.729235
18	46	gini	5	6	0.729235
12	46	gini	4	2	0.729235
34	49	entropy	2	6	0.723862
33	49	entropy	2	4	0.723862
32	49	entropy	2	2	0.723862
35	49	entropy	2	8	0.723862
25	53	gini	15	4	0.718124
21	53	gini	10	4	0.718124
26	55	gini	15	6	0.707013
22	55	gini	10	6	0.707013

Using the best model you have, report the test accuracy and print out the confusion matrix

In [41]:
```
predicted = grid.predict(test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
draw_confusion_matrix(target_test, predicted, ['healthy', 'sick'])
```

```
Accuracy:    0.737705
```



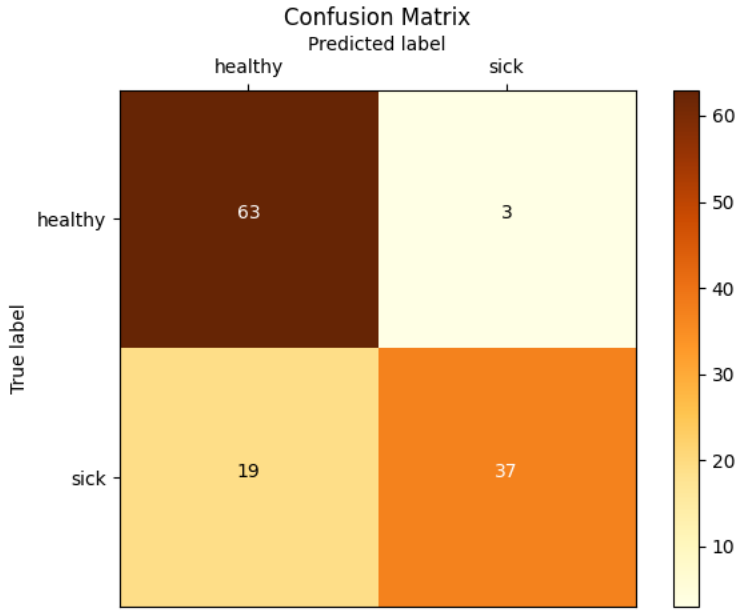
(20 pts) Multi-Layer Perceptron

[5 pts] Applying a Multi-Layer Perceptron

Apply the MLP on the **train data** with hidden_layer_sizes=(100,100) and max_iter = 800. **Report the accuracy and print the confusion matrix**. Make sure to set random_state=0.

In [42]:
```
clf = MLPClassifier(hidden_layer_sizes = (100,100), max_iter = 800, random_state = 0)
clf.fit(train, target)
predicted = clf.predict(test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['healthy', 'sick'])
```

```
Accuracy:    0.819672
Confusion Matrix:
 [[63  3]
 [19 37]]
```



[10 pts] Speedtest between Decision Tree and MLP

Let us compare the training times and prediction times of a Decision Tree and an MLP. **Time how long it takes for a Decision Tree and an MLP to perform a .fit operation (i.e. training the model). Then, time how long it takes for a Decision Tree and an MLP to perform a .predict operation (i.e. predicting the testing data). Print out the timings and specify which model was quicker for each operation.** We recommend using the time (https://docs.python.org/3/library/time.html) python module to time your code. An example of the time module was shown in project 2. Use the default Decision Tree Classifier and the MLP with the previously mentioned parameters.

In [43]:
```
clfd = DecisionTreeClassifier(criterion="gini", random_state = 0)
t0 = time.time()
clfd.fit(train, target)
t1 = time.time()
dtcttime = t1-t0
print("Decision Tree Training Time : ", dtcttime)
t0 = time.time()
clfd.predict(test)
t1 = time.time()
dtcptime = t1-t0
print("Decision Tree Predict Time : ", dtcptime)

clfm = MLPClassifier(hidden_layer_sizes = (100,100), max_iter = 800, random_state = 0)
t0 = time.time()
clfm.fit(train, target)
t1 = time.time()
mlpttime = t1-t0
print("MLP Training Time : ", mlpttime)
t0 = time.time()
clfm.predict(test)
t1 = time.time()
mlpptime = t1-t0
print("MLP Predict Time : ", mlpptime)
```

```
Decision Tree Training Time :  0.0033843517303466797
Decision Tree Predict Time :  0.0005855560302734375
MLP Training Time :  1.2351632118225098
MLP Predict Time :  0.0008776187896728516
```

As seen above, the decision tree was faster for both training and prediction.

[5 pts] Compare and contrast Decision Trees and MLPs.

Describe at least one advantage and disadvantage of using an MLP over a Decision Tree.

Response: MLP models perform better the more complex a data set it. This is especially true when the decision boundaries for classification/regression tasks cannot be seperated by axis based bounds. However, when decision boundaries can be set by horizontal and vertical bounds then decision trees often perform better and are easier to use and interpret.

(35 pts) PCA

[5 pts] Transform the train data using PCA

Train a PCA model to project the train data on the top 10 components. **Print out the 10 principal components**. Look at the documentation of PCA (https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html) for reference.

In [44]:
```
pca = PCA(n_components = 10)
pca_pipe = Pipeline([("scaler",StandardScaler()), #Scikit learn PCA does not standardize so we need to add
                     ("pca",pca)])
pca_pipe.fit(train)

print(pca.singular_values_)
```

```
[30.93700171 22.00270214 20.79491454 18.50632992 17.43476832 16.75037207
 16.37675581 16.27252985 15.25552037 14.84463047]
```

[5 pts] Percentage of variance explained by top 10 principal components

Using PCA's "explained_variance_ratio_", print the percentage of variance explained by the top 10 principal components.

In [45]:
```
print(pca.explained_variance_ratio_)
```

```
[0.17626116 0.08915634 0.07963692 0.06307261 0.05597995 0.05167126
 0.04939192 0.04876524 0.0428602  0.04058251]
```

[5 pts] Transform the train and test data into train_pca and test_pca using PCA

Note: Use fit_transform for train and transform for test

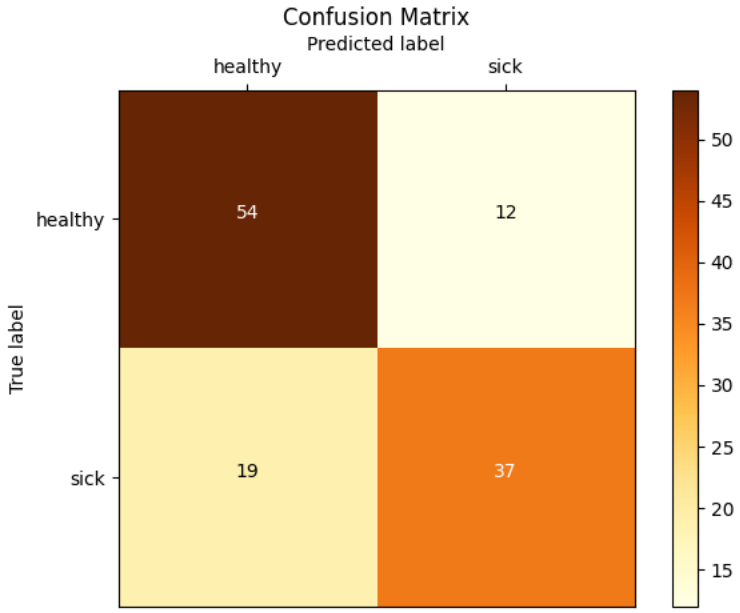
In [46]:
```
train_pca = pca.transform(train)
test_pca = pca.transform(test)
```

[5 pts] PCA+Decision Tree

Train the default Decision Tree Classifier using train_pca. **Report the accuracy using test_pca and print the confusion matrix**.

In [47]:
```
clf = DecisionTreeClassifier(criterion="gini", random_state = 0)
clf.fit(train_pca, target)
predicted = clf.predict(test_pca)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['healthy', 'sick'])
```

```
Accuracy:    0.745902
Confusion Matrix:
 [[54 12]
 [19 37]]
```



Does the model perform better with or without PCA?

