Classification

Note: We've adapted this Mini Project from Lab 5 in the CS109 course. Please feel free to check out the original lab, both for more exercises, as well as solutions.

We turn our attention to **classification**. Classification tries to predict, which of a small set of classes, an observation belongs to. Mathematically, the aim is to find y, a **label** based on knowing a feature vector $\mathbf{x}$. For instance, consider predicting gender from seeing a person's face, something we do fairly well as humans. To have a machine do this well, we would typically feed the machine a bunch of images of people which have been labelled "male" or "female" (the training set), and have it learn the gender of the person in the image from the labels and the *features* used to determine gender. Then, given a new photo, the trained algorithm returns us the gender of the person in the photo.

There are different ways of making classifications. One idea is shown schematically in the image below, where we find a line that divides "things" of two different types in a 2-dimensional feature space. The classification show in the figure below is an example of a maximum-margin classifier where construct a decision boundary that is far as possible away from both classes of points. The fact that a line can be drawn to separate the two classes makes the problem *linearly separable.* Support Vector Machines (SVM) are an example of a maximum-margin classifier.

In [1]:

```
%matplotlib inline
import numpy as np
import scipy as sp
import matplotlib as mpl
import matplotlib.cm as cm
from matplotlib.colors import ListedColormap
import matplotlib.pyplot as plt
import pandas as pd
pd.set_option('display.width', 500)
pd.set_option('display.max_columns', 100)
pd.set_option('display.notebook_repr_html', True)
import seaborn as sns
sns.set_style("whitegrid")
sns.set_context("poster")
import sklearn.model_selection

c0=sns.color_palette()[0]
c1=sns.color_palette()[1]
c2=sns.color_palette()[2]

cmap_light = ListedColormap(['#FFAAAA', '#AAFFAA', '#AAAAFF'])
cmap_bold = ListedColormap(['#FF0000', '#00FF00', '#0000FF'])
cm = plt.cm.RdBu
cm_bright = ListedColormap(['#FF0000', '#0000FF'])

def points_plot(ax, Xtr, Xte, ytr, yte, clf, mesh=True, colorscale=cmap_light,
                cdiscrete=cmap_bold, alpha=0.1, psize=10, zfunc=False, predicted=False):
    h = .02
    X=np.concatenate((Xtr, Xte))
    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.linspace(x_min, x_max, 100),
                         np.linspace(y_min, y_max, 100))

    #plt.figure(figsize=(10,6))
    if zfunc:
        p0 = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 0]
        p1 = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
        Z=zfunc(p0, p1)
    else:
        Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    ZZ = Z.reshape(xx.shape)
    if mesh:
        plt.pcolormesh(xx, yy, ZZ, cmap=cmap_light, alpha=alpha, axes=ax)
    if predicted:
        showtr = clf.predict(Xtr)
        showte = clf.predict(Xte)
    else:
        showtr = ytr
        showte = yte
    ax.scatter(Xtr[:, 0], Xtr[:, 1], c=showtr-1, cmap=cmap_bold,
               s=psize, alpha=alpha,edgecolor="k")
    # and testing points
    ax.scatter(Xte[:, 0], Xte[:, 1], c=showte-1, cmap=cmap_bold,
               alpha=alpha, marker="s", s=psize+10)
    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    return ax,xx,yy

def points_plot_prob(ax, Xtr, Xte, ytr, yte, clf, colorscale=cmap_light,
                     cdiscrete=cmap_bold, ccolor=cm, psize=10, alpha=0.1):
    ax,xx,yy = points_plot(ax, Xtr, Xte, ytr, yte, clf, mesh=False,
                           colorscale=colorscale, cdiscrete=cdiscrete,
                           psize=psize, alpha=alpha, predicted=True)
    Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, cmap=ccolor, alpha=.2, axes=ax)
    cs2 = plt.contour(xx, yy, Z, cmap=ccolor, alpha=.6, axes=ax)
    plt.clabel(cs2, fmt = '%2.1f', colors = 'k', fontsize=14, axes=ax)
    return ax
```

A Motivating Example Using `sklearn`: Heights and Weights

We'll use a dataset of heights and weights of males and females to hone our understanding of classifiers. We load the data into a dataframe and plot it.

