Back Propagation

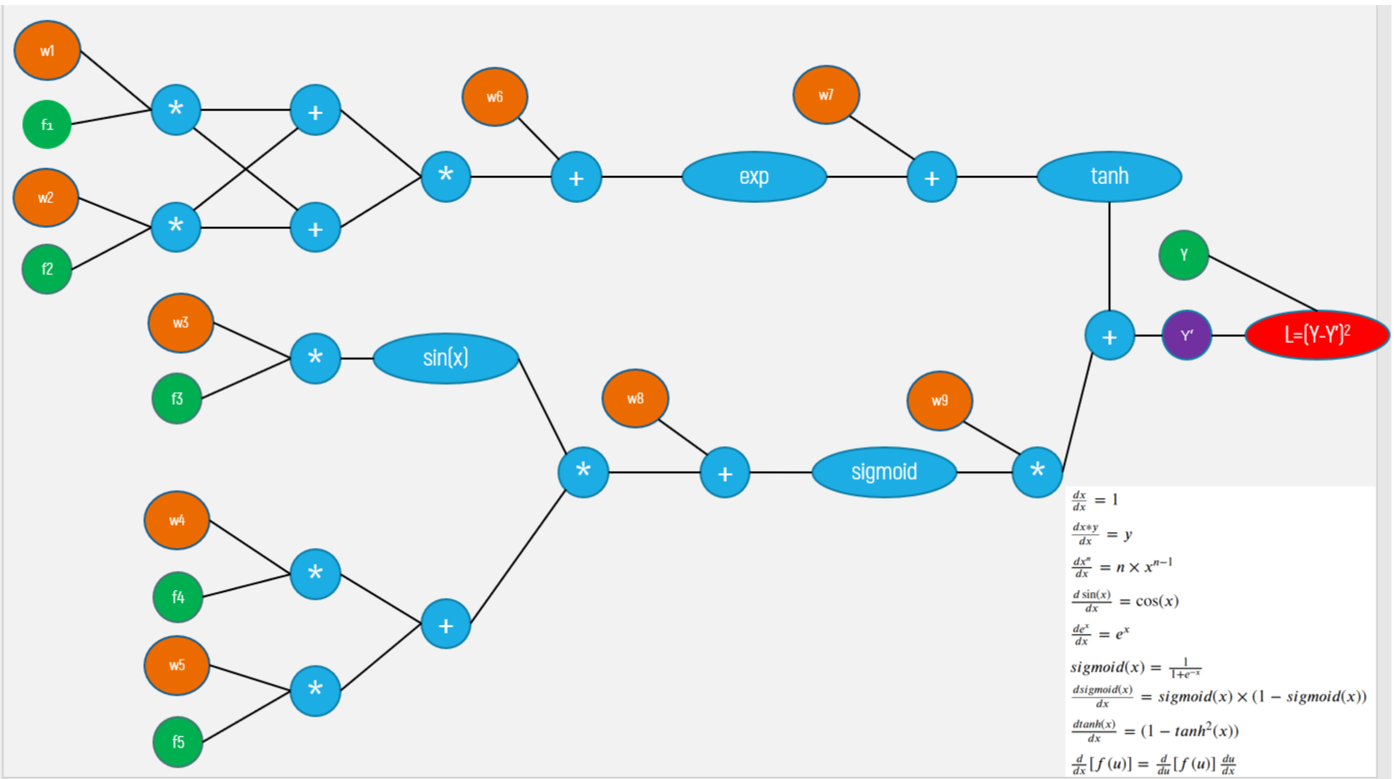
1. loading of data

In [1]:

```
import pickle
with open('data.pkl', 'rb') as f:
    data = pickle.load(f)
print(data.shape)
X = data[:, :5]
y = data[:, -1]
print(X.shape, y.shape)
```

```
(506, 6)
(506, 5) (506,)
```

2. Computational graph



1. if you observe the graph, we are having input features [f1, f2, f3, f4, f5] and 9 weights [w1, w2, w3, w4, w5, w6, w7, w8, w9]
2. the final output of this graph is a value L which is computed as (Y-Y')^2

Task 1: Implementing backpropagation and Gradient checking

1. **Check this video for better understanding of the computational graphs and back propagation:** [https://www.youtube.com/watch?v=i94OvYb6noo (https://www.youtube.com/watch?v=i94OvYb6noo#t=1m33s)](https://www.youtube.com/watch?v=i94OvYb6noo#t=1m33s)

2. **write two functions**

```
#you can modify the definition of this function according to your needs

def forward_propagation(X, y, W):

        # X: input data point, note that in this assignment you are having 5-d data points
        # y: output varible
        # W: weight array, its of length 9, W[0] corresponds to w1 in graph, W[1] corresponds to w2 in graph, ..., W[8] corresponds to w9 in graph.
        # write code to compute the value of L=(y-y')^2

        return (L, any other variables which you might need to use for back propagation)

        # Hint: you can use dict type to store the required intermediate variables



# you can modify the definition of this function according to your needs

def backward_propagation(L, Variables):

        # L: the loss we calculated for the current point
        # Variables: the outputs of the forward_propagation() function
        # write code to compute the gradients of each weight [w1,w2,w3,...,w9]

        return dW

        # here dW can be a list, or dict or any other data type wich will have gradients of all the weights
        # Hint: you can use dict type to store the required variables
```