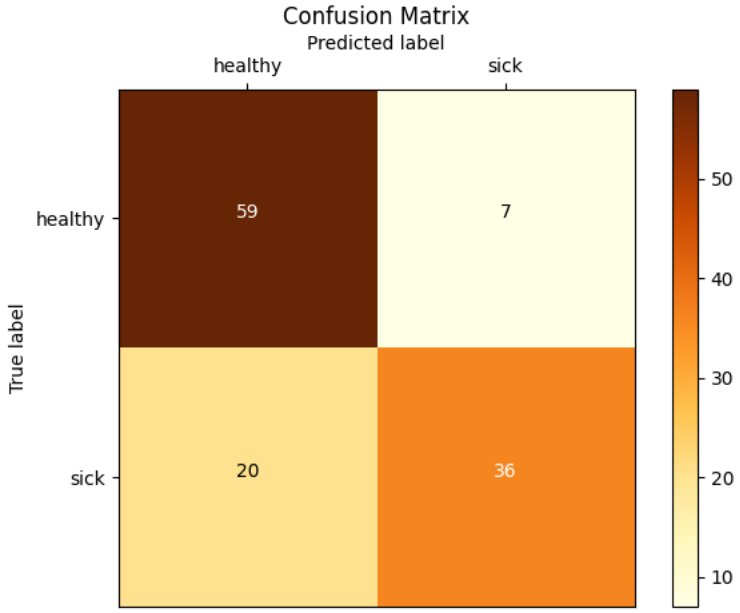
Response: The model performed better with pca.

[5 pts] PCA+MLP

Train the MLP classifier with the same parameters as before using train_pca. **Report the accuracy using test_pca and print the confusion matrix**.

In [48]:
```
clf = MLPClassifier(hidden_layer_sizes = (100,100), max_iter = 800, random_state = 0)
clf.fit(train_pca, target)
predicted = clf.predict(test_pca)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
print("Confusion Matrix: \n", metrics.confusion_matrix(target_test,predicted))
draw_confusion_matrix(target_test, predicted, ['healthy', 'sick'])
```

```
Accuracy:    0.778689
Confusion Matrix:
 [[59  7]
 [20 36]]
```



Does the model perform better with or without PCA?

Response: The model performs worse with pca.

[10 pts] Pros and Cons of PCA

In your own words, provide at least two pros and at least two cons for using PCA

Response: PCA is beneficial as it reduces the dimensionality of the data which prevents overfitting and helps with visualization. PCA however cannot be used effectively when the data has uncorrelated features or is not linear.

(20 pts) K-Means Clustering

[5 pts] Apply K-means to the train data and print out the Inertia score

Use n_cluster = 5 and random_state = 0.

In [49]:
```
kmeans = KMeans(n_clusters = 5, random_state = 0)
kmeans.fit(train)
print(f"Inertia for K = 5: {kmeans.inertia_}")
```

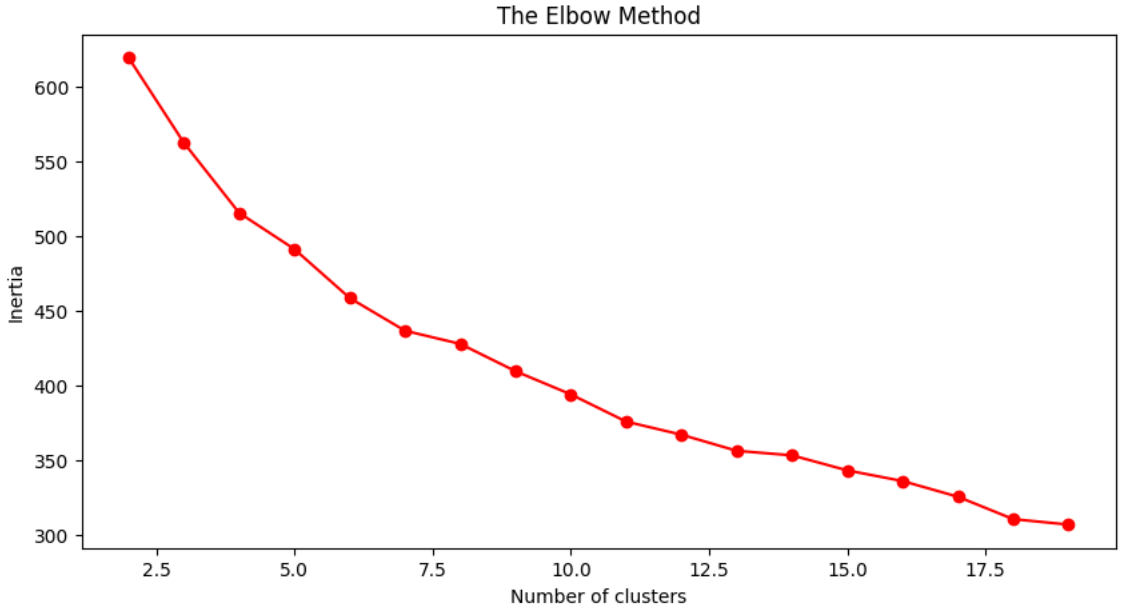
```
Inertia for K = 5: 491.0665663612592
```

[10 pts] Find the optimal cluster size using the elbow method.

Use the elbow method to find the best cluster size or range of best cluster sizes for the train data. Check the cluster sizes from 2 to 20. Make sure to plot the Inertia and state where you think the elbow starts. Make sure to use random_state = 0.

In [50]:
```
ks = list(range(2,20))
inertia = []
for k in ks:
    kmeans = KMeans(n_clusters = k, init = 'k-means++', random_state = 0)
    kmeans.fit(train)
    # inertia method returns wcss for that model
    inertia.append(kmeans.inertia_)
    print(f"Inertia for K = {k}: {kmeans.inertia_}")
plt.figure(figsize=(10,5))
plt.plot(ks, inertia,marker='o',color='red')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
```

```
Inertia for K = 2: 619.2596852490838
Inertia for K = 3: 562.2941749488493
Inertia for K = 4: 515.3501104402982
Inertia for K = 5: 491.0665663612592
Inertia for K = 6: 458.34490628572456
Inertia for K = 7: 436.4673131159211
Inertia for K = 8: 427.64243132453544
Inertia for K = 9: 409.3453854307659
Inertia for K = 10: 393.8362013824141
Inertia for K = 11: 375.627142914177
Inertia for K = 12: 366.8725741918041
Inertia for K = 13: 356.07044286127075
Inertia for K = 14: 353.0506627827144
Inertia for K = 15: 342.9664892654279
Inertia for K = 16: 335.82888467728145
Inertia for K = 17: 325.33654094415056
Inertia for K = 18: 310.3448076066396
Inertia for K = 19: 306.7095752890683
```



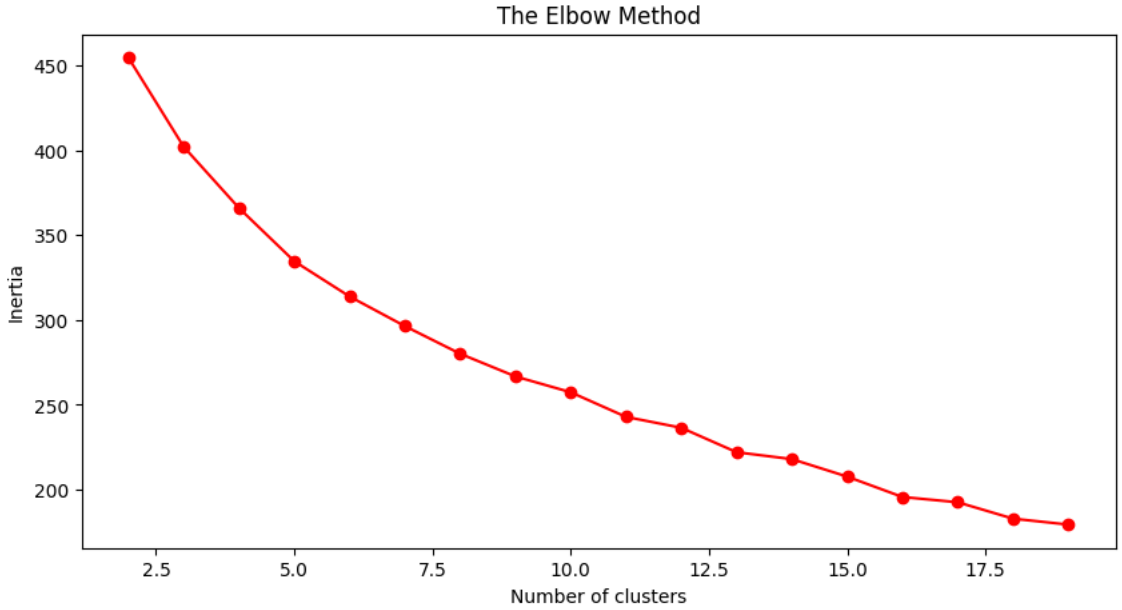
The elbow appears to be between 5 and 10 clusters

[5 pts] Find the optimal cluster size for the train_pca data

Repeat the same experiment but use train_pca instead of train.