In [2]:

```
dflog = pd.read_csv("C:/01_heights_weights_genders.csv")
dflog.head()
```

Out[2]:

	Gender	Height	Weight
0	Male	73.847017	241.893563
1	Male	68.781904	162.310473
2	Male	74.110105	212.740856
3	Male	71.730978	220.042470
4	Male	69.881796	206.349801

Remember that the form of data we will use always is

with the "response" or "label" y as a plain array of 0s and 1s for binary classification. Sometimes we will also see -1 and +1 instead. There are also *multiclass* classifiers that can assign an observation to one of $K > 2$ classes and the labe may then be an integer, but we will not be discussing those here.

```
y = [1,1,0,0,0,1,0,1,0....].
```

Checkup Exercise Set I

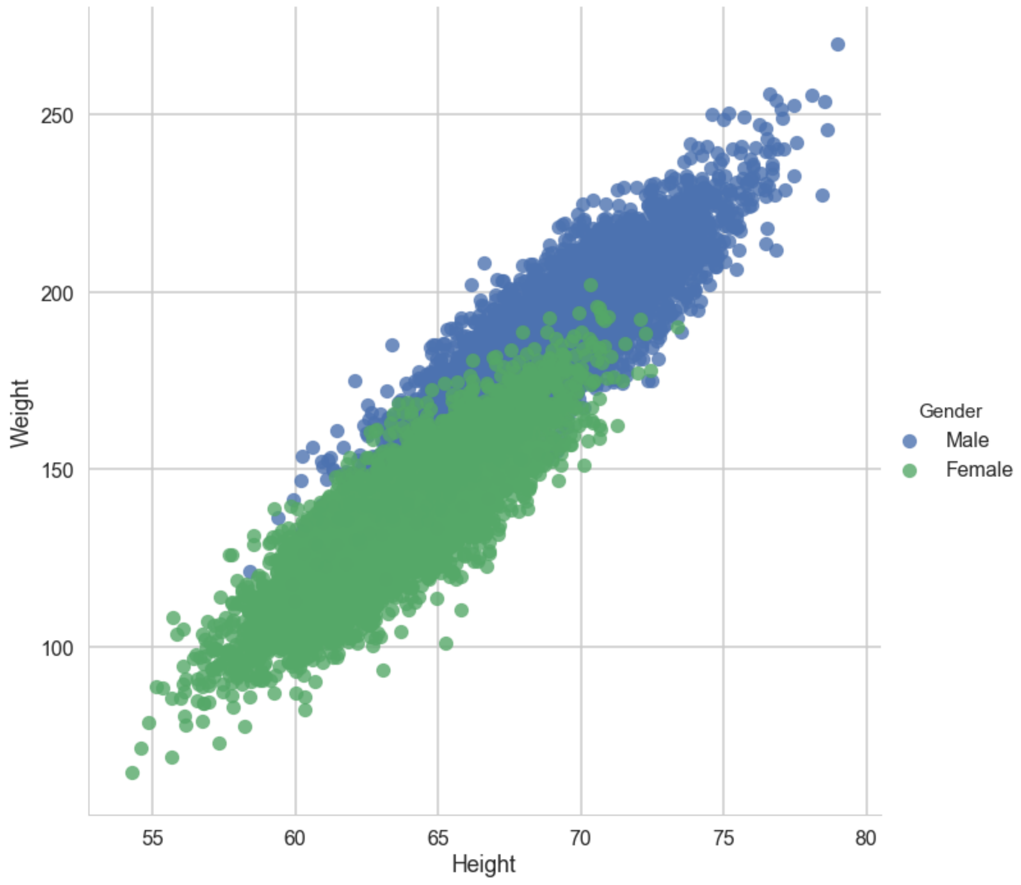
- **Exercise:** Create a scatter plot of Weight vs. Height
- **Exercise:** Color the points differently by Gender

In [3]:

```
import matplotlib.pyplot
# your turn
sns.lmplot(x="Height", y="Weight", hue="Gender",data=dflog, fit_reg=False, size=10)
```

Out[3]:

```
<seaborn.axisgrid.FacetGrid at 0x573acf8>
```



Training and Test Datasets

When fitting models, we would like to ensure two things:

- We have found the best model (in terms of model parameters).
- The model is highly likely to generalize i.e. perform well on unseen data.

Purpose of splitting data into Training/testing sets

- We built our model with the requirement that the model fit the data well.
- As a side-effect, the model will fit **THIS** dataset well. What about new data?
    - We wanted the model for predictions, right?
- One simple solution, leave out some data (for **testing**) and **train** the model on the rest
- This also leads directly to the idea of cross-validation, next section.

