Decision Boundaries

- #### The aim of this notebook is to understand or visualize the decision boundaries for the below tasks:
 - #### Comparing different classifiers
 - #### Evaluating classifier for overfitting or underfitting

```
import os
In [1]:
          import sys
          import shutil
          import numpy as np
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
          from matplotlib.colors import ListedColormap
          from itertools import product
          from sklearn import datasets
          from sklearn.datasets import load iris
          from sklearn.preprocessing import StandardScaler
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn.svm import SVC
          from sklearn.ensemble import VotingClassifier
         %matplotlib inline
In [2]: | # Loading some example data
         iris = load_iris()
         X = iris.data[:, [0, 2]]
          y = iris.target
In [3]:
         # Training classifiers
          clf1 = DecisionTreeClassifier(max_depth=4)
          clf2 = KNeighborsClassifier(n_neighbors=7)
          clf3 = SVC(gamma=.1, kernel='rbf', probability=True)
          eclf = VotingClassifier(estimators=[('dt', clf1), ('knn', clf2),
                                                ('svc', clf3)],
                                   voting='soft', weights=[2, 1, 2])
          clf1.fit(X, y)
          clf2.fit(X, y)
          clf3.fit(X, y)
          eclf.fit(X, y)
Out[3]: VotingClassifier(estimators=[('dt', DecisionTreeClassifier(max_depth=4)),
                                        ('knn', KNeighborsClassifier(n_neighbors=7)),
('svc', SVC(gamma=0.1, probability=True))],
                           voting='soft', weights=[2, 1, 2])
         # grid cell size
In [4]:
         h = .02
          x_{min}, x_{max} = X[:, 0].min() - 1, <math>X[:, 0].max() + 1
          y_{min}, y_{max} = X[:, 1].min() - 1, <math>X[:, 1].max() + 1
```

localhost:8888/lab 1/12

Q. How Numpy ravel works?

```
In [5]:
           XX
 Out[5]: array([[3.3 , 3.32, 3.34, ..., 8.84, 8.86, 8.88],
                  [3.3, 3.32, 3.34, \ldots, 8.84, 8.86, 8.88]])
 In [6]:
           xx.shape
 Out[6]: (395, 280)
           pd.DataFrame(xx)
 In [7]:
                                 3
                                          5
                                                     7
                                                           8
                                                                9 ... 270
                                                                            271
                                                                                 272
 Out[7]:
                                                6
                                                                                      273
                                                                                            274
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                                                                       8.7
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          393 3.3 3.32 3.34 3.36 3.38 3.4 3.42 3.44 3.46
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          394 3.3 3.32 3.34 3.36 3.38 3.4 3.42 3.44 3.46 3.48 ...
                                                                       8.7
                                                                           8.72 8.74
                                                                                     8.76
                                                                                           8.78
                                                                                                  8.8
                                                                                                     8
         395 rows × 280 columns
           xx.ravel()
 In [8]:
 Out[8]: array([3.3, 3.32, 3.34, ..., 8.84, 8.86, 8.88])
           xx.ravel().shape
 In [9]:
 Out[9]: (110600,)
In [10]:
           pd.DataFrame(xx.ravel())
Out[10]:
                     0
                0 3.30
                1 3.32
```

localhost:8888/lab 2/12

```
2 3.34
3 3.36
4 3.38
... ...
110595 8.80
110596 8.82
110597 8.84
110598 8.86
110599 8.88
```