In [51]:
```
ks = list(range(2,20))
inertia = []
for k in ks:
    kmeans = KMeans(n_clusters = k, init = 'k-means++', random_state = 0)
    kmeans.fit(train_pca)
    # inertia method returns wcss for that model
    inertia.append(kmeans.inertia_)
    print(f"Inertia for K = {k}: {kmeans.inertia_}")
plt.figure(figsize=(10,5))
plt.plot(ks, inertia,marker='o',color='red')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
```

```
Inertia for K = 2: 454.6323855838633
Inertia for K = 3: 402.1013219723234
Inertia for K = 4: 366.00606255931257
Inertia for K = 5: 334.64480327877766
Inertia for K = 6: 313.87091527065974
Inertia for K = 7: 296.41743714338634
Inertia for K = 8: 280.1237570630844
Inertia for K = 9: 266.7442004340305
Inertia for K = 10: 257.4176549517501
Inertia for K = 11: 242.91165865721095
Inertia for K = 12: 236.47596329430155
Inertia for K = 13: 222.07641841588259
Inertia for K = 14: 218.01180007302983
Inertia for K = 15: 207.70820145485737
Inertia for K = 16: 195.68790653680145
Inertia for K = 17: 192.5872790431151
Inertia for K = 18: 182.91446968159318
Inertia for K = 19: 179.43395320163512
```



Notice that the inertia is much smaller for every cluster size when using PCA features. Why do you think this is happening? Hint: Think about what Inertia is calculating and consider the number of features that PCA outputs.

Response: One reason intertia may be smaller is because the data is standardized before being passed through pca. Furthermore, by projecting the data onto its pca components we are reducing the variance in the data to only the variance explained by those 10 principle components.

(100 pts) Putting it all together

Through all the homeworks and projects, you have learned how to apply many different models to perform a supervised learning task. We are now asking you to take everything that you learned to create a model that can predict whether a hotel reservation will be canceled or not.

Context

Hotels see millions of people every year and always wants to keep rooms occupied and payed for. Cancellations make the business lose money since it may make it difficult to reserve to another customer on such short notice. As such, it is useful for a hotel to know whether a reservation is likely to cancel or not. The following dataset will provide a variety of information about a booking that you will use to predict whether that booking will cancel or not.

Property Management System - PMS

Attribute Information

(C) is for Categorical

(N) is for Numeric

```
1) is_canceled (C) : Value indicating if the booking was canceled (1) or not (0).
2) hotel (C) : The datasets contains the booking information of two hotel. One of the hotels is a resort ho
tel and the other is a city hotel.
3) arrival_date_month (C): Month of arrival date with 12 categories: “January” to “December”
4) stays_in_weekend_nights (N): Number of weekend nights (Saturday or Sunday) the guest stayed or booked to
stay at the hotel
5) stays_in_week_nights (N): Number of week nights (Monday to Friday) the guest stayed or booked to stay at
the hotel BO and BL/Calculated by counting the number of week nights
6) adults (N): Number of adults
7) children (N): Number of children
8) babies (N): Number of babies
9) meal (C): Type of meal
10) country (C): Country of origin.
11) previous_cancellations (N): Number of previous bookings that were canceled by the customer prior to the
current booking
12) previous_bookings_not_canceled (N) : Number of previous bookings not canceled by the customer prior to
the current booking
13) reserved_room_type (C): Code of room type reserved. Code is presented instead of designation for anonym
ity reasons
14) booking_changes (N) : Number of changes/amendments made to the booking from the moment the booking was
entered on the PMS until the moment of check-in or cancellation
15) deposit_type (C) : No Deposit – no deposit was made; Non Refund – a deposit was made in the value of th
e total stay cost; Refundable – a deposit was made with a value under the total cost of stay
16) days_in_waiting_list (N): Number of days the booking was in the waiting list before it was confirmed to
the customer
17) customer_type (C): Group – when the booking is associated to a group; Transient – when the booking is n
ot part of a group or contract, and is not associated to other transient booking; Transient-party – when th
e booking is transient, but is associated to at least other transient booking
18) adr (N): Average Daily Rate (Calculated by dividing the sum of all lodging transactions by the total nu
mber of staying nights)
19) required_car_parking_spaces (N): Number of car parking spaces required by the customer
20) total_of_special_requests (N): Number of special requests made by the customer (e.g. twin bed or high f
loor)
21) name (C): Name of the Guest (Not Real)
22) email (C): Email (Not Real)
23) phone-number (C): Phone number (not real)
```

This dataset is quite large with 86989 samples. This makes it difficult to just brute force running a lot of models. As such, you have to be thoughtful when designing your models.

The file name for the training data is "hotel_booking.csv".

Challenge

This project is about being able to predict whether a reservation is likely to cancel based on the input parameters available to us. We will ask you to perform some specific instructions to lead you in the right direction but you are given free reign on which models to use and the preprocessing steps you make. We will ask you to **write out a description of what models you choose and why you choose them**.

(50 pts) Preprocessing

Preprocessing: For the dataset, the following are mandatory pre-processing steps for your data:

- Use One-Hot Encoding on all categorical features (specify whether you keep the extra feature or not for features with multiple values)
- Determine which fields need to be dropped
- Handle missing values (Specify your strategy)
- Rescale the real valued features using any strategy you choose (StandardScaler, MinMaxScaler, Normalizer, etc)
- Augment at least one feature
- Implement a train-test split with 20% of the data going to the test data. Make sure that the test and train data are balanced in terms of the desired class.

After writing your preprocessing code, write out a description of what you did for each step and provide a justification for your choices. All descriptions should be written in the markdown cells of the jupyter notebook. Make sure your writing is clear and professional.

We highly recommend reading through the scikit-learn documentation (https://scikit-learn.org/stable/data_transforms.html) to make this part easier.

