Neural Networks for Heart Disease Recognition, Multiclass

In this assignment, you will use a neural network to recognize the heart disease categories 0-4.

1 - Packages

First, let's run the cell below to import all the packages that you will need during this assignment.

- numpy is the fundamental package for scientific computing with Python.
- matplotlib is a popular library to plot graphs in Python.
- tensorflow a popular platform for machine learning.

In [1]:

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.activations import linear, relu, sigmoid
import matplotlib.pyplot as plt
```

2 - ReLU Activation

In our lecture, a new activation was introduced, the Rectified Linear Unit (ReLU).

$$a = max(0, z) \qquad \text{\# ReLU function}$$

An activation value from a hidden layer represents a high-level feature (e.g. size of tumor) which is often not binary but has a continuous range of values. The sigmoid is best for on/off or binary situations. The ReLU provides a continuous linear relationship. Additionally it has an 'off' range where the output is zero. The "off" feature makes the ReLU a Non-Linear activation. Why is this needed? This enables multiple units to contribute to the resulting function without interfering.

3 - Softmax Function

A multiclass neural network generates N outputs. One output is selected as the predicted answer. In the output layer, a vector $\mathbf{z}$ is generated by a linear function which is fed into a softmax function. The softmax function converts $\mathbf{z}$ into a probability distribution as described below. After applying softmax, each output will be between 0 and 1 and the outputs will sum to 1. They can be interpreted as probabilities. The larger inputs to the softmax will correspond to larger output probabilities.

The softmax function can be written:

$$a_j = \frac{e^{z_j}}{\sum_{k=0}^{N-1} e^{z_k}} \tag{1}$$

Where $z = \mathbf{w} \cdot \mathbf{x} + b$ and N is the number of feature/categories in the output layer.

Exercise 1

Let's create a NumPy implementation:

In [2]:
```
def my_softmax(z):
    """ Softmax converts a vector of values to a probability distribution.
    Args:
      z (ndarray (N,))  : input data, N features
    Returns:
      a (ndarray (N,))  : softmax of z
    """
    ### START CODE HERE ###

    rows = z.shape
    a = np.zeros(rows)
    denominator = np.sum(np.exp(z))

    for i in range(0, rows[0]):
        a[i] = np.exp(z[i]) / denominator

    ### END CODE HERE ###
    return a
```

In [3]:
```
### test
z = np.array([1., 2., 3., 4.])
a = my_softmax(z)
atf = tf.nn.softmax(z)
print(f"my_softmax(z):         {a}")
print(f"tensorflow softmax(z): {atf}")
```

```
my_softmax(z):         [0.0320586  0.08714432 0.23688282 0.64391426]
tensorflow softmax(z): [0.0320586  0.08714432 0.23688282 0.64391426]
```

Expected Output

```
my_softmax(z):         [0.0320586  0.08714432 0.23688282 0.64391426]
tensorflow softmax(z): [0.0320586  0.08714432 0.23688282 0.64391426]
```

4 - Neural Networks

In the last assignment, you implemented a neural network to do binary classification. In this assignment, you will extend that to multiclass classification. This will utilize the softmax activation.

4.1 Problem Statement

You will use a neural network to recognize heart disease categories 0-4. This is a multiclass classification task where one of n choices is selected.

4.2 Dataset

You will use a data set from Cleveland Clinic Foundation (i.e., processed.cleveland.data). The data set contains 303 training examples with the following attribute information:

```
-- 1. (age)
-- 2. (sex)
-- 3. (cp)
-- 4. (trestbps)
-- 5. (chol)
-- 6. (fbs)
-- 7. (restecg)
-- 8. (thalach)
-- 9. (exang)
-- 10. (oldpeak)
-- 11. (slope)
-- 12. (ca)
-- 13. (thal)
-- 14. (num)       (the predicted attribute)
```

For more detailed information of each attribute, please refer to the attached file (i.e., heart-disease.names). You will start by loading the data set into variables `X` and `y`

- Each training example becomes a single row in our data matrix `X`.
- This gives us a 303 x 13 matrix `X` where every row is a training example of a heart disease cetegory.

$$X = \begin{pmatrix} ---(x^{(1)})--- \\ ---(x^{(2)})--- \\ \vdots \\ ---(x^{(m)})--- \end{pmatrix}$$

- The second part of the training set is a 303 x 1 dimensional vector y that contains labels (i.e., 0-4) for the training set.

Note that a real data set often has missing data. For the data set being used in this assignment, a missing data item is designated as '?'. A common method for dealing with a missing item is to use the average value of the other data items in the same attribute/feature to replace the missing one. So, your first step is to write a function called 'preprocess_data' that covert string value to float, computes the average value of each attribute (i.e., each column of X), and replaces the missing item (if any) using the average value.

In [4]:

```python
def preprocess_data(X):
    '''
    Proprocess the data so that the missing item is replaced by the average value of e
    Args:
        X  : (ndarray Shape(m,n)) data with string type

    Return:
        Xp : (ndarray Shape(m,n)) data with float type - the missing element has been
        the average value of each attribute
    '''
    # Get the shape of X
    rows, cols = X.shape

    # For each column
    for j in range(0, cols):
        sumCol = 0             # Sum of the data in the column
        count = 0              # Number of data entries in the column
        missing = np.empty(0) # Row numbers of missing data points

        # For each row in the column
        for i in range(0, rows):
            # Check if data is present
            if X[i, j] == '?':
                # Add to the missing array
                missing = np.append(missing, i)
            else:
                # Add to the sum of the column
                sumCol += float(X[i, j])
                count += 1

        # If there was missing data
        if count > 0:
            # Calculate the average of the column
            avg = sumCol / count
            avg = str(avg)
            for k in range(0, missing.size):
                # Fill in missing data with the average of the column
                X[int(missing[k]),j] = avg

    # Return matrix as floats
    return X.astype(float)
```

In [5]:

```python
# Create 2-D numpy array
arr = np.array([['5.0', '9.0', '7.0', '?'], ['8.0', '14.0', '?', '19.0'],['32.0', '24.

processed_arr = preprocess_data(arr)

print(processed_arr)
```

```
[[ 5.   9.   7.  23.5]
 [ 8.  14.  13.  19. ]
 [32.  24.  19.  28. ]]
```

Expected Output

```
[[ 5.   9.   7.  23.5]
 [ 8.  14.  13.  19. ]
 [32.  24.  19.  28. ]]
```

Now you need to write a function to load the data, preprocess them, and put them in X and y.

In [6]:
```
# Load dataset

def load_data(filename):
     # Load the data from the file
    data = np.loadtxt(filename, dtype=str, delimiter=',')

    # Store the 13 features from each example into a 2D matrix and convert the type to
    X = np.array(data[:,0:13])
    X = preprocess_data(X)

    # Store the outputs for each example and set each 'M' to a 1 and each 'B' to a 0
    y = np.array([data[:,13]])
    y = y.T
    y = y.astype(float)

    return X, y
```

In [7]:
```
X, y = load_data("./data/processed.cleveland.data")
```

4.2.1 View the variables

Let's get more familiar with your dataset.

- A good place to start is to print out each variable and see what it contains.

The code below prints the first element in the variables `X`.

In [8]:
```
print ('The first element of X is: ', X[0])
```

```
The first element of X is:  [ 63.    1.    1.  145.  233.    1.    2.  150.    0.
2.3   3.    0.
   6. ]
```

In [9]:
```
print ('The first element of y is: ', y[0,0])
print ('The second element of y is: ', y[1,0])
```

```
The first element of y is:  0.0
The second element of y is:  2.0
```

4.2.2 Check the dimensions of your variables

Another way to get familiar with your data is to view its dimensions. Please print the shape of `X` and `y` and see how many training examples you have in your dataset.

In [10]:
```
print ('The shape of X is: ' + str(X.shape))
print ('The shape of y is: ' + str(y.shape))
```

```
The shape of X is: (303, 13)
The shape of y is: (303, 1)
```

Expected Output