3. [**Gradient checking (https://towardsdatascience.com/how-to-debug-a-neural-network-with-gradient-checking-41deec0357a9)**](https://towardsdatascience.com/how-to-debug-a-neural-network-with-gradient-checking-41deec0357a9):[blog link (https://towardsdatascience.com/how-to-debug-a-neural-network-with-gradient-checking-41deec0357a9)](https://towardsdatascience.com/how-to-debug-a-neural-network-with-gradient-checking-41deec0357a9)

we know that the derivative of any function is

$$\lim_{\epsilon \to 0} \frac{f(x+\epsilon) - f(x-\epsilon)}{2\epsilon}$$

```
The definition above can be used as a numerical approximation of the derivat
ive. Taking an epsilon small enough, the calculated approximation will have
an error in the range of epsilon squared.

In other words, if epsilon is 0.001, the approximation will be off by 0.0000
1.

Therefore, we can use this to approximate the gradient, and in turn make sur
e that backpropagation is implemented properly. This forms the basis of grad
ient checking!
```

lets understand the concept with a simple example: $f(w1, w2, x1, x2) = w_1^2 . x_1 + w_2 . x_2$

from the above function lets assume $w_1 = 1, w_2 = 2, x_1 = 3, x_2 = 4$ the gradient of f w.r.t w_1 is

$$\begin{aligned} \frac{df}{dw_1} = dw_1 &= 2.w_1 . x_1 \\ &= 2.1.3 \\ &= 6 \end{aligned}$$

let calculate the aproximate gradient of w_1 as mentinoned in the above formula and considering $\epsilon = 0.0001$

$$\begin{aligned} dw_1^{approx} &= \frac{f(w1+\epsilon, w2, x1, x2) - f(w1-\epsilon, w2, x1, x2)}{2\epsilon} \\ &= \frac{((1+0.0001)^2.3+2.4) - ((1-0.0001)^2.3+2.4)}{2\epsilon} \\ &= \frac{(1.00020001.3+2.4) - (0.99980001.3+2.4)}{2*0.0001} \\ &= \frac{(11.00060003) - (10.99940003)}{0.0002} \\ &= 5.99999999999 \end{aligned}$$

Then, we apply the following formula for gradient check: *gradient_check* = $\frac{\|(dW - dW^{approx})\|_2}{\|(dW)\|_2 + \|(dW^{approx})\|_2}$

The equation above is basically the Euclidean distance normalized by the sum of the norm of the vectors. We use normalization in case that one of the vectors is very small. As a value for epsilon, we usually opt for 1e-7. Therefore, if gradient check return a value less than 1e-7, then it means that backpropagation was implemented correctly. Otherwise, there is potentially a mistake in your implementation. If the value exceeds 1e-3, then you are sure that the code is not correct.

in our example: $gradient\_check = \frac{(6-5.999999999994898)}{(6+5.999999999994898)} = 4.2514140356330737e^{-13}$