Plan: 1)Import Data 2)Correct Missing Values 3)Augment Features -Cancelation Rate 4)Drop Fields 5)Pipeline

In [52]:
```
#Preprocess Data
#1)Import Data
data = pd.read_csv('datasets/hotel_booking.csv')
data.head()
```

Out[52]:

	is_canceled	hotel	lead_time	arrival_date_month	stays_in_weekend_nights	stays_in_week_nights	adults	children	babies	meal	...	booking_changes
0	0	Resort Hotel	4	February	1	2	2	0.0	0	FB	...	0
1	1	City Hotel	172	June	0	2	1	0.0	0	BB	...	0
2	0	City Hotel	4	November	2	1	1	0.0	0	BB	...	0
3	1	City Hotel	68	September	0	2	2	0.0	0	HB	...	0
4	1	City Hotel	149	July	2	4	3	0.0	0	BB	...	0

5 rows × 24 columns

In [53]:
```
data["is_canceled"].value_counts()
```

Out[53]:
```
0    46519
1    31771
Name: is_canceled, dtype: int64
```

In [54]:
```
#2)Correct Missing Values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 78290 entries, 0 to 78289
Data columns (total 24 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   is_canceled                     78290 non-null  int64
 1   hotel                           78290 non-null  object
 2   lead_time                       78290 non-null  int64
 3   arrival_date_month              78290 non-null  object
 4   stays_in_weekend_nights         78290 non-null  int64
 5   stays_in_week_nights            78290 non-null  int64
 6   adults                          78290 non-null  int64
 7   children                        78287 non-null  float64
 8   babies                          78290 non-null  int64
 9   meal                            78290 non-null  object
 10  country                         78290 non-null  object
 11  previous_cancellations          78290 non-null  int64
 12  previous_bookings_not_canceled  78290 non-null  int64
 13  reserved_room_type              78290 non-null  object
 14  booking_changes                 78290 non-null  int64
 15  deposit_type                    78290 non-null  object
 16  days_in_waiting_list            78290 non-null  int64
 17  customer_type                   78290 non-null  object
 18  adr                             78290 non-null  float64
 19  required_car_parking_spaces     78290 non-null  int64
 20  total_of_special_requests       78290 non-null  int64
 21  name                            78290 non-null  object
 22  email                           78290 non-null  object
 23  phone-number                    78290 non-null  object
dtypes: float64(2), int64(12), object(10)
memory usage: 14.3+ MB
```

After placing the data into a pandas df, I used the info function to see if there were any missing values in the data. There were a few null values in the 'children' column so I assumed no children and replaced those nan values with 0.

In [55]:
```
data["children"].fillna(0.0, inplace=True)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 78290 entries, 0 to 78289
Data columns (total 24 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   is_canceled                     78290 non-null  int64
 1   hotel                           78290 non-null  object
 2   lead_time                       78290 non-null  int64
 3   arrival_date_month              78290 non-null  object
 4   stays_in_weekend_nights         78290 non-null  int64
 5   stays_in_week_nights            78290 non-null  int64
 6   adults                          78290 non-null  int64
 7   children                        78290 non-null  float64
 8   babies                          78290 non-null  int64
 9   meal                            78290 non-null  object
 10  country                         78290 non-null  object
 11  previous_cancellations          78290 non-null  int64
 12  previous_bookings_not_canceled  78290 non-null  int64
 13  reserved_room_type              78290 non-null  object
 14  booking_changes                 78290 non-null  int64
 15  deposit_type                    78290 non-null  object
 16  days_in_waiting_list            78290 non-null  int64
 17  customer_type                   78290 non-null  object
 18  adr                             78290 non-null  float64
 19  required_car_parking_spaces     78290 non-null  int64
 20  total_of_special_requests       78290 non-null  int64
 21  name                            78290 non-null  object
 22  email                           78290 non-null  object
 23  phone-number                    78290 non-null  object
dtypes: float64(2), int64(12), object(10)
memory usage: 14.3+ MB
```

In [56]:
```
#3)Augment Features
data["cancel_rate"] = data["previous_cancellations"] / (data["previous_cancellations"] + data["previous_bookings_no
data["cancel_rate"].fillna(data["cancel_rate"].mean(), inplace=True)
pd.set_option('display.max_columns', None)
data.head()
```

Out[56]:

	is_canceled	hotel	lead_time	arrival_date_month	stays_in_weekend_nights	stays_in_week_nights	adults	children	babies	meal	country	previous_canc
0	0	Resort Hotel	4	February	1	2	2	0.0	0	FB	ESP	
1	1	City Hotel	172	June	0	2	1	0.0	0	BB	PRT	
2	0	City Hotel	4	November	2	1	1	0.0	0	BB	PRT	
3	1	City Hotel	68	September	0	2	2	0.0	0	HB	PRT	
4	1	City Hotel	149	July	2	4	3	0.0	0	BB	DEU	

The augmentation that came to mind was the cancelation rate. This would be the proportion of bookings that customer has canceled in the past (canceled_bookings / total_bookings). I felt that if the customer had a history if canceling their bookings then it would be a good indicator as to whether or not this particular booking would get canceled. By using a percentage instead of a single number we could get a better indication as to whether or not a customer consistently cancels bookings or if it was a one time thing. For customers without a history of cancelations we set their cancelation rate as the mean of those with a history as that would be the expected chance they would cancel their booking.

In [57]:
```
#4)Drop Columns
data = data.drop(["name", "email", "phone-number"],axis= 1)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 78290 entries, 0 to 78289
Data columns (total 22 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   is_canceled                     78290 non-null  int64  
 1   hotel                           78290 non-null  object 
 2   lead_time                       78290 non-null  int64  
 3   arrival_date_month              78290 non-null  object 
 4   stays_in_weekend_nights         78290 non-null  int64  
 5   stays_in_week_nights            78290 non-null  int64  
 6   adults                          78290 non-null  int64  
 7   children                        78290 non-null  float64
 8   babies                          78290 non-null  int64  
 9   meal                            78290 non-null  object 
 10  country                         78290 non-null  object 
 11  previous_cancellations          78290 non-null  int64  
 12  previous_bookings_not_canceled  78290 non-null  int64  
 13  reserved_room_type              78290 non-null  object 
 14  booking_changes                 78290 non-null  int64  
 15  deposit_type                    78290 non-null  object 
 16  days_in_waiting_list            78290 non-null  int64  
 17  customer_type                   78290 non-null  object 
 18  adr                             78290 non-null  float64
 19  required_car_parking_spaces     78290 non-null  int64  
 20  total_of_special_requests       78290 non-null  int64  
 21  cancel_rate                     78290 non-null  float64
dtypes: float64(3), int64(12), object(7)
memory usage: 13.1+ MB
```

Dropped name, email, and phone number columns as they hold no real value. Features like required car spaces, meal, country of origin, etc may not appear directly related to chances of canceling a booking but I justified keeping them under the assumption that they may indicate income or other external attributes that may influence that persons attitudes towards canceling bookings.

In [58]:
```
corr_matrix = data.corr()
corr_matrix["is_canceled"].sort_values(ascending=False)
```

```
/tmp/ipykernel_17811/1951794863.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprec
ated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_onl
y to silence this warning.
  corr_matrix = data.corr()
```

Out[58]:
```
is_canceled                      1.000000
lead_time                        0.326806
cancel_rate                      0.293942
previous_cancellations           0.119770
days_in_waiting_list             0.070779
adults                           0.057706
adr                              0.035421
stays_in_week_nights             0.019298
stays_in_weekend_nights         -0.012650
children                        -0.018884
babies                          -0.035107
previous_bookings_not_canceled  -0.067611
booking_changes                 -0.167787
required_car_parking_spaces     -0.216903
total_of_special_requests       -0.248947
Name: is_canceled, dtype: float64
```

As we can see cancel rate is highly correlated with the cancelation status of our current booking.

In [59]:
```
#5)Pipeline
"""
#Transform target feature into numerical
le = LabelEncoder()
data['hotel'] = le.fit_transform(data['hotel'])
data['arrival_date_month'] = le.fit_transform(data['arrival_date_month'])
data['meal'] = le.fit_transform(data['meal'])
data['country'] = le.fit_transform(data['country'])
data['reserved_room_type'] = le.fit_transform(data['reserved_room_type'])
data['deposit_type'] = le.fit_transform(data['deposit_type'])
data['customer_type'] = le.fit_transform(data['customer_type'])
"""

#Split target and data
y = data["is_canceled"]
x = data.drop(["is_canceled"],axis = 1)

#Train test split
train_raw, test_raw, target, target_test = train_test_split(x,y, test_size=0.2, stratify= y, random_state=0)

#Splits names into numerical and categorical features
numerical_features = ["stays_in_weekend_nights", "stays_in_week_nights", "adults", "children", "babies"
                      "previous_cancellations", "previous_bookings_not_canceled", "booking_changes",
                      "days_in_waiting_list", "adr", "required_car_parking_spaces", "total_of_special_requests",
                      "cancel_rate"]
categorical_features = ["hotel", "arrival_date_month", "meal", "country", "reserved_room_type", "deposit_type",
                        "customer_type"]

num_pipeline = Pipeline([('std_scaler', StandardScaler())])

#Applies different transformations on numerical columns vs categorial columns
full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numerical_features),
        ("cat", OneHotEncoder(categories='auto'), categorical_features),
    ])

#Transform raw data
train = pipeline.fit_transform(train_raw)
test = pipeline.transform(test_raw)

#Names of Features after Pipeline
feature_names = list(pipeline.get_feature_names_out(list(x.columns)))
```

We used a stratified 80-20 split on our data in accordance with the spec. We scaled our numeric values with the standard scalar and one hot encoded our categorical data.