```
The shape of X is: (303, 13)
The shape of y is: (303, 1)
```

Tile/copy our data to increase the training set size and reduce the number of training epochs.

In [11]:
```
X = np.tile(X,(100,1))
y= np.tile(y,(100,1))

print(X.shape, y.shape)
```

```
(30300, 13) (30300, 1)
```

Expected Output

```
(30300, 13) (30300, 1)
```

4.3 Model representation

The neural network you will use in this assignment is shown in the figure below.

- This has two dense layers with ReLU activations followed by an output layer with a linear activation.

- The parameters have dimensions that are sized for a neural network with 25 units in layer 1, 15 units in layer 2, and 5 output units in layer 3, one for each heart disease category.

- Recall that the dimensions of these parameters is determined as follows:
    - If network has s_{in} units in a layer and s_{out} units in the next layer, then
        - W will be of dimension $s_{in} \times s_{out}$.
        - b will be a vector with s_{out} elements
- Therefore, the shapes of `W`, and `b`, are
    - layer1: The shape of `W1` is (13, 25) and the shape of `b1` is (25,)
    - layer2: The shape of `W2` is (25, 15) and the shape of `b2` is: (15,)
    - layer3: The shape of `W3` is (15, 5) and the shape of `b3` is: (5,)

    > **Note:** The bias vector `b` could be represented as a 1-D (n,) or 2-D (n,1) array. Tensorflow utilizes a 1-D representation and this assignment will maintain that convention:

4.4 Tensorflow Model Implementation

Tensorflow models are built layer by layer. A layer's input dimensions (s_{in} above) are calculated for you. You specify a layer's *output dimensions* and this determines the next layer's input dimension. The input dimension of the first layer is derived from the size of the input data specified in the `model.fit` statement below.

> **Note:** It is also possible to add an input layer that specifies the input dimension of the first layer. For example:
> `tf.keras.Input(shape=(13,)),    #specify input shape`
> We will include that here to illuminate some model sizing.

4.5 Softmax placement

As described in the lecture, numerical stability is improved if the softmax is grouped with the loss function rather than the output layer during training. This has implications when *building* the model and *using* the model.
Building:

- The final Dense layer should use a 'linear' activation. This is effectively no activation.
- The `model.compile` statement will indicate this by including `from_logits=True`.
  `loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)`
- This does not impact the form of the target. In the case of SparseCategorialCrossentropy, the target is the expected category, 0-4.

Using the model:

- The outputs are not probabilities. If output probabilities are desired, apply a softmax function.

Exercise 2

Below, using Keras Sequential model and Dense Layer with a ReLU activation to construct the three layer network described above.

In [12]:
```
tf.random.set_seed(1234) # for consistent results
model = Sequential(
    [
        tf.keras.Input(shape=(13,)),    #specify input size
        ### START CODE HERE ###
        Dense(units = 25, activation = 'relu'),
        Dense(units = 15, activation = 'relu'),
        Dense(units = 5,  activation = 'linear'),
        ### END CODE HERE ###
    ], name = "my_model"
)
```

In [13]:
```
model.summary()
```

```
Model: "my_model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 25)                350

 dense_1 (Dense)             (None, 15)                390

 dense_2 (Dense)             (None, 5)                 80

=================================================================
Total params: 820
Trainable params: 820
Non-trainable params: 0
_________________________________________________________________
```

▶ **Expected Output (Click to expand)**

The parameter counts shown in the summary correspond to the number of elements in the weight and bias arrays as shown below.

Let's further examine the weights to verify that tensorflow produced the same dimensions as we calculated above.

In [14]:
```
[layer1, layer2, layer3] = model.layers
```

In [15]:
```
#### Examine Weights shapes
W1,b1 = layer1.get_weights()
W2,b2 = layer2.get_weights()
W3,b3 = layer3.get_weights()
print(f"W1 shape = {W1.shape}, b1 shape = {b1.shape}")
print(f"W2 shape = {W2.shape}, b2 shape = {b2.shape}")
print(f"W3 shape = {W3.shape}, b3 shape = {b3.shape}")
```

```
W1 shape = (13, 25), b1 shape = (25,)
W2 shape = (25, 15), b2 shape = (15,)
W3 shape = (15, 5), b3 shape = (5,)
```

Expected Output