First, we try a basic Logistic Regression:

- Split the data into a training and test (hold-out) set
- Train on the training set, and test for accuracy on the testing set

In [4]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Split the data into a training and test set.
Xlr, Xtestlr, ylr, ytestlr = train_test_split(dflog[['Height','Weight']].values,
                                              (dflog.Gender == "Male").values,random_state=5)

clf = LogisticRegression()
# Fit the model on the trainng data.
clf.fit(Xlr, ylr)
# Print the accuracy from the testing data.
print(accuracy_score(clf.predict(Xtestlr), ytestlr))
```

```
0.9252
```

Tuning the Model

The model has some hyperparameters we can tune for hopefully better performance. For tuning the parameters of your model, you will use a mix of *cross-validation* and *grid search*. In Logistic Regression, the most important parameter to tune is the *regularization parameter* `C`. Note that the regularization parameter is not always part of the logistic regression model.

The regularization parameter is used to control for unlikely high regression coefficients, and in other cases can be used when data is sparse, as a method of feature selection.

You will now implement some code to perform model tuning and selecting the regularization parameter C.

We use the following `cv_score` function to perform K-fold cross-validation and apply a scoring function to each test fold. In this incarnation we use accuracy score as the default scoring function.

In [5]:

```
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score

def cv_score(clf, x, y, score_func=accuracy_score):
    result = 0
    nfold = 5
    for train, test in KFold(nfold).split(x): # split data into train/test groups, 5 times
        clf.fit(x[train], y[train]) # fit
        result += score_func(clf.predict(x[test]), y[test]) # evaluate score function on held-out data
    return result / nfold # average
```

Below is an example of using the `cv_score` function for a basic logistic regression model without regularization.

In [6]:

```
clf = LogisticRegression()
score = cv_score(clf, Xlr, ylr)
print(score)
```

```
0.917066666667
```

Checkup Exercise Set II

Exercise: Implement the following search procedure to find a good model

- You are given a list of possible values of `C` below
- For each C:
    1. Create a logistic regression model with that value of C

    2. Find the average score for this model using the `cv_score` function **only on the training set** `(Xlr, ylr)`
- Pick the C with the highest average score

Your goal is to find the best model parameters based *only* on the training set, without showing the model test set at all (which is why the test set is also called a *hold-out* set).

In [7]:

```
#the grid of parameters to search over
# your turn
Cs = [0.001, 0.1, 1, 10, 100]
for c in Cs:
    score = []
    clf = LogisticRegression(C=c)
    c_score = cv_score(clf, Xlr, ylr)
    score.append(c_score)
    print("for C = " + str(c) + " | Avg_score = " + str(c_score))
print ("Highest avg sore is: "+ str(max(score)))
```

```
for C = 0.001 | Avg_score = 0.916933333333
for C = 0.1 | Avg_score = 0.917066666667
for C = 1 | Avg_score = 0.917066666667
for C = 10 | Avg_score = 0.917066666667
for C = 100 | Avg_score = 0.917066666667
Highest avg sore is: 0.917066666667
```

Checkup Exercise Set III

Exercise: Now you want to estimate how this model will predict on unseen data in the following way:

1. Use the C you obtained from the procedure earlier and train a Logistic Regression on the training data
2. Calculate the accuracy on the test data

You may notice that this particular value of `C` may or may not do as well as simply running the default model on a random train-test split.

- Do you think that's a problem?
- Why do we need to do this whole cross-validation and grid search stuff anyway?

In [8]:

```
# your turn
# when C= 0.1
clf = LogisticRegression(C=0.1)
clf.fit(Xlr,ylr)
accuracy1 = accuracy_score(clf.predict(Xtestlr), ytestlr)
print(accuracy1)
# print (accuracy_score(clf.predict(Xtestlr,ytestlr)))

#When C= 1
clf = LogisticRegression(C=1)
clf.fit(Xlr,ylr)
accuracy2 = accuracy_score(clf.predict(Xtestlr), ytestlr)
print (accuracy2)
```

```
0.9252
0.9252
```

Accuracy score comes out to be the same at C = 1 and .1

Black Box Grid Search in `sklearn`

Scikit-learn, as with many other Python packages, provides utilities to perform common operations so you do not have to do it manually. It is important to understand the mechanics of each operation, but at a certain point, you will want to use the utility instead to save time...

In [9]:

```
{'C': [0.001, 0.1, 1, 10, 100]}
```

Checkup Exercise Set IV

```
C:\Users\anands\AppData\Local\Continuum\Anaconda3\lib\site-packages\sklearn\cross_validation.py:44: DeprecationWarning:
This module was deprecated in version 0.18 in favor of the model_selection module into which all the refactored classes and
functions are moved. Also note that the interface of the new CV iterators are different from that of this module. This modu
le will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
C:\Users\anands\AppData\Local\Continuum\Anaconda3\lib\site-packages\sklearn\grid_search.py:43: DeprecationWarning: This
module was deprecated in version 0.18 in favor of the model_selection module into which all the refactored classes and funct
ions are moved. This module will be removed in 0.20.
  DeprecationWarning)
```

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