you can mathamatically derive the same thing like this

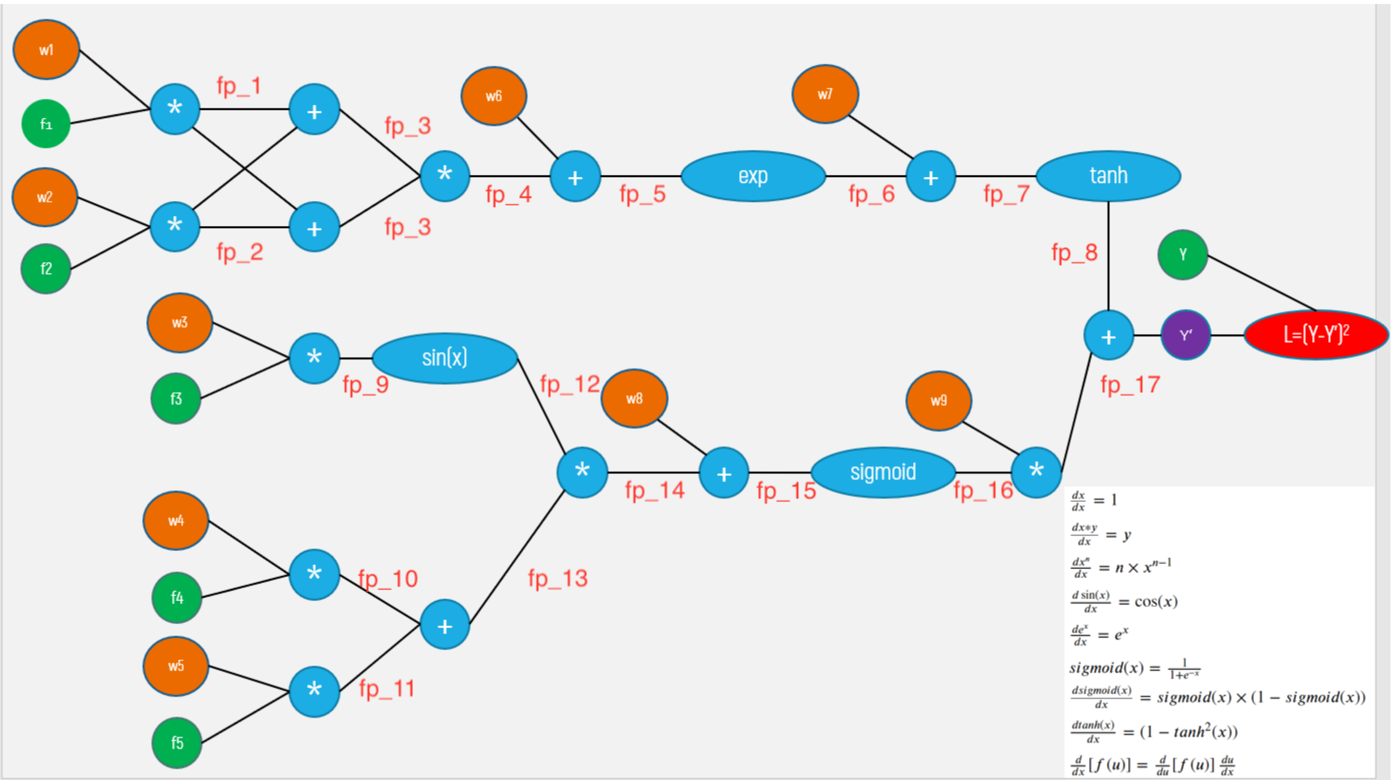
$$\begin{aligned} dw_1^{approx} &= \frac{f(w1+\epsilon, w2, x1, x2) - f(w1-\epsilon, w2, x1, x2)}{2\epsilon} \\ &= \frac{((w_1+\epsilon)^2.x_1 + w_2.x_2) - ((w_1-\epsilon)^2.x_1 + w_2.x_2)}{2\epsilon} \\ &= \frac{4.\epsilon.w_1.x_1}{2\epsilon} \\ &= 2.w_1 . x_1 \end{aligned}$$

to do this task you need to write a function

```
W = initilize_randomly
def gradient_checking(data_point, W):

    # compute the L value using forward_propagation()
    # compute the gradients of W using backword_propagation()

    approx_gradients = []
    for each wi weight value in W:

        # add a small value to weight wi, and then find the values of L with
the updated weights
        # subtract a small value to weight wi, and then find the values of L
with the updated weights
        # compute the approximation gradients of weight wi

        approx_gradients.append(approximation gradients of weight wi)

    # compare the gradient of weights W from backword_propagation() with the
aproximation gradients of weights with      gradient_check formula

    return gradient_check
```

NOTE: you can do sanity check by checking all the return values of gradient_checking(), they have to be zero. if not you have bug in your code

Implemented graph flow & forward propagation



Finding gradients

$$\boxed{\frac{\partial L}{\partial w_1}} = \overset{1}{\frac{\partial L}{\partial fp\_8}} \cdot \overset{2}{\frac{\partial fp\_8}{\partial fp\_7}} \cdot \overset{3}{\frac{\partial fp\_7}{\partial fp\_6}} \cdot \overset{4}{\frac{\partial fp\_6}{\partial fp\_5}} \cdot \overset{5}{\frac{\partial fp\_5}{\partial fp\_4}} \left[\overset{6}{\frac{\partial fp\_4}{\partial fp\_3}} \; \overset{7}{\frac{\partial fp\_3}{\partial fp\_1}} \right] \overset{8}{\frac{\partial fp\_1}{\partial w_1}}$$

1 $\boxed{\frac{\partial L}{\partial fp\_8}} = \frac{\partial (y - fp\_8 - fp\_12)^2}{\partial fp\_8} = 2(y - fp\_8 - fp\_12)(-1)$

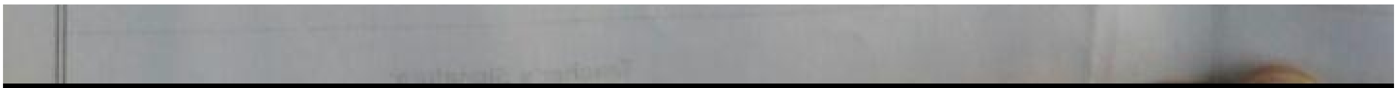
2 $\boxed{\frac{\partial fp\_8}{\partial fp\_7}} = 1 - \tanh^2(fp\_7)$ #Trinath Reddy

