Decision Regions

There are many machine learning algorithms, each with very different properties. How can we gain better understanding of how a given algorithm "sees" the data? In this course, we won't study the mathematical structure of our algorithms, but we can in certain cases visualize how they work.

In this lecture, we'll take a look at the **decision regions** of various classifiers. The decision regions are just the parts of data space that the classifier assigns to each label. As we'll see, different classifiers can create very different decision regions, even when they are trained on the same input data.

In [1]:
```
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np
```

Grabbing the data

In [2]:
```
url = "https://raw.githubusercontent.com/liaochunyang/PIC16/refs/heads
penguins = pd.read_csv(url)
```

Data Prep

For our purposes today, it's useful to encode the three penguin species with labels 0, 1, and 2. We are going to focus on modeling using only two predictor variables today, the culmen length and depth. We use `df.dropna()` to drop the two penguins for which these variables were not measured.

In [3]:
```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
penguins["label"] = le.fit_transform(penguins["Species"])
# penguins[["Species","label"]]
penguins = penguins.dropna(subset = ["Culmen Length (mm)", "Culmen Dep
X = penguins[["Culmen Length (mm)", "Culmen Depth (mm)"]]
y = penguins["label"]
```

In [4]:
```
X
```

Out[4]:

	Culmen Length (mm)	Culmen Depth (mm)
0	39.1	18.7
1	39.5	17.4
2	40.3	18.0
4	36.7	19.3
5	39.3	20.6
...	...	...
338	47.2	13.7
340	46.8	14.3
341	50.4	15.7
342	45.2	14.8
343	49.9	16.1

342 rows × 2 columns

In [5]:
```
y
```

Out[5]:
```
0      0
1      0
2      0
4      0
5      0
      ..
338    2
340    2
341    2
342    2
343    2
Name: label, Length: 342, dtype: int64
```

Decision Regions By Hand

The core idea of decision regions is to evaluate a given classifier on a large set of points -- often much larger than the actual data. We can then visualize in considerable detail how the classifier "makes decisions." The set of points where the model returns "0", for example, is the decision region for 0. The contours along which different decision regions meet are called **decision boundaries.**

The limitation of this approach is that it works best for classifiers which use only two numerical features. Let's see how to create decision regions by hand! For now, we'll use as our example a decision tree classifier.

```
In [7]: from sklearn import tree
        T = tree.DecisionTreeClassifier(max_depth = 2)
        T.fit(X, y)

Out[7]: DecisionTreeClassifier(max_depth=2)
```

Next, we'll create a 2d grid of `501 x 501` points using `np.meshgrid` :

```
In [8]: x0 = X["Culmen Length (mm)"]
        x1 = X["Culmen Depth (mm)"]

        # create grid

        grid_x = np.linspace(x0.min(), x0.max(), 501)
        grid_y = np.linspace(x1.min(), x1.max(), 501)
        xx, yy = np.meshgrid(grid_x, grid_y)

        # a single point for prediction:

        xx[1, 2], yy[1, 2]

Out[8]: (32.21, 13.1168)
```

As is, we can't really use our classifier on these data. We need to reshape `xx` and `yy` so that they "look" more like the columns of a data frame. That is, all the points of `xx` should be in a 1d array. We can do this with `np.ravel()` and the `numpy` *concatenation* operator `np.c_` :

```
In [9]: XX = xx.ravel() # shortcut for reshape
        XX.shape # size is 501 x 501

Out[9]: (251001,)
```

In [10]:
```
XX = xx.ravel()
YY = yy.ravel()

XY = pd.DataFrame({
    "Culmen Length (mm)" : XX,
    "Culmen Depth (mm)"  : YY
})
```

Better! Now we can make a prediction using our standard approach:

In [11]:
```
p = T.predict(XY)
p
```

Out[11]:
```
array([2, 2, 2, ..., 1, 1, 1])
```

Almost there! The next step toward visualization is to reshape the predictions back into a square grid that we can plot.

In [12]:
```
p = p.reshape(xx.shape)
```

Now we're ready to make the plot!

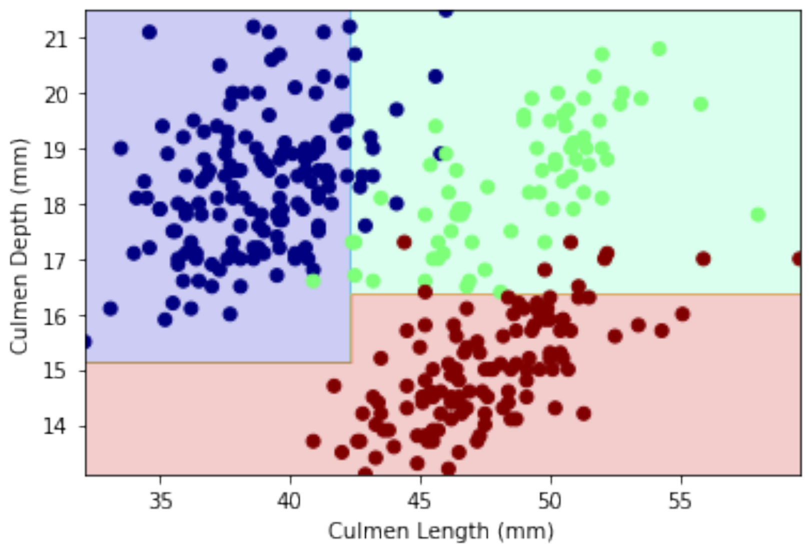
In [13]:
```
fig, ax = plt.subplots(1)

ax.contourf(xx, yy, p, cmap = "jet", alpha = 0.2)

ax.scatter(x0, x1, c = y, cmap = "jet")

ax.set(xlabel = "Culmen Length (mm)",
       ylabel = "Culmen Depth (mm)")
```

Out[13]:
```
[Text(0.5, 0, 'Culmen Length (mm)'), Text(0, 0.5, 'Culmen Depth (m
m)')]
```


Culmen Depth (mm)
Culmen Length (mm)