In [60]:
```
train.shape
```

Out[60]:
```
(62632, 21)
```

In [61]:
```
test.shape
```

Out[61]:
```
(15658, 21)
```

(50 pts) Try out a few models

Now that you have pre-processed your data, you are ready to try out different models.

For this part of the project, we want you to experiment with all the different models demonstrated in the course to determine which one performs best on the dataset.

You must perform classification using at least 3 of the following models:

- Logistic Regression
- K-nearest neighbors
- SVM
- Decision Tree
- Multi-Layer Perceptron

Due to the size of the dataset, be careful which models you use and look at their documentation to see how you should tackle this size issue for each model.

For full credit, you must perform some hyperparameter optimization on your models of choice. You may find the following scikit-learn library on hyperparameter optimization (https://scikit-learn.org/stable/modules/grid_search.html#grid-search) useful.

For each model chosen, write a description of which models were chosen, which parameters you optimized, and which parameters you choose for your best model. While the previous part of the project asked you to pre-process the data in a specific manner, you may alter pre-processing step as you wish to adjust for your chosen classification models.

Decision Tree

In [62]:
```
parameters = [
    {"max_depth": [1,2,3,4,5,10,15],
    "min_samples_split": [2,4,6,8],
    "criterion": ["gini","entropy"]}
]

k = 10
kf = KFold(n_splits=k, random_state=None)

clf = DecisionTreeClassifier(criterion="gini", random_state = 0)
grid = GridSearchCV(clf, parameters, cv = kf, scoring = "accuracy")
grid.fit(train,target)
#Put results into Dataframe
res= pd.DataFrame(grid.cv_results_)
res
```

Out[62]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criterion	param_max_depth	param_min_samples_split	params	split0_test_sc
0	0.050227	0.016618	0.001747	0.000305	gini	1	2	{'criterion': 'gini', 'max_depth': 1, 'min_sam...	0.761
1	0.044542	0.003412	0.001889	0.000402	gini	1	4	{'criterion': 'gini', 'max_depth': 1, 'min_sam...	0.761
2	0.043774	0.002608	0.001593	0.000090	gini	1	6	{'criterion': 'gini', 'max_depth': 1, 'min_sam...	0.761
								{'criterion': 'gini',	

In [63]:
```
res[["rank_test_score","param_criterion", "param_max_depth", "param_min_samples_split",
     "mean_test_score"]].sort_values(by=['rank_test_score'])
```

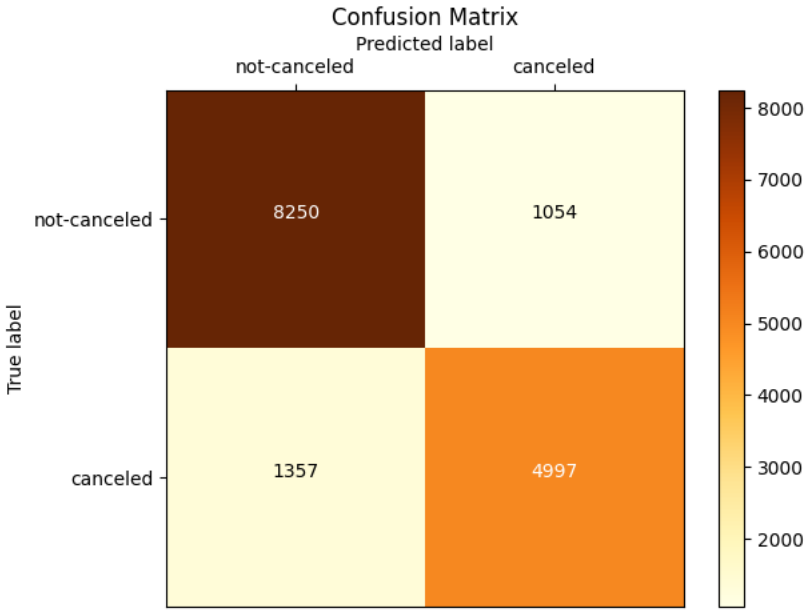
Out[63]:

	rank_test_score	param_criterion	param_max_depth	param_min_samples_split	mean_test_score
27	1	gini	15	8	0.841087
26	2	gini	15	6	0.841024
25	3	gini	15	4	0.840912
24	4	gini	15	2	0.840672
53	5	entropy	15	4	0.839682
54	6	entropy	15	6	0.839571
55	7	entropy	15	8	0.839491
52	8	entropy	15	2	0.839283
20	9	gini	10	2	0.828618
22	10	gini	10	6	0.828602
21	10	gini	10	4	0.828602
23	12	gini	10	8	0.828586
51	13	entropy	10	8	0.825728
50	14	entropy	10	6	0.825616
48	14	entropy	10	2	0.825616
49	16	entropy	10	4	0.825600
16	17	gini	5	2	0.792039
17	17	gini	5	4	0.792039
18	19	gini	5	6	0.792023
19	19	gini	5	8	0.792023
47	21	entropy	5	8	0.784391
44	21	entropy	5	2	0.784391
45	21	entropy	5	4	0.784391
46	21	entropy	5	6	0.784391
14	25	gini	4	6	0.781980
15	25	gini	4	8	0.781980
12	25	gini	4	2	0.781980
13	25	gini	4	4	0.781980
11	29	gini	3	8	0.781805
9	29	gini	3	4	0.781805
8	29	gini	3	2	0.781805
10	29	gini	3	6	0.781805
38	33	entropy	3	6	0.781725
36	33	entropy	3	2	0.781725
37	33	entropy	3	4	0.781725
39	33	entropy	3	8	0.781725
43	37	entropy	4	8	0.781661
42	37	entropy	4	6	0.781661
41	37	entropy	4	4	0.781661
40	37	entropy	4	2	0.781661
6	41	gini	2	6	0.781214
4	41	gini	2	2	0.781214
5	41	gini	2	4	0.781214
7	41	gini	2	8	0.781214
34	45	entropy	2	6	0.781054
33	45	entropy	2	4	0.781054
32	45	entropy	2	2	0.781054
35	45	entropy	2	8	0.781054
1	49	gini	1	4	0.756450
31	49	entropy	1	8	0.756450
29	49	entropy	1	4	0.756450
28	49	entropy	1	2	0.756450
2	49	gini	1	6	0.756450
3	49	gini	1	8	0.756450

	rank_test_score	param_criterion	param_max_depth	param_min_samples_split	mean_test_score
30	49	entropy	1	6	0.756450
0	49	gini	1	2	0.756450

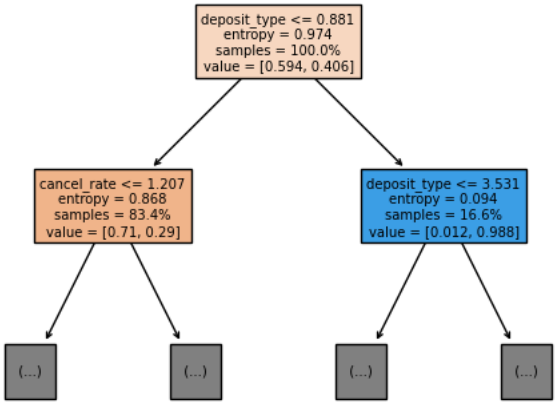
In [64]:
```
predicted = grid.predict(test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
draw_confusion_matrix(target_test, predicted, ['not-canceled', 'canceled'])
```

```
Accuracy:    0.846021
```