3 $\frac{\partial fp\_7}{\partial fp\_6} = 1$; (4) $\frac{\partial fp\_6}{\partial fp\_5} = \exp(fp\_5) = fp\_6$; (5) $\frac{\partial fp\_5}{\partial fp\_4} = 1$

6 $\frac{\partial fp\_4}{\partial fp\_3} = 2 \cdot (fp\_3)$; (7) $\frac{\partial fp\_3}{\partial fp\_1} = 1$; (8) $\frac{\partial fp\_1}{\partial w_1} = f1$.

$$\boxed{\frac{\partial L}{\partial w_2}} = \overset{1}{\frac{\partial L}{\partial fp\_8}} \cdot \overset{2}{\frac{\partial fp\_8}{\partial fp\_7}} \cdot \overset{3}{\frac{\partial f\_7}{\partial f\_6}} \cdot \overset{4}{\frac{\partial fp\_6}{\partial fp\_5}} \cdot \overset{5}{\frac{\partial fp\_5}{\partial fp\_4}} \left[\overset{6}{\frac{\partial fp\_4}{\partial fp\_3}} \cdot \overset{9}{\frac{\partial fp\_3}{\partial fp\_2}} \right] \overset{10}{\frac{\partial fp\_2}{\partial w_2}}$$

9 $\frac{\partial fp\_3}{\partial fp\_2} = 1$; (10) $\frac{\partial fp\_2}{\partial w_2} = f_2$



[redacted]

$$\boxed{\frac{\partial L}{\partial w_3}} = \underbrace{\frac{\partial L}{\partial fp\_17}}_{11} \cdot \underbrace{\frac{\partial fp\_17}{\partial fp\_16}}_{12} \cdot \underbrace{\frac{\partial fp\_16}{\partial fp\_15}}_{13} \cdot \underbrace{\frac{\partial fp\_15}{\partial fp\_14}}_{14} \cdot \left[\underbrace{\frac{\partial fp\_14}{\partial fp\_12}}_{15} \cdot \underbrace{\frac{\partial fp\_12}{\partial fp\_9}}_{16}\right] \cdot \underbrace{\frac{\partial fp\_9}{\partial w_3}}_{17}$$

11 $$\frac{\partial L}{\partial fp\_17} = -2(y - fp\_8 - fp\_17)$$

12 $$\frac{\partial fp\_17}{\partial fp\_16} = w_9 \; ; \; \frac{\partial fp\_16}{\partial fp\_15} = sig(fp_{15})(1 - sig(fp_{15})) = fp_{16}\cdot(1-fp_{16})$$

$$= sig(fp\_15)(1 - sig(fp\_15)) = fp_{16}\cdot(1-fp_{16})$$

14 $$\frac{\partial fp\_15}{\partial fp\_14} = 1 \; ; \; \frac{\partial fp_{14}}{\partial fp\_12} = fp\_13 \; ; \; \frac{\partial fp\_12}{\partial fp\_9} = \cos(fp\_9)$$

