Lesson 0001 - Iris Classification Linear Classifier

In this lesson, we will

- import the iris data set
- do some exploratory analysis on this data set
- build a linear classifier for this data set in tensorflow

We will begin by importing the data set which we can find in the Python package scikit-learn:

In [1]:
```
import sklearn as sklearn
from sklearn import datasets

data = datasets.load_iris()

print( sklearn.__version__ )
```

```
0.19.1
```

For reproducability of this lesson, we print the version number of sklearn, which is, in our case, 0.19.1.
Ok, we have loaded the data set and stored the result in **data**. We used the function load_iris.
We will extract **data_x**, a set of features we will use to classify, and **data_y**, a set of target values which store the classification of each data item.

In [2]:
```
data_x = data.data

data_y = data.target
```

Now let's have a look at the entries of **data_x**:

In [3]:
```
print( data_x[ 0 ] )
```

```
[5.1 3.5 1.4 0.2]
```

Seems like that the data in **data_x** are numerical data.
Let's have a look at the data in **data_y**:

In [4]:
```
print( data_y[ 0 ] )
```

```
0
```

It seems, like the data in **data_y** are also numerical.
Let's find out, how many different values there are in **data_y**.
For this end, we import the Python package NumPy, and from this package, we employ the function unique:

In [5]:
```
import numpy as np

print( np.unique( data_y ) )
```

```
[0 1 2]
```

In [6]:
```
print( np.__version__ )
```

```
1.14.3
```

For reproducability of this notebook, we print the version number of NumPy, in our case 1.14.3.
Now let's find out, how many data items we got:

In [7]:
```
print( len( data_y ) )
```

```
150
```

Above, we found out, that we have 4 dimensions in **data_x**, so we can plot our data in 4 3-d plots to get some idea of the data set.
We will start by encoding the different classes in different colors:

- **class 0** will be __blue__
- **class 1** will be __red__
- **class 2** will be **black**

In [8]:
```
colors = []

for i in range( len( data_y ) ):

    if data_y[ i ] == 0:

        colors.append( 'b' )

    elif data_y[ i ] == 1:

        colors.append( 'r' )

    else:

        colors.append( 'k' )
```

Now, we will import the Matplotlib which we will use for plotting.
For sake of reproducability, we print the version number of the matplotlib.

In [9]:
```
import matplotlib as matplotlib
from matplotlib import pyplot as plt

print( matplotlib.__version__ )
```

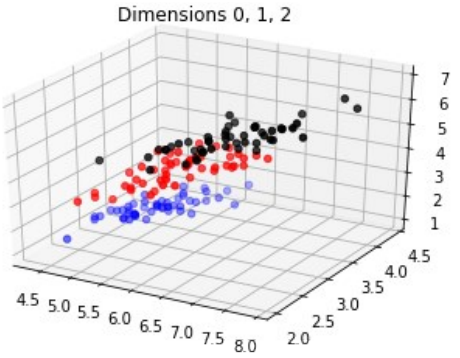
```
2.2.2
```

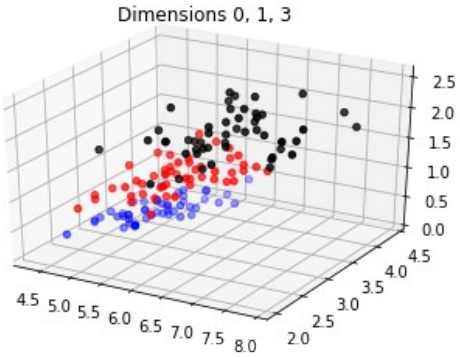
For 3-d plotting we import from Matplotlib the mpl_toolkits.