```
W1 shape = (13, 25), b1 shape = (25,)
W2 shape = (25, 15), b2 shape = (15,)
W3 shape = (15, 5), b3 shape = (5,)
```

The following code:

- defines a loss function, `SparseCategoricalCrossentropy` and indicates the softmax should be included with the loss calculation by adding `from_logits=True`)
- defines an optimizer. A popular choice is Adaptive Moment (Adam) which was described in lecture.

In [16]:
```
model.compile(
    loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits = True), # ADD CO
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.001),
)

history = model.fit(
    X,y,
    epochs=100
)
```

```
Epoch 1/100
947/947 [==============================] - 2s 2ms/step - loss: 2.8470
Epoch 2/100
947/947 [==============================] - 2s 2ms/step - loss: 0.9988
Epoch 3/100
947/947 [==============================] - 2s 2ms/step - loss: 0.9527
Epoch 4/100
947/947 [==============================] - 2s 2ms/step - loss: 0.9161
Epoch 5/100
947/947 [==============================] - 2s 2ms/step - loss: 0.9073
Epoch 6/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8910
Epoch 7/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8751
Epoch 8/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8395
Epoch 9/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8415
Epoch 10/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8295
Epoch 11/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8245
Epoch 12/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8150
Epoch 13/100
947/947 [==============================] - 2s 2ms/step - loss: 0.8073
Epoch 14/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7940
Epoch 15/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7841
Epoch 16/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7686
Epoch 17/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7562
Epoch 18/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7520
Epoch 19/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7433
Epoch 20/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7397
Epoch 21/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7274
Epoch 22/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7167
Epoch 23/100
947/947 [==============================] - 2s 2ms/step - loss: 0.7027
Epoch 24/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6944
Epoch 25/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6829
Epoch 26/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6776
Epoch 27/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6725
Epoch 28/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6607
Epoch 29/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6404
Epoch 30/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6353
```

```
Epoch 31/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6216
Epoch 32/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6132
Epoch 33/100
947/947 [==============================] - 2s 2ms/step - loss: 0.6055
Epoch 34/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5926
Epoch 35/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5779
Epoch 36/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5715
Epoch 37/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5628
Epoch 38/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5618
Epoch 39/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5529
Epoch 40/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5322
Epoch 41/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5353
Epoch 42/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5114
Epoch 43/100
947/947 [==============================] - 2s 2ms/step - loss: 0.5057
Epoch 44/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4989
Epoch 45/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4881
Epoch 46/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4787
Epoch 47/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4757
Epoch 48/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4643
Epoch 49/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4517
Epoch 50/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4636
Epoch 51/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4449
Epoch 52/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4308
Epoch 53/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4273
Epoch 54/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4265
Epoch 55/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4208
Epoch 56/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4030
Epoch 57/100
947/947 [==============================] - 2s 2ms/step - loss: 0.4111
Epoch 58/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3911
Epoch 59/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3980
Epoch 60/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3948
```

```
Epoch 61/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3895
Epoch 62/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3703
Epoch 63/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3589
Epoch 64/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3599
Epoch 65/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3430
Epoch 66/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3500
Epoch 67/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3576
Epoch 68/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3299
Epoch 69/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3151
Epoch 70/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3126
Epoch 71/100
947/947 [==============================] - 2s 2ms/step - loss: 0.3007
Epoch 72/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2969
Epoch 73/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2954
Epoch 74/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2927
Epoch 75/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2772
Epoch 76/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2783
Epoch 77/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2720
Epoch 78/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2693
Epoch 79/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2564
Epoch 80/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2483
Epoch 81/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2444
Epoch 82/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2201
Epoch 83/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2133
Epoch 84/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2130
Epoch 85/100
947/947 [==============================] - 2s 2ms/step - loss: 0.2016
Epoch 86/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1936
Epoch 87/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1801
Epoch 88/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1692
Epoch 89/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1614
Epoch 90/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1577
```

```
Epoch 91/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1569
Epoch 92/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1349
Epoch 93/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1473
Epoch 94/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1228
Epoch 95/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1049
Epoch 96/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1123
Epoch 97/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1209
Epoch 98/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1325
Epoch 99/100
947/947 [==============================] - 2s 2ms/step - loss: 0.0875
Epoch 100/100
947/947 [==============================] - 2s 2ms/step - loss: 0.1077
```

Epochs and batches

In the `compile` statement above, the number of `epochs` was set to 100. This specifies that the entire data set should be applied during training 100 times. During training, you see output describing the progress of training that looks like this:

```
Epoch 1/100
947/947 [==============================] - 0s 1ms/step - loss: 2.6479
```

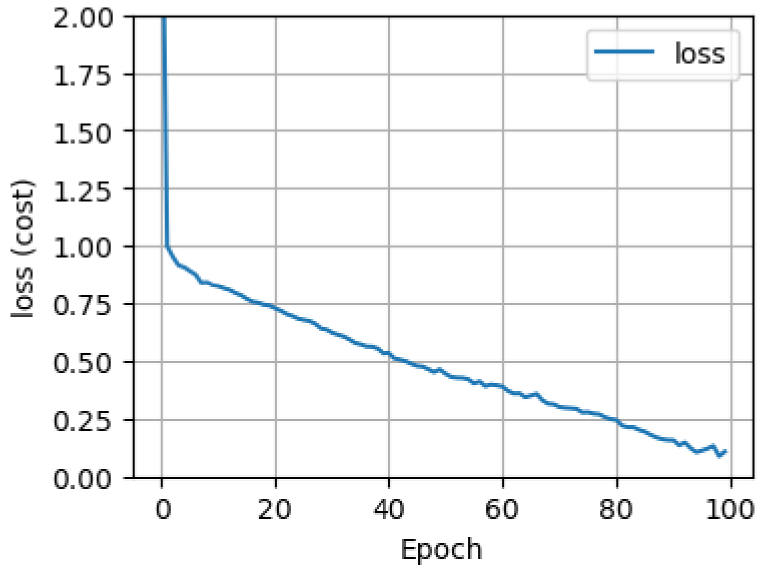
The first line, `Epoch 1/100`, describes which epoch the model is currently running. For efficiency, the training data set is broken into 'batches'. The default size of a batch in Tensorflow is 32. There are 30300 examples in our extended data set or roughly 947 batches. The notation on the 2nd line `947/947 [====` is describing which batch has been executed.

Loss (cost)

In the previous lectures, we learned to track the progress of gradient descent by monitoring the cost. Ideally, the cost will decrease as the number of iterations of the algorithm increases. Tensorflow refers to the cost as `loss`. Above, you saw the loss displayed each epoch as `model.fit` was executing. The .fit method returns a variety of metrics including the loss. This is captured in the `history` variable above. This can be used to examine the loss in a plot as shown below.

In [17]:
```
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'          # to support higher OS versions
fig,ax = plt.subplots(1,1, figsize = (4,3))
ax.plot(history.history['loss'], label='loss')
ax.set_ylim([0, 2])
ax.set_xlabel('Epoch')
ax.set_ylabel('loss (cost)')
ax.legend()
```

```
ax.grid(True)
plt.show()
```



Prediction

To make a prediction, use Keras `predict`. Below, X[0] contains an training example with category 0.

In [18]:
```
first_patient = X[0]

prediction = model.predict(first_patient.reshape(1,13))  # prediction

print(f" predicting a category Zero: \n{prediction}")
print(f" Largest Prediction index: {np.argmax(prediction)}")
```

```
1/1 [==============================] - 0s 80ms/step
 predicting a category Zero:
[[ 17.41642   -12.82461     4.13905   -11.09326    -3.1084456]]
 Largest Prediction index: 0
```

The largest output is prediction[0], indicating the predicted category is a '0'. If the problem only requires a selection, that is sufficient. Use NumPy argmax to select it. If the problem requires a probability, a softmax is required:

In [19]:
```
prediction_p = tf.nn.softmax(prediction)

print(f" predicting a Zero. Probability vector: \n{prediction_p}")
print(f"Total of predictions: {np.sum(prediction_p):0.3f}")
```

```
 predicting a Zero. Probability vector:
[[9.9999833e-01 7.3533790e-14 1.7128154e-06 4.1533893e-13 1.2194478e-09]]
Total of predictions: 1.000
```

To return an integer representing the predicted target, you want the index of the largest probability. This is accomplished with the Numpy argmax function.

In [20]:
```
yhat = np.argmax(prediction_p)
```

```python
print(f"np.argmax(prediction_p): {yhat}")
```

```
np.argmax(prediction_p): 0
```

In [21]:
```python
f = model.predict(X)
yhat = np.argmax(f, axis=1)
print('Train Accuracy: %f'%(np.mean(yhat == y[:,0]) * 100))
```

```
947/947 [==============================] - 1s 1ms/step
Train Accuracy: 96.369637
```