17 $$\frac{\partial fp\_9}{\partial w_3} = f_3$$

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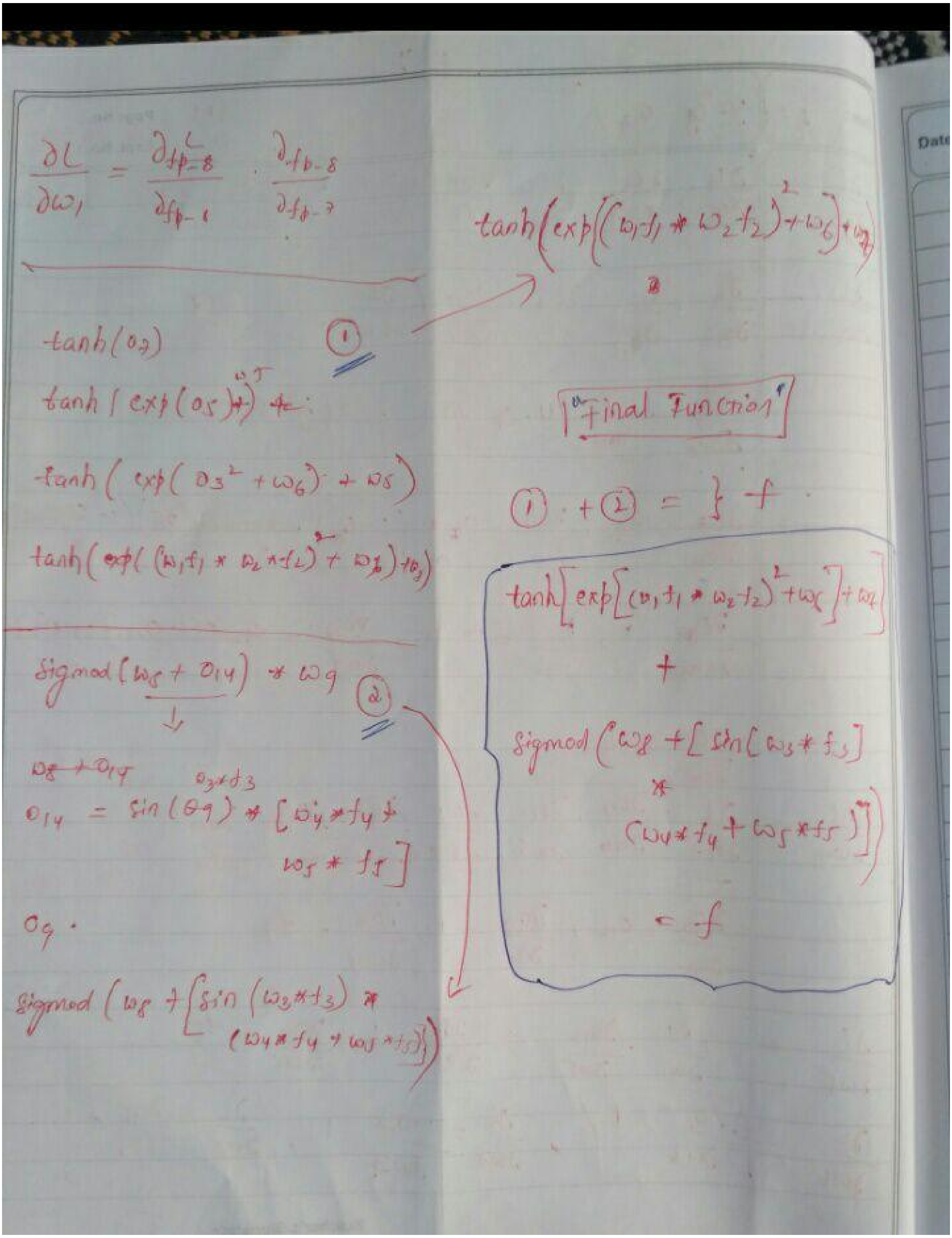
$$\boxed{\frac{\partial L}{\partial w_4}} = \underbrace{\frac{\partial L}{\partial fp\_17}}_{11} \cdot \underbrace{\frac{\partial fp\_17}{\partial fp\_16}}_{12} \cdot \underbrace{\frac{\partial fp\_16}{\partial fp\_15}}_{13} \cdot \underbrace{\frac{\partial fp\_15}{\partial fp\_14}}_{14} \left[\underbrace{\frac{\partial fp\_14}{\partial fp\_13}}_{18} \cdot \underbrace{\frac{\partial fp\_13}{\partial fp\_10}}_{19}\right] \underbrace{\frac{\partial fp\_10}{\partial w_4}}_{20}$$

18 $$\frac{\partial fp\_14}{\partial fp\_13} = fp\_12 \; ; \; \frac{\partial fp\_13}{\partial fp\_10} = 1 \; ; \; \frac{\partial fp\_10}{\partial w_4} = f_4$$

Final function for graph



$$\frac{\partial L}{\partial w_1} = \frac{\partial f_{b-8}}{\partial f_{b-1}} \cdot \frac{\partial f_{b-8}}{\partial f_{b-7}}$$

$\tanh(o_7)$ ①

$\tanh(\exp(o_5)^2 + w_6) + w_7$

$\tanh(\exp(o_3^2 + w_6) + w_5)$

$\tanh(\exp((w_1 f_1 * w_2 * f_2)^2 + w_6) + w_7)$

$\text{sigmod}(w_8 + o_{14}) * w_9$ ②

$o_{14} = \sin(o_9) * [w_4 * f_4 + w_5 * f_5]$, $o_9 = w_3 * f_3$

$\text{sigmod}(w_8 + [\sin(w_3 * f_3) * (w_4 * f_4 + w_5 * f_5)])$

$\tanh(\exp((w_1 f_1 * w_2 f_2)^2 + w_6) + w_7)$

"Final Function"