110600 rows × 1 columns

Q. How np.c and np.r works?

np.c_

- It concatenates the array-1 and array-2 column wise

np.r_

- It concatenates the array-1 and array-2 row wise

Different Classifiers Decision Boundaries

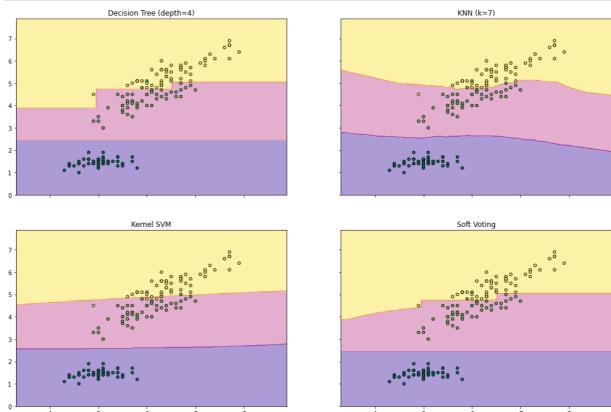
localhost:8888/lab 3/12

```
['Decision Tree (depth=4)', 'KNN (k=7)', 'Kernel SVM', 'Soft

Z = clf.predict(np.c_[xx.ravel(), yy.ravel()]) ## This first flattens the xx and
Z = Z.reshape(xx.shape)

axarr[idx[0], idx[1]].contourf(xx, yy, Z, alpha=0.4,cmap='plasma')
axarr[idx[0], idx[1]].scatter(X[:, 0], X[:, 1], c=y, s=20, edgecolor='k',cmap='s axarr[idx[0], idx[1]].set_title(tt)

plt.show()
```