In [65]:
```
clf = DecisionTreeClassifier(criterion = "entropy", max_depth = 15, min_samples_split = 2, random_state = 0)
clf.fit(train, target)
tree.plot_tree(clf,max_depth=1, proportion=True,feature_names=feature_names, filled=True)
```

Out[65]:
```
[Text(0.5, 0.8333333333333334, 'deposit_type <= 0.881\nentropy = 0.974\nsamples = 100.0%\nvalue = [0.594, 0.40
6]'),
 Text(0.25, 0.5, 'cancel_rate <= 1.207\nentropy = 0.868\nsamples = 83.4%\nvalue = [0.71, 0.29]'),
 Text(0.125, 0.16666666666666666, '\n  (...)  \n'),
 Text(0.375, 0.16666666666666666, '\n  (...)  \n'),
 Text(0.75, 0.5, 'deposit_type <= 3.531\nentropy = 0.094\nsamples = 16.6%\nvalue = [0.012, 0.988]'),
 Text(0.625, 0.16666666666666666, '\n  (...)  \n'),
 Text(0.875, 0.16666666666666666, '\n  (...)  \n')]
```



Logistic Regression

In [66]:
```
from sklearn.linear_model import LogisticRegression
parameters = [
    {"penalty": ["l2"],
    "C": [0.0001, 0.001, 0.01, 0.1, 1],
    "solver": ["lbfgs", "sag", "saga"]},
    {"penalty": ["l1"],
    "C": [0.0001, 0.001, 0.01, 0.1, 1],
    "solver": ["saga"]},
]

k = 3
kf = KFold(n_splits=k, random_state=None)

clf = LogisticRegression(penalty = "none",max_iter = 1000, solver = "lbfgs")
grid = GridSearchCV(clf, parameters, cv = kf, scoring = "accuracy")
grid.fit(train,target)
#Put results into Dataframe
res= pd.DataFrame(grid.cv_results_)
res
```

```
/home/josh/.local/lib/python3.10/site-packages/sklearn/linear_model/_sag.py:350: ConvergenceWarning: The max_ite
r was reached which means the coef_ did not converge
  warnings.warn(
```

Out[66]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	param_penalty	param_solver	params	split0_test_score	split1_test_score	sp
0	0.083977	0.021646	0.003094	0.000648	0.0001	l2	lbfgs	{'C': 0.0001, 'penalty': 'l2', 'solver': 'lbfgs'}	0.789348	0.784883	
1	0.303062	0.009218	0.004302	0.002251	0.0001	l2	sag	{'C': 0.0001, 'penalty': 'l2', 'solver': 'sag'}	0.789252	0.784931	
								{'C':			

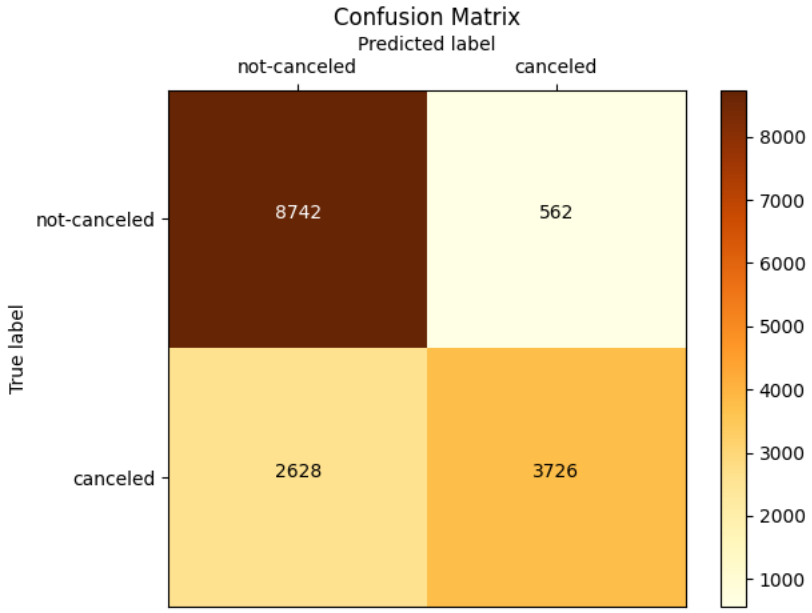
In [67]:
```
res[["rank_test_score", "param_C", "param_solver", "param_penalty",
     "mean_test_score"]].sort_values(by=['rank_test_score'])
```

Out[67]:

	rank_test_score	param_C	param_solver	param_penalty	mean_test_score
4	1	0.001	sag	l2	0.793524
3	2	0.001	lbfgs	l2	0.793508
5	2	0.001	saga	l2	0.793508
17	4	0.01	saga	l1	0.792454
6	5	0.01	lbfgs	l2	0.792422
7	5	0.01	sag	l2	0.792422
8	5	0.01	saga	l2	0.792422
14	8	1	saga	l2	0.792055
13	8	1	sag	l2	0.792055
19	10	1	saga	l1	0.792039
12	11	1	lbfgs	l2	0.792039
9	12	0.1	lbfgs	l2	0.792039
10	13	0.1	sag	l2	0.792023
11	13	0.1	saga	l2	0.792023
18	15	0.1	saga	l1	0.791991
2	16	0.0001	saga	l2	0.785653
0	16	0.0001	lbfgs	l2	0.785653
1	18	0.0001	sag	l2	0.785637
16	19	0.001	saga	l1	0.785637
15	20	0.0001	saga	l1	0.594185

In [68]:
```
predicted = grid.predict(test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
draw_confusion_matrix(target_test, predicted, ['not-canceled', 'canceled'])
```

```
Accuracy:    0.796270
```



MLP

In [69]:
```
parameters = [
    {"hidden_layer_sizes": [(10,), (10,10), (100,), (100,100)],
    "alpha": [0.00001, 0.0001, 0.001]},
]

k = 3
kf = KFold(n_splits=k, random_state=None)

clf = MLPClassifier(hidden_layer_sizes = (100,), max_iter = 200, random_state = 0)
grid = GridSearchCV(clf, parameters, cv = kf, scoring = "accuracy")
grid.fit(train,target)
#Put results into Dataframe
res= pd.DataFrame(grid.cv_results_)
res
```

Out[69]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	param_hidden_layer_sizes	params	split0_test_score	split1_test
0	16.913344	5.564310	0.008191	0.002488	0.00001	(10,)	{'alpha': 1e-05, 'hidden_layer_sizes': (10,)}	0.840741	0.
1	27.589745	5.463018	0.007555	0.000175	0.00001	(10, 10)	{'alpha': 1e-05, 'hidden_layer_sizes': (10, 10)}	0.844813	0.
2	54.040271	2.331868	0.017389	0.001083	0.00001	(100,)	{'alpha': 1e-05, 'hidden_layer_sizes': (100,)}	0.851854	0.
3	102.295348	0.318944	0.038646	0.006081	0.00001	(100, 100)	{'alpha': 1e-05, 'hidden_layer_sizes': (100, 1...	0.843759	0.
4	15.675079	4.940015	0.006630	0.001087	0.0001	(10,)	{'alpha': 0.0001, 'hidden_layer_sizes': (10,)}	0.839975	0.