① + ② = f

$\tanh[\exp[(w_1 f_1 * w_2 f_2)^2 + w_6] + w_7]$

+

$\text{sigmod}(w_8 + [\sin[w_3 * f_3] * (w_4 * f_4 + w_5 * f_5)])$

= f

In [2]:

```
import numpy as np
import matplotlib.pyplot as plt
```

In [3]:

```
class BackPropagrationUsingGradientsCheck():
    def __init__(self):
        self.author = 'trinath'
        self.assignment = 'BackPropagation & Gradients Checking'

    #function for attributes intilization
    def initialization(self,X,y):
        self.X = X
        self.y = y
        self.w = np.ones(9)*0.1
        self.epsilon = 0.0001

    '''
        @function : compute_forward_propagation
        @params   : X - train data, y - labels, w - weights
        @logic    : for doing forward propagation for the given graph
        @return   : loss
    '''
    def compute_forward_propagation(self,X, y, w):
        self.forward_propagation = {}
        #fp_1 = w1 * f1
        self.forward_propagation['fp_1'] = w[0] * X[0]

        #fp_2 = w2 * f2
        self.forward_propagation['fp_2'] = w[1] * X[1]

        self.forward_propagation['fp_3'] = self.forward_propagation['fp_1'] + self.f

        self.forward_propagation['fp_4'] = self.forward_propagation['fp_3'] * self.f

        #fp_5 = fp_4 + w6
        self.forward_propagation['fp_5'] = self.forward_propagation['fp_4'] + w[5]

        self.forward_propagation['fp_6'] = np.exp(self.forward_propagation['fp_5'])

        #fp_7 = fp_6 + w7
        self.forward_propagation['fp_7'] = self.forward_propagation['fp_6'] + w[6]

        self.forward_propagation['fp_8'] = np.tanh(self.forward_propagation['fp_7'])

        #fp_9 = w3 * x3
        self.forward_propagation['fp_9'] = w[2] * X[2]

        #fp_10 = w4 * f4
        self.forward_propagation['fp_10'] = w[3] * X[3]

        #fp_11 = w5 * f5
        self.forward_propagation['fp_11'] = w[4] * X[4]

        self.forward_propagation['fp_12'] = np.sin(self.forward_propagation['fp_9'])

        self.forward_propagation['fp_13'] = self.forward_propagation['fp_10'] + self

        self.forward_propagation['fp_14'] = self.forward_propagation['fp_12'] * self

        #fp_15 = fp_14 + w8
        self.forward_propagation['fp_15'] = self.forward_propagation['fp_14'] + w[7]

        self.forward_propagation['fp_16'] = 1/(1 + np.exp(-self.forward_propagation[
```

```
        #fp_17 = fp_16 * w9
        self.forward_propagation['fp_17'] = self.forward_propagation['fp_16'] * w[8]

        y_hat = self.forward_propagation['fp_8'] + self.forward_propagation['fp_17']

        L = (y-y_hat)**2
        #print(self.forward_propagation)
        return L


    '''
        @function : compute_backward_propagation
        @params   : L - loss, x - train data, y - labels, w - weights
        @logic    : for doing backward propagation for the given graph
        @return   : updated gradients
    '''
    def compute_backward_propagation(self, L, x, y, w):
        self.d_gradients = {}
        self.update_weights = []

        '''
           For calculating ∂L/∂w1
        '''
        # ∂fp_1/∂w1 = f1
        self.d_gradients['∂fp_1/∂w1'] = x[0]

        # ∂fp_3/∂fp_1 = 1
        self.d_gradients['∂fp_3/∂fp_1'] = 1

        #∂fp_4/∂fp_3 = 2*(fp_3)
        self.d_gradients['∂fp_4/∂fp_3'] = 2 * (self.forward_propagation['fp_3'])

        #∂fp_5/∂fp_4 = 1
        self.d_gradients['∂fp_5/∂fp_4'] = 1

        #∂fp_6/∂fp_5 = exp(fp_5) = fp_6
        self.d_gradients['∂fp_6/∂fp_5'] = self.forward_propagation['fp_6']

        #∂fp_7/∂fp_6 = 1
        self.d_gradients['∂fp_7/∂fp_6'] = 1

        #∂fp_8/∂fp_7 = 1 - tanh(fp_7)^2 = 1-fp_8^2
        self.d_gradients['∂fp_8/∂fp_7'] = 1- (self.forward_propagation['fp_8']**2)

        #∂L/∂fp_8 = 2(y-fp_8-fp_17)(-1)
        self.d_gradients['∂L/∂fp_8'] = (-2)*(y-self.forward_propagation['fp_8']-self

        #∂L/∂w1 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w1'] = self.d_gradients['∂L/∂fp_8'] * self.d_gradients
                                     self.d_gradients['∂fp_6/∂fp_5'] * self.d_gradien
                                     self.d_gradients['∂fp_3/∂fp_1'] * self.d_gradien


        #print("w0:",d_gradients['∂L/∂w1'])



        '''
           For calculating ∂L/∂w2
        '''
```

```
        #∂fp_3/∂fp_2 = 1
        self.d_gradients['∂fp_3/∂fp_2'] = 1

        #∂fp_2/∂w2 = fp_2
        self.d_gradients['∂fp_2/∂w2'] = x[1]

        #∂L/∂w2 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w2'] = self.d_gradients['∂L/∂fp_8'] * self.d_gradients
                                     self.d_gradients['∂fp_6/∂fp_5'] * self.d_gradien
                                     self.d_gradients['∂fp_3/∂fp_2'] * self.d_gradien

        #print("w1:",d_gradients['∂L/∂w2'])


        '''
           For calculating ∂L/∂w3
        '''
        # ∂fp_9/∂w3= f3
        self.d_gradients['∂fp_9/∂w3'] = x[2]

        # ∂fp_12/∂fp_9 = cos(fp_9)
        self.d_gradients['∂fp_12/∂fp_9'] = np.cos(self.forward_propagation['fp_9'])

        # ∂fp_14/∂fp_12 = fp_13
        self.d_gradients['∂fp_14/∂fp_12'] = self.forward_propagation['fp_13']

        # ∂fp_15/∂fp_14 = 1
        self.d_gradients['∂fp_15/∂fp_14'] = 1