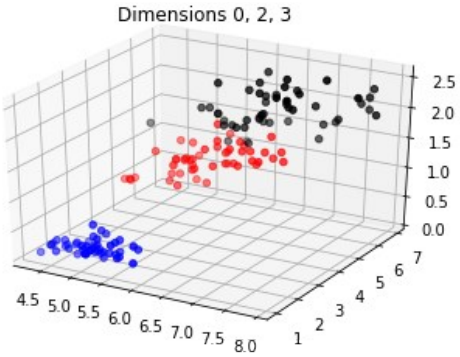
In [10]:
```
from mpl_toolkits.mplot3d import Axes3D
```

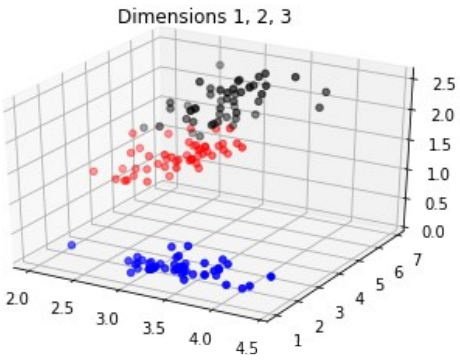
Now we use from Matplotlib the function figure to create a figure into which we plot.
We then add an Axes object to that figure, and finally use that Axes object to create a 3-d Scatter.
Then we employ the function show to finally show the plot.
Using the function title, we assign to each plot, what dimensions are plotted.

In [11]:
```
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure()

ax = fig.add_subplot( 111, projection = '3d' )

ax.scatter( data_x[ :, 0 ], data_x[ :, 1 ], data_x[ :, 2 ], c = colors )

plt.title( 'Dimensions 0, 1, 2' )

plt.show()


fig = plt.figure()

ax = fig.add_subplot( 111, projection = '3d' )

ax.scatter( data_x[ :, 0 ], data_x[ :, 1 ], data_x[ :, 3 ], c = colors )

plt.title( 'Dimensions 0, 1, 3' )

plt.show()


fig = plt.figure()

ax = fig.add_subplot( 111, projection = '3d' )

ax.scatter( data_x[ :, 0 ], data_x[ :, 2 ], data_x[ :, 3 ], c = colors )

plt.title( 'Dimensions 0, 2, 3' )

plt.show()


fig = plt.figure()

ax = fig.add_subplot( 111, projection = '3d' )

ax.scatter( data_x[ :, 1 ], data_x[ :, 2 ], data_x[ :, 3 ], c = colors )

plt.title( 'Dimensions 1, 2, 3' )

plt.show()
```









The four plots tell us, that **class 0** can be separated from the other two classes quite easily, but classes **1** and **2** intermingle.
For the next step, we will set a seed for the random number generator. This seed is used as a starting point for the random number generator and will make this lesson reproducable. For this end, we employ the function seed.

In [12]:
```
np.random.seed( 1234567890 )
```

Next, we will create a vector of 100 sorted unique random integers. For this end, we employ the functions choice and sort.
We will use these 100 random integers to draw randomly samples from **data_x** and **data_y** that we later use to train the classifier.
The remaining samples are there to validate the model.

In [13]:
```
random_integers = np.random.choice( range( 150 ), 100, replace = False )

random_integers = np.sort( random_integers )
```

Now, we employ the function zeros to create four matrices:

- the first matrix will have 100 rows and 4 columns, this matrix will store the training data from **data_x**
- the second matrix will have 50 rows and 4 columns, this matrix will store the validation data from **data_x**

For the target data, we will employ one hot encoding. This means, we will map the one dimensional data from **data_y** to 3d-data, where each data item i assumes the value $\delta_{i,j} = \begin{cases} 0 \text{ if data item } i \text{ is not in class } j \\ 1 \text{ else} \end{cases}$
Then one hot encoded target data will be stored in the third and fourth matrices.

In [14]:
```
train_x = np.zeros( shape = [ 100, 4 ] )

train_y = np.zeros( shape = [ 100, 3 ] )

test_x = np.zeros( shape = [ 50, 4 ] )

test_y = np.zeros( shape = [ 50, 3 ] )


j = 0

k = 0

for i in range( 150 ):

    if i == random_integers[ j ]:

        train_x[ j, : ] = data_x[ i, : ]

        train_y[ j, data_y[ i ] ] = 1.0

        j = j + 1

        if j == 100:

            j = 0

    else:

        test_x[ k, : ] = data_x[ i, : ]

        test_y[ k, data_y[ i ] ] = 1.0

        k = k + 1
```