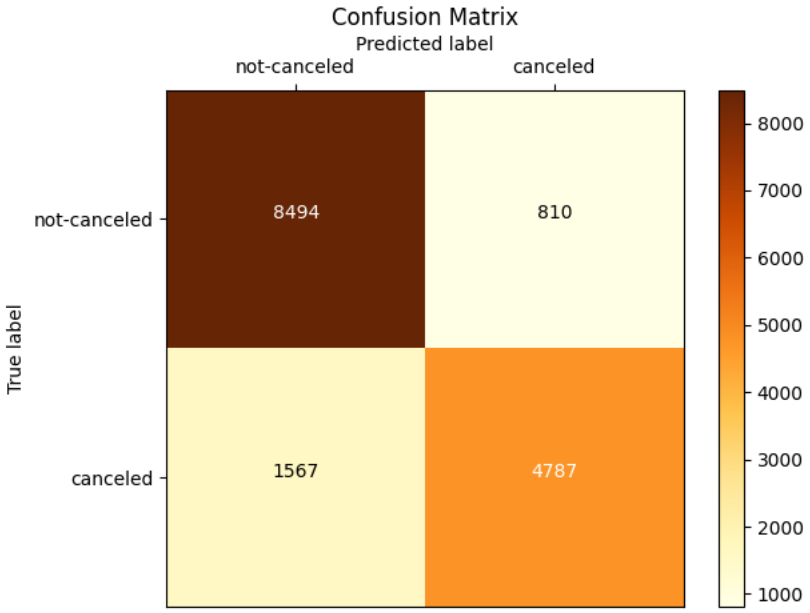
In [70]:
```
res[["rank_test_score", "param_hidden_layer_sizes", "param_alpha",
     "mean_test_score"]].sort_values(by=['rank_test_score'])
```

Out[70]:

	rank_test_score	param_hidden_layer_sizes	param_alpha	mean_test_score
10	1	(100,)	0.001	0.848959
2	2	(100,)	0.00001	0.848879
6	3	(100,)	0.0001	0.848528
3	4	(100, 100)	0.00001	0.846005
11	5	(100, 100)	0.001	0.844409
7	6	(100, 100)	0.0001	0.843818
5	7	(10, 10)	0.0001	0.842620
9	8	(10, 10)	0.001	0.842604
1	9	(10, 10)	0.00001	0.841135
0	10	(10,)	0.00001	0.835659
4	11	(10,)	0.0001	0.835579
8	12	(10,)	0.001	0.834701

In [71]:
```
predicted = grid.predict(test)
print("%-12s %f" % ('Accuracy:', metrics.accuracy_score(target_test,predicted)))
draw_confusion_matrix(target_test, predicted, ['not-canceled', 'canceled'])
```

```
Accuracy:    0.848193
```



Model and Parameter Choices

Decision Tree: On top of being quick to train, I felt that decision trees would work well since there are a few features where we could very easily split on values. In particular there was the cancel rate column I created as well as the deposit type. It seemed very likely that people who have a history of canceling (ie more than the average value) would be more likely to cancel the current booking. Also, whether or not a booking fee was refundable would play a part in deciding to cancel the booking or not. The model performed above what was expected with an accuracy of ~84.6%.

Logistic Regression: I felt that logistic regression worked well here since it was a classification task and it appeared linearly seperable. For solvers I chose lbfgs as it is the default and sag/saga since they work quickly on large data sets. I decided to test lower Cs for stronger regularization as we knew some features did not correlate much with the chance of a booking being canceled. All models used l2 reg except saga which was capable of both l2 and l1 regularization so I decided to also test its l1 regularization capabilities. Although still exceeding the baseline accuracy at ~79% accuracy, it did not perform as well as

MLP: Although slow to train I hoped the added complexity of MLP would allow it to outperform the logistic regression model. I altered the hidden layer sizes parameters to capture some extra complexity in the data. I also altered alpha since alpha was the most influential hyperparameter in the logistic regression model. I did not alter the other parameters due to time contraints. The MLP model beformed the best of all models I tested, just barely surpassing the decision tree classifier with an accuracy of ~84.8%

KNN & SVM: Both of these models would be infeasible to train/predict with the amount of data we have so I did not choose them.

Extra Credit

We have provided an extra test dataset named "hotel_booking_test.csv" that does not have the target labels. Classify the samples in the dataset with your best model and write them into a csv file. Submit your csv file to our Kaggle (https://www.kaggle.com/t/ed725123bf124e9199c1d8fdc8a2d9c7) contest. The website will specify your classification accuracy on the test set. We will award a bonus point for the project for every percentage point over 75% that you get on your kaggle test accuracy.

To get the bonus points, you must also write out a summary of the model that you submit including any changes you made to the pre-processing steps. The summary must be written in a markdown cell of the jupyter notebook. Note that you should not change earlier parts of the project to complete the extra credit.

Kaggle Submission Instruction Submit a two column csv where the first column is named "ID" and is the row number. The second column is named "target" and is the classification for each sample. Make sure that the sample order is preserved.

In [78]:
```
#import
data = pd.read_csv('datasets/hotel_booking_test.csv')
data.head()
```

Out[78]:

	hotel	lead_time	arrival_date_month	stays_in_weekend_nights	stays_in_week_nights	adults	children	babies	meal	country	previous_cancellations	pre
0	City Hotel	177	August	0	2	2	0.0	0	SC	FRA	0	
1	Resort Hotel	217	August	2	5	2	1.0	0	HB	PRT	0	
2	City Hotel	65	September	2	1	2	0.0	0	HB	PRT	0	
3	City Hotel	377	October	0	2	2	0.0	0	HB	DEU	0	
4	City Hotel	75	May	2	1	2	0.0	0	BB	PRT	0	

In [79]:
```
#2)Correct Missing Values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8699 entries, 0 to 8698
Data columns (total 23 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   hotel                           8699 non-null   object
 1   lead_time                       8699 non-null   int64
 2   arrival_date_month              8699 non-null   object
 3   stays_in_weekend_nights         8699 non-null   int64
 4   stays_in_week_nights            8699 non-null   int64
 5   adults                          8699 non-null   int64
 6   children                        8698 non-null   float64
 7   babies                          8699 non-null   int64
 8   meal                            8699 non-null   object
 9   country                         8699 non-null   object
 10  previous_cancellations          8699 non-null   int64
 11  previous_bookings_not_canceled  8699 non-null   int64
 12  reserved_room_type              8699 non-null   object
 13  booking_changes                 8699 non-null   int64
 14  deposit_type                    8699 non-null   object
 15  days_in_waiting_list            8699 non-null   int64
 16  customer_type                   8699 non-null   object
 17  adr                             8699 non-null   float64
 18  required_car_parking_spaces     8699 non-null   int64
 19  total_of_special_requests       8699 non-null   int64
 20  name                            8699 non-null   object
 21  email                           8699 non-null   object
 22  phone-number                    8699 non-null   object
dtypes: float64(2), int64(11), object(10)
memory usage: 1.5+ MB
```

In [80]:
```
data["children"].fillna(0.0, inplace=True)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8699 entries, 0 to 8698
Data columns (total 23 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   hotel                           8699 non-null   object
 1   lead_time                       8699 non-null   int64
 2   arrival_date_month              8699 non-null   object
 3   stays_in_weekend_nights         8699 non-null   int64
 4   stays_in_week_nights            8699 non-null   int64
 5   adults                          8699 non-null   int64
 6   children                        8699 non-null   float64
 7   babies                          8699 non-null   int64
 8   meal                            8699 non-null   object
 9   country                         8699 non-null   object
 10  previous_cancellations          8699 non-null   int64
 11  previous_bookings_not_canceled  8699 non-null   int64
 12  reserved_room_type              8699 non-null   object
 13  booking_changes                 8699 non-null   int64
 14  deposit_type                    8699 non-null   object
 15  days_in_waiting_list            8699 non-null   int64
 16  customer_type                   8699 non-null   object
 17  adr                             8699 non-null   float64
 18  required_car_parking_spaces     8699 non-null   int64
 19  total_of_special_requests       8699 non-null   int64
 20  name                            8699 non-null   object
 21  email                           8699 non-null   object
 22  phone-number                    8699 non-null   object
dtypes: float64(2), int64(11), object(10)
memory usage: 1.5+ MB
```

In [81]:
```
#3)Augment Features
data["cancel_rate"] = data["previous_cancellations"] / (data["previous_cancellations"] + data["previous_bookings_no
data["cancel_rate"].fillna(data["cancel_rate"].mean(), inplace=True)
pd.set_option('display.max_columns', None)
data.head()
```

Out[81]:

	hotel	lead_time	arrival_date_month	stays_in_weekend_nights	stays_in_week_nights	adults	children	babies	meal	country	previous_cancellations	pre
0	City Hotel	177	August	0	2	2	0.0	0	SC	FRA	0	
1	Resort Hotel	217	August	2	5	2	1.0	0	HB	PRT	0	
2	City Hotel	65	September	2	1	2	0.0	0	HB	PRT	0	
3	City Hotel	377	October	0	2	2	0.0	0	HB	DEU	0	
4	City Hotel	75	May	2	1	2	0.0	0	BB	PRT	0	