        # ∂fp_16/∂fp_15 = fp_16 * (1- fp_16)
        self.d_gradients['∂fp_16/∂fp_15'] = self.forward_propagation['fp_16'] * (1-s

        # ∂fp_17/∂fp_16= w9
        self.d_gradients['∂fp_17/∂fp_16'] = w[8]


        #∂L/∂fp_17 = 2(y-fp_8-fp_17)(-1)
        self.d_gradients['∂L/∂fp_17'] = (-2)*(y-self.forward_propagation['fp_8']-sel


        #∂L/∂w3 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w3'] = self.d_gradients['∂L/∂fp_17'] * self.d_gradients
                                     self.d_gradients['∂fp_15/∂fp_14'] * self.d_gradi
                                     self.d_gradients['∂fp_9/∂w3']


        #print("w2:",d_gradients['∂L/∂w3'])


        '''
           For calculating ∂L/∂w4
        '''
        # ∂fp_10/∂w4= f4
        self.d_gradients['∂fp_10/∂w4'] = x[3]

        # ∂fp_13/∂fp_10= 1
        self.d_gradients['∂fp_13/∂fp_10'] = 1

        # ∂fp_14/∂fp_13= fp_12
        self.d_gradients['∂fp_14/∂fp_13'] = self.forward_propagation['fp_12']
```

```
        #∂L/∂w3 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w4'] = self.d_gradients['∂L/∂fp_17'] * self.d_gradient:
                                     self.d_gradients['∂fp_15/∂fp_14'] * self.d_gradi
                                     self.d_gradients['∂fp_10/∂w4']

        #print("w3:",d_gradients['∂L/∂w4'])


        '''
           For calculating ∂L/∂w5
        '''
        # ∂fp_10/∂w4= f5
        self.d_gradients['∂fp_11/∂w5'] = x[4]

        #∂fp_13/∂fp_11= 1
        self.d_gradients['∂fp_13/∂fp_11'] = 1


        #∂L/∂w3 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w5'] = self.d_gradients['∂L/∂fp_17'] * self.d_gradient:
                                     self.d_gradients['∂fp_15/∂fp_14'] * self.d_gradi
                                     self.d_gradients['∂fp_11/∂w5']

        #print("w4:",d_gradients['∂L/∂w5'])



        '''
           For calculating ∂L/∂w6
        '''
        # ∂fp_6/∂fp_5 =  1
        self.d_gradients['∂fp_5/∂w6'] = 1

        #∂L/∂w3 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w6'] = self.d_gradients['∂L/∂fp_8'] * self.d_gradients
                                     self.d_gradients['∂fp_6/∂fp_5']

        #print("w5:",d_gradients['∂L/∂w6'])


        '''
           For calculating ∂L/∂w7
        '''
         # ∂fp_6/∂fp_5 =  1
        self.d_gradients['∂fp_7/∂w7'] = 1

        #∂L/∂w3 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w7'] = self.d_gradients['∂L/∂fp_8'] * self.d_gradients

        #print("w6:",d_gradients['∂L/∂w7'])



        '''
           For calculating ∂L/∂w8
        '''
         # ∂fp_6/∂fp_5 =  1
        self.d_gradients['∂fp_15/∂w8'] = 1
```

```
        #∂L/∂w3 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w8'] = self.d_gradients['∂L/∂fp_17'] * self.d_gradients
                                    self.d_gradients['∂fp_15/∂w8']

        #print("w7:",d_gradients['∂L/∂w8'])


        '''
           For calculating ∂L/∂w9
        '''
         # ∂fp_17/∂w9 =  1
        self.d_gradients['∂fp_17/∂w9'] = self.forward_propagation['fp_16']

        #∂L/∂w3 = ∂L/∂fp_8 * ∂fp_8/∂fp_7 * ∂fp_7/∂fp_6 * ∂fp_6/∂fp_5 * ∂fp_5/∂fp_4 * [
        self.d_gradients['∂L/∂w9'] = self.d_gradients['∂L/∂fp_17'] *  self.d_gradien

        #print("w8:",d_gradients['∂L/∂w9'])


        update_gradients = [self.d_gradients['∂L/∂w1'], self.d_gradients['∂L/∂w2'], s
                            self.d_gradients['∂L/∂w6'], self.d_gradients['∂L/∂w7'], s
        return update_gradients

    #for finding the appox gradients
    def approximation_gradients(self,plus_loss, minus_loss, epsilon):
        return (plus_loss-minus_loss)/(2*epsilon)

    #for checking the gradeitns
    def compute_gradients_checking(self,data_point, weights, epsilon):
        approx_gradients = []
        get_weights = weights
        for indx, each_weight in enumerate(get_weights):
            # adding small value to weight with epsilon
            get_weights[indx]   = get_weights[indx]  + epsilon
            epsilon_plus_L = self.compute_forward_propagation(X[0], y[0], get_weight
            #print(epsilon_plus_L)
            get_weights[indx]   = get_weights[indx]  - epsilon

            # subtracting small value to weight wi
            get_weights[indx]   = get_weights[indx]  - epsilon
            epsilon_minus_L = self.compute_forward_propagation(X[0], y[0], get_weigh
            #print(epsilon_minus_L)
            approx_grad = self.approximation_gradients(epsilon_plus_L, epsilon_minus
            approx_gradients.append(approx_grad)

            get_weights[indx]   = get_weights[indx]  + epsilon
            #print("\noriginal",get_weights)
        return approx_gradients

    #function to check the gradients are correct
    def gradient_check(self,original_grads, approx_grads):
        for org, approx in zip(original_grads, approx_grads):
            val = np.linalg.norm(org - approx)/ (np.linalg.norm(org) + np.linalg.nor
            if val < 1e-7:
                print("correct")
            else:
                print("Wrong")
            print(org, approx,val)
```