Decision Boundaries of K-Nearest Neighbors

localhost:8888/lab 4/12

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5/12

1

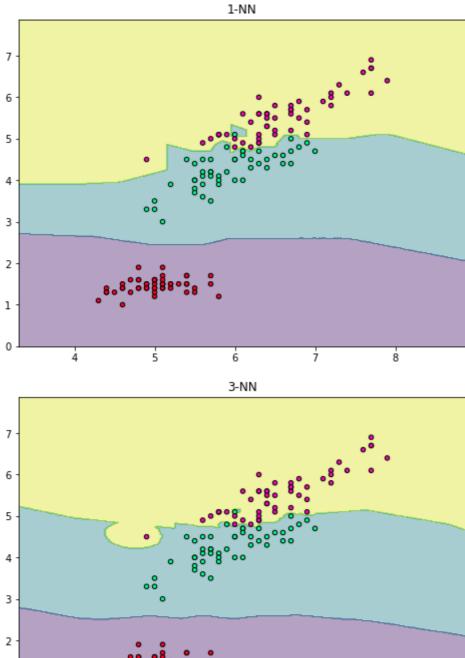
0 -

4

5

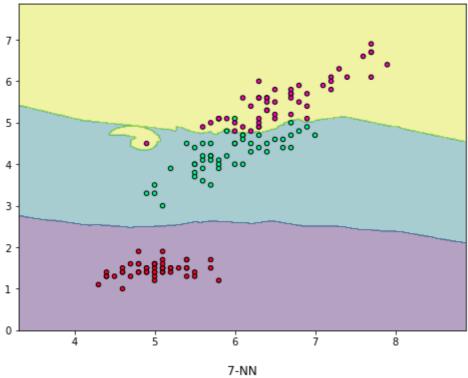
6

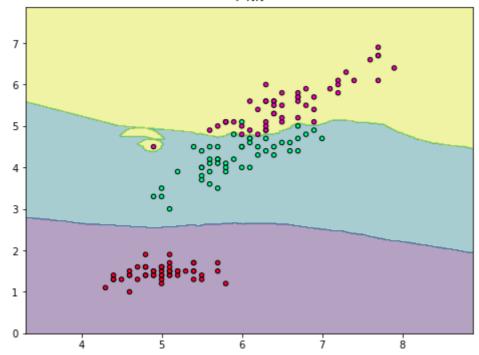




localhost:8888/lab

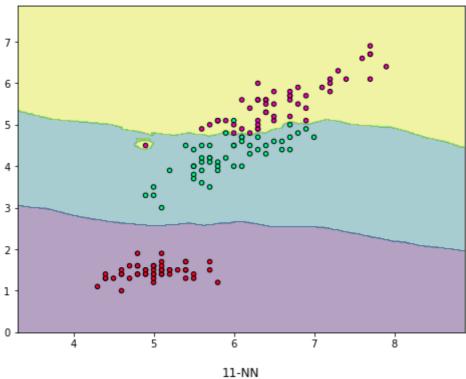


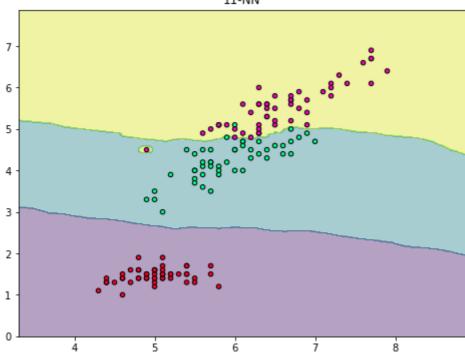




localhost:8888/lab







Work with some random shaped datasets

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
import seaborn as sns

%matplotlib inline

# Import statements required for Plotly
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
from plotly import tools
from plotly import subplots
```

localhost:8888/lab 7/12

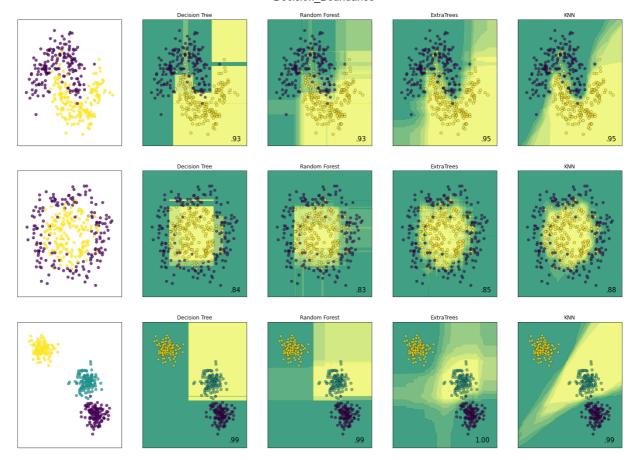
Decision boundaries on some random shaped toy datasets

```
In [18]:
         random_shaped_toy_datasets = [make_moons(noise=0.25, random_state=41,n_samples=500),
                                        make_circles(noise=0.2, factor=0.5, random_state=23,n_
                                        make_blobs(random_state=44,n_samples=500)]
          classifier_names = ["Decision Tree", "Random Forest", "ExtraTrees", "KNN"]
          # Creating a list with 4 classifiers
          diff classifiers = [
              DecisionTreeClassifier(max_depth=5),
              RandomForestClassifier(max_depth=5, n_estimators=20, max_features=1),
              ExtraTreesClassifier(),
              KNeighborsClassifier(n_neighbors=9,weights='distance',algorithm='kd_tree',leaf_s
In [19]:
         def plot_decision_boundaries(datasets,clf_names,classifiers,test_label=False):
              Description: This function is created for generating the decision boundaries of
              Inputs : It accepts the below parameters:
                  1. datasets --> list
                      This is the list which contains the pandas dataframe object
                  2. clf names --> list
                      List containing names of classifiers
                  3. classifiers --> list
                      List containing actual classifier objects
                  4. test_label --> boolean
                      Flag that handles whether test data points to be generated
              Return : None
              figure = plt.figure(figsize=(20, 18))
                                                       # Defining figure size
              h = 0.02 # Defining the cell size of a grid
              i = 1
                           # Counter for iterating over datasets
              for ds in datasets:
                  # Scaling dataset, split into training and test part
                  X, y = ds
                  X = StandardScaler().fit_transform(X)
                  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.3)
                  # Creating the data point grid
                  x_{min}, x_{max} = X[:, 0].min() -.5, X[:, 0].max() + .5
                  y_{min}, y_{max} = X[:, 1].min() -.5, X[:, 1].max() + .5
                  xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                                       np.arange(y_min, y_max, h))
```

localhost:8888/lab 8/12