Now we standardize the data. This means, that we compute for each column in **test_x** the mean μ and the standard deviation σ. We will store these data in the vectors **mu** and **sigma** which we create using the function zeros from above. We will compute the mean using the function mean and the standard deviation using the function std.
Once we have computed these values, we map each column **c** of **train_x** and **test_x** to
$c \to \frac{c-\mu}{\sigma}$
This way, we map **train_x** to a data set which has in each column zero mean and a standard deviation of 1.
In the end of this lesson, we will train a linear classifier using gradient descent, and for this, we will initialize the weights in this classifier randomly with zero mean. If we would not standardize the data, we might get stuck and train a bad model.

In [15]:
```
mu = np.zeros( shape = [ 4 ] )

sigma = np.zeros( shape = [ 4 ] )


for i in range( 4 ):

    mu[ i ] = np.mean( train_x[ :, i ] )

    sigma[ i ] = np.std( train_x[ :, i ] )

for i in range( 4 ):

    train_x[ :, i ] = ( train_x[ :, i ] - mu[ i ] ) / sigma[ i ]

    test_x[ :, i ] = ( test_x[ :, i ] - mu[ i ] ) / sigma[ i ]
```

Now we are almost done.
We want to train a model of the form
$c(x) = Wx + b$
where $c(x)$ is the predicted classification of data item x, W is a weight matrix and b is a vector.
We will create this model in tensorflow, therefore we import tensorflow, set the seed for the random number generation in tensorflow (for reproducability) and print the version number of tensorflow. We set the seed using the function set random seed.

In [16]:
```
import tensorflow as tf

tf.random.set_random_seed( 1234567890 )

print( tf.__version__ )
```

```
C:\Users\Robert\Anaconda3\lib\site-packages\h5py\__init__.py:36: FutureWarning: Conversion of the secon
d argument of issubdtype from `float` to `np.floating` is deprecated. In future, it will be treated as
`np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
```

```
1.12.0
```

Now we create the placeholders **x_tf** and **y_tf**. These store the training data items from **train_x** and **train_y**.
Next, we create the variables **W_tf** and **b_tf**. **W_tf** will be a $3 * 4$ matrix storing the weights of matrix W, **b_tf** will be a vector of length 3 storing the vector b.
Then, we combine these data items to the classifier **classifier**.

In [17]:
```
x_tf = tf.placeholder( tf.float32, shape = [ None, 4 ] )

y_tf = tf.placeholder( tf.float32, shape = [ None, 3 ] )

W_tf = tf.Variable( tf.zeros( [ 4, 3 ] ) )

b_tf = tf.Variable( tf.zeros( [ 3 ] ) )

classifier = tf.matmul( x_tf, W_tf ) + b_tf
```

The famous mathematician C. E. Shannon presented in his famous paper A mathematical theory of communications the idea of entropy of information. In short: the less we know about the outcome of a random experiment, the more information we gain from observing the experiment. For example: if you toss a coin that always ends up showing heads, you gain no information by tossing the coin.
His formula for entropy is

$$E = -\sum_i p_i \log(p_i)$$

where p_i is the probability of event i.
This inspired Kullback and Leibler to formulate their cross entropy. This entropy measures the distance between a distribution p and its approximation q.
This cross entropy is

$$C = \sum_i p_i \log\left(\frac{p_i}{q_i}\right) = \sum_i p_i \log(p_i) - \sum_i p_i \log(q_i)$$

Now consider our case: if we have a data item i we say

$$p_{i,c} = \begin{cases} 1 \text{ if data item } i \text{ is in class } c \\ 0 \text{ else} \end{cases}$$

Our classifier is basically computing a probability $q_{i,c}$, that assigns how probable it is, that i is in c. If our model q were perfect, then the term

$$-\sum_i p_i \log(q_i)$$

would be 0.
Therefore minimizing that last term is equivalent to approximating p by q ideally.
Our classifier will create an output $c(x)$ which will be three dimensional. We translate this vector of numbers to probabilities by mapping

$$c_i(x) \to \frac{e^{c_i(x)}}{\sum_j e^{c_j(x)}}$$

which is the soft max function.
We employ the function reduce mean to compute the mean of the cross entropy applied to the soft max transformed predictions made by our **classifier** and the true data **y_tf** using the function softmax cross entropy with logits.

In [18]:
```
cross_entropy = tf.reduce_mean( tf.nn.softmax_cross_entropy_with_logits_v2( logits = classifier, labe
ls = y_tf ) )
```

We optimize the **cross entropy** using gradient descent. We set the learning rate to 0.0001.

In [19]:
```
gd = tf.train.GradientDescentOptimizer( 1e-4 ).minimize( cross_entropy )
```

Now we define a function that decides on each data item whether the prediction made by the **classifier** is correct.
For this end, we employ the function argmax to return the index of the maximum value in a vector and the function equal to return, whether two values are identical. We store the result in **hit**.

In [20]:
```
hit = tf.equal( tf.argmax( classifier, 1 ), tf.argmax( y_tf, 1 ) )
```

Now, we transform the result stored in **hit** to a floating point number using cast, and then apply reduce mean to compute the mean over a set of **hit** s to compute the **accuracy**. Since we want the accuracy in $\%$, we multiply the result by 100.

In [21]:
```
accuracy = 100 * tf.reduce_mean( tf.cast( hit, tf.float32 ) )
```

Now we perform the learning.
We create three empty lists, **progress_train_s**, in which we store the accuracy on the current training set, **progress_train**, in which we store the accuracy on the complete training set, and **progress_test**, in which we store the accuracy on the test set.
We train for 500 iterations, and use in each iteration 30 randomly drawn data items from the training set to train which are stored in **local_x** and **local_y**.
We create a tensorflow session **sess**, initialize the variables in our model randomly using global variables initializer. We execute the

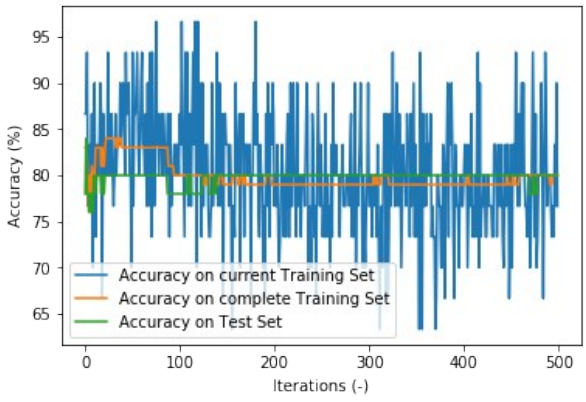
commands for tensorflow using run.

In [22]:
```
progress_train_s = []

progress_train = []

progress_test = []


sess = tf.Session()

sess.run( tf.global_variables_initializer() )

for i in range( 500 ):

    random_integers = np.random.choice( range( 100 ), 30, replace = False )

    local_x = train_x[ random_integers, : ]

    local_y = train_y[ random_integers, : ]

    sess.run( gd, feed_dict = { x_tf : local_x, y_tf : local_y } )

    progress_train_s.append( sess.run( accuracy, feed_dict = { x_tf : local_x, y_tf : local_y } ) )

    progress_train.append( sess.run( accuracy, feed_dict = { x_tf : train_x, y_tf : train_y } ) )

    progress_test.append( sess.run( accuracy, feed_dict = { x_tf : test_x, y_tf : test_y } ) )
```

Now we plot the accuracy we achieved.
We create a legend and label the axes using xlabel and ylabel.

In [23]:
```
plt.plot( progress_train_s, label = 'Accuracy on current Training Set' )

plt.plot( progress_train, label = 'Accuracy on complete Training Set' )

plt.plot( progress_test, label = 'Accuracy on Test Set' )

plt.legend( loc = 'best' )

plt.xlabel( 'Iterations (-)' )

plt.ylabel( 'Accuracy (%)' )
```

Out[23]:
```
Text(0,0.5,'Accuracy (%)')
```



We achieve an accuracy of roundabout 80% which is not too bad, but not great either.
But for now, we end this lesson and close **sess**.

In [24]:
```
sess.close()
```

Class dismissed.