In [4]:

```
#get te object of model
model = BackPropagrationUsingGradientsCheck()
```

In [5]:

```
#model initlization
model.initialization(X,y)
```

In [6]:

```
#finding model loss
loss = model.compute_forward_propagation(model.X[0], model.y[0], model.w)
```

In [7]:

```
#computing the gradeints using forward propagation
original_grads = model.compute_backward_propagation(loss, model.X[0], model.y[0], mo
```

In [8]:

```
#checking the values
loss, original_grads
```

Out[8]:

```
(0.9298048963072919,
 [-0.22973323498702,
  -0.02140761471775293,
  -0.005625405580266319,
  -0.004657941222712423,
  -0.0010077228498574246,
  -0.6334751873437471,
  -0.561941842854033,
  -0.04806288407316516,
  -1.0181044360187037])
```

In [9]:

```
#checking the gradients using compute_gradients_checking
approx_grads = model.compute_gradients_checking(model.X[0], model.w, model.epsilon)
```

In [10]:

```
approx_grads
```

Out[10]:

```
[-0.22973323022201786,
 -0.021407614714252787,
 -0.0056254055608162545,
 -0.004657941222729889,
 -0.0010077228507210378,
 -0.6334751863784627,
 -0.5619418463920223,
 -0.0480628840343611,
 -1.0181044360180191]
```

In [11]:

```
#cross checking if the gradints are correct
model.gradient_check(original_grads, approx_grads)
```

```
correct
-0.22973323498702 -0.22973323022201786 1.0370728885929153e-08
correct
-0.02140761471775293 -0.021407614714252787 8.17499099168924e-11
correct
-0.005625405580266319 -0.0056254055608162545 1.7287700041112022e-09
correct
-0.004657941222712423 -0.004657941222729889 1.87486944153289e-12
correct
-0.0010077228498574246 -0.0010077228507210378 4.2849738752544037e-10
correct
-0.6334751873437471 -0.6334751863784627 7.618959889684771e-10
correct
-0.561941842854033 -0.5619418463920223 3.1480030084674753e-09
correct
-0.04806288407316516 -0.0480628840343611 4.0368014625577295e-10
correct
-1.0181044360187037 -1.0181044360180191 3.361951351774315e-13
```

Task 2: Optimizers

1. As a part of this task, you will be implementing 3 type of optimizers(methods to update weight)
2. check this video and blog: https://www.youtube.com/watch?v=gYpoJMlgyXA (https://www.youtube.com/watch?v=gYpoJMlgyXA), http://cs231n.github.io/neural-networks-3/ (http://cs231n.github.io/neural-networks-3/)
3. use the same computational graph that was mentioned above to do this task
4. initilze the 9 weights from normal distribution with mean=0 and std=0.01
5.

```
for each epoch(1-100):
    for each data point in your data:
        using the functions forward_propagation() and backword_propagati
on() compute the gradients of weights
        update the weigts with help of gradients  ex: w1 = w1-learning_r
ate*dw1
```

6.

task 2.1: you will be implementing the above algorithm with **Vanilla update** of weights
task 2.2: you will be implementing the above algorithm with **Momentum update** of weights
task 2.3: you will be implementing the above algorithm with **Adam update** of weights

In [12]:

```
class Optimizer():
    def __init__(self):
        self.task = 'optimizing the gradients'
        self.author = 'Trinath Reddy'
        self.total_epocs = 100
        self.learning_rate = 0.01

    #fuction for epocs vs plotting loss
    def draw_loss_plot(self, epoch_loss, loss_type):
        plt.plot(epoch_loss)
        plt.title(loss_type)
        plt.xlabel('no of epocs')
        plt.ylabel('loss')
        plt.show()

    #function for doing vanilla optimization
    def vanilla_optimization