In [82]:
```
#4)Drop Columns
data = data.drop(["name", "email", "phone-number"],axis= 1)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8699 entries, 0 to 8698
Data columns (total 21 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   hotel                           8699 non-null   object 
 1   lead_time                       8699 non-null   int64  
 2   arrival_date_month              8699 non-null   object 
 3   stays_in_weekend_nights         8699 non-null   int64  
 4   stays_in_week_nights            8699 non-null   int64  
 5   adults                          8699 non-null   int64  
 6   children                        8699 non-null   float64
 7   babies                          8699 non-null   int64  
 8   meal                            8699 non-null   object 
 9   country                         8699 non-null   object 
 10  previous_cancellations          8699 non-null   int64  
 11  previous_bookings_not_canceled  8699 non-null   int64  
 12  reserved_room_type              8699 non-null   object 
 13  booking_changes                 8699 non-null   int64  
 14  deposit_type                    8699 non-null   object 
 15  days_in_waiting_list            8699 non-null   int64  
 16  customer_type                   8699 non-null   object 
 17  adr                             8699 non-null   float64
 18  required_car_parking_spaces     8699 non-null   int64  
 19  total_of_special_requests       8699 non-null   int64  
 20  cancel_rate                     8699 non-null   float64
dtypes: float64(3), int64(11), object(7)
memory usage: 1.4+ MB
```

In [92]:
```
#for some reason the one hot encoder did not work here
le = LabelEncoder()
data['hotel'] = le.fit_transform(data['hotel'])
data['arrival_date_month'] = le.fit_transform(data['arrival_date_month'])
data['meal'] = le.fit_transform(data['meal'])
data['country'] = le.fit_transform(data['country'])
data['reserved_room_type'] = le.fit_transform(data['reserved_room_type'])
data['deposit_type'] = le.fit_transform(data['deposit_type'])
data['customer_type'] = le.fit_transform(data['customer_type'])

x = data

#Splits names into numerical and categorical features
numerical_features = ["stays_in_weekend_nights", "stays_in_week_nights", "adults", "children", "babies"
                      "previous_cancellations", "previous_bookings_not_canceled", "booking_changes",
                      "days_in_waiting_list", "adr", "required_car_parking_spaces", "total_of_special_requests",
                      "cancel_rate"]
categorical_features = ["hotel", "arrival_date_month", "meal", "country", "reserved_room_type", "deposit_type",
                        "customer_type"]

num_pipeline = Pipeline([('std_scaler', StandardScaler())])

#Applies different transformations on numerical columns vs categorial columns
full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numerical_features),
        ("cat", OneHotEncoder(categories='auto'), categorical_features),
    ])

#Transform raw data
target = pipeline.fit_transform(x)
print(target[:10])
```

```
[[-7.49319083e-01  6.14800602e-01 -1.27387691e+00 -8.73391035e-01
  -2.20632369e-01  3.33554908e-01 -2.49806311e-01 -9.07139559e-02
   2.44179153e+00 -7.50424564e-01 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01 -4.54904775e-01 -1.38732447e-01
  -2.30363260e-01 -8.18605500e-02 -2.67037478e-01  6.21052915e-01
  -7.44229949e-16]
 [ 1.33454495e+00  9.68791689e-01 -1.27387691e+00  1.14967610e+00
   1.37832429e+00  3.33554908e-01  2.37150262e+00 -9.07139559e-02
   1.45936035e+00  7.39463210e-01 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01 -4.54904775e-01 -1.38732447e-01
  -2.30363260e-01  1.44605142e+00 -2.67037478e-01 -6.77010350e-01
  -7.44229949e-16]
 [-7.49319083e-01 -3.76374441e-01  1.54382428e+00  1.14967610e+00
  -7.53617922e-01  3.33554908e-01 -2.49806311e-01 -9.07139559e-02
   1.45936035e+00  7.39463210e-01 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01  2.15024114e+00 -1.38732447e-01
  -2.30363260e-01 -2.53877129e-01 -2.67037478e-01 -6.77010350e-01
  -7.44229949e-16]
 [-7.49319083e-01  2.38475604e+00  1.26205416e+00 -8.73391035e-01
  -2.20632369e-01  3.33554908e-01 -2.49806311e-01 -9.07139559e-02
   1.45936035e+00 -2.24031234e+00 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01 -4.54904775e-01 -1.38732447e-01
   1.42032043e+00  3.33002964e-01 -2.67037478e-01  6.21052915e-01
  -7.44229949e-16]
 [-7.49319083e-01 -2.87876669e-01  6.98513924e-01  1.14967610e+00
  -7.53617922e-01  3.33554908e-01 -2.49806311e-01 -9.07139559e-02
  -5.05502007e-01  7.39463210e-01 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01 -4.54904775e-01 -1.38732447e-01
   1.42032043e+00 -1.72928151e-01 -2.67037478e-01 -6.77010350e-01
  -7.44229949e-16]
 [-7.49319083e-01 -8.98511294e-01  1.54382428e+00  1.14967610e+00
  -1.28660347e+00 -1.72870106e+00 -2.49806311e-01 -9.07139559e-02
  -5.05502007e-01  7.39463210e-01  1.05026505e+00 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01  2.15024114e+00 -1.38732447e-01
  -2.30363260e-01 -1.72928151e-01 -2.67037478e-01 -6.77010350e-01
   2.24094299e+00]
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  -5.05502007e-01  7.39463210e-01 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01  2.15024114e+00 -1.38732447e-01
  -2.30363260e-01  8.38934079e-01 -2.67037478e-01 -6.77010350e-01
  -7.44229949e-16]
 [-7.49319083e-01 -1.10881126e-01  9.80284044e-01 -8.73391035e-01
  -7.53617922e-01 -1.72870106e+00 -2.49806311e-01 -9.07139559e-02
  -5.05502007e-01  7.39463210e-01 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01 -3.22895545e-01 -4.54904775e-01 -1.38732447e-01
   1.42032043e+00 -4.76486820e-01 -2.67037478e-01 -6.77010350e-01
  -7.44229949e-16]
 [ 1.33454495e+00 -3.40975332e-01 -7.10336673e-01  1.38142531e-01
   1.37832429e+00  2.39581088e+00 -2.49806311e-01 -9.07139559e-02
  -5.05502007e-01  7.39463210e-01 -1.29367703e-01 -1.10870181e-01
  -5.41164341e-01  1.20035193e+00 -4.54904775e-01 -1.38732447e-01
   1.42032043e+00 -8.20519978e-01 -2.67037478e-01 -6.77010350e-01
  -7.44229949e-16]
 [-7.49319083e-01 -5.88769093e-01 -9.92106793e-01 -8.73391035e-01
  -7.53617922e-01 -1.72870106e+00 -2.49806311e-01 -9.07139559e-02
  -5.05502007e-01  7.39463210e-01  1.05026505e+00  6.57410572e+00
  -5.41164341e-01  4.24684688e+00 -4.54904775e-01 -1.38732447e-01
  -2.30363260e-01 -2.13402640e-01  3.71745485e+00  6.21052915e-01
  -3.90386550e+00]]
```

In [94]:
```
#predict
#last grid was best performing model
predicted = grid.predict(target)
temp = []
for i, pred in enumerate(predicted):
    temp.append([i, pred])
np.savetxt("extra_credit.csv", temp, fmt='%i', delimiter=",", header="ID,target", comments='')
```

Summary

I went with the same prepreocessing steps except I had to use a label encoder before passing the data into the one hot encoder. Was not sure why I needed to do this despite not needing to do it for the original dataset. Regardless the results should be the same. For the model I went with the MLP model with a hidden layer size of (100,), and an alpha of 0.001. These were the parameters that worked best for the training data so I also used them here.

In [ ]:
```

```