```
# First, only plotting the dataset
   ax = plt.subplot(len(datasets), len(classifiers) + 1, i) # i means index sta
   # Plot the training points
   ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap='viridis', alpha=0.
   # Plot the testing points
   if test label:
        ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap='gist_rainbow', al
   ax.set_xlim(xx.min(), xx.max())
   ax.set_ylim(yy.min(), yy.max())
   ax.set_xticks(())
   ax.set_yticks(())
   i += 1
   # Iterate over classifiers
   for name, clf in zip(clf names, classifiers):
        ax = plt.subplot(len(datasets), len(classifiers) + 1, i)
       clf.fit(X_train, y_train)
       score = clf.score(X_test, y_test) # Calculating the accuracy
       # Inplace of below if else statement we can also use the classifier pred
       \# Decision function tells on which side of the hyperplane(generated by t
       # Mathematically we can say that it is the result of dot product it +ve
       if hasattr(clf, "decision_function"):
            Z = clf.decision_function(np.c_[xx.ravel(), yy.ravel()])
       else:
            Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
       Z = Z.reshape(xx.shape) # The height values over which the contour is d
       # Put the result into a color plot
       ax.contourf(xx, yy, Z, cmap='summer', alpha=.8)
       # Plot the training points
       ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap='viridis', alph
       # Plot the testing points
       if test label:
            ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap='gist_rainbow'
       ax.set xlim(xx.min(), xx.max())
       ax.set_ylim(yy.min(), yy.max())
       ax.set_xticks(())
       ax.set yticks(())
       ax.set_title(name)
       ax.text(xx.max() - .3, yy.min() + .2, ('%.2f' % score).lstrip('0'), size
       i += 1
figure.subplots adjust(left=.02, right=.98)
plt.show()
```

localhost:8888/lab 9/12



In []:

```
iris = load_iris()
In [27]:
          X = iris.data[:, [0, 2]]
          y = iris.target
          h = .02 # step size in the mesh
          X = StandardScaler().fit_transform(X)
          # Train two Random Forests. One with normal reasonable parameters and the other with
          rf_trees = RandomForestClassifier(max_depth=4,
                                          n estimators=20,
                                          random_state=42)
          rf trees.fit(X, y)
          rf_trees_overfit = RandomForestClassifier(max_depth=128,
                                                  n_estimators=5,
                                                  random_state=42)
          rf_trees_overfit.fit(X, y)
          x_{min}, x_{max} = X[:, 0].min() - 1, X[:, 0].max() + 1
          y_{min}, y_{max} = X[:, 1].min() - 1, X[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, h)
                                , np.arange(y_min, y_max, h))
          y_ = np.arange(y_min, y_max, h)
          Z = rf_trees.predict(np.c_[xx.ravel(), yy.ravel()])
          Z = Z.reshape(xx.shape)
          fig = subplots.make_subplots(rows=1, cols=2,
                                     subplot_titles=("Random Forest (Depth = 4)",
                                                     "Random Forest (Depth = 200)")
```

localhost:8888/lab 10/12

```
trace1 = go.Heatmap(x=xx[0], y=y_, z=Z)
                  colorscale='Viridis',
                  showscale=False)
trace2 = go.Scatter(x=X[:, 0], y=X[:, 1],
                    mode='markers',
                    showlegend=False,
                    marker=dict(size=10,
                                color=y,
                                colorscale='Viridis',
                                line=dict(color='black', width=1))
fig.append_trace(trace1, 1, 1)
fig.append_trace(trace2, 1, 1)
# transform grid using ExtraTreesClassifier
# y_grid_pred = trees.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
Z = rf_trees_overfit.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
trace3 = go.Heatmap(x=xx[0], y=y_,
                    z=Z
                    colorscale='Viridis',
                    showscale=True)
trace4 = go.Scatter(x=X[:, 0], y=X[:, 1],
                    mode='markers',
                    showlegend=False,
                    marker=dict(size=10,
                                 color=y,
                                 colorscale='Viridis',
                                line=dict(color='black', width=1))
fig.append_trace(trace3, 1, 2)
fig.append_trace(trace4, 1, 2)
for i in map(str, range(1, 3)):
    x = 'xaxis' + i
    y = 'yaxis' + i
    fig['layout'][x].update(showgrid=False,
                             zeroline=False,
                             showticklabels=False,
                             ticks='',
                             autorange=True)
    fig['layout'][y].update(showgrid=False,
                             zeroline=False,
                             showticklabels=False,
                             ticks='',
                             autorange=True)
py.iplot(fig)
```

localhost:8888/lab 11/12

| In []: | |
|---------|--|
| In []: | |

localhost:8888/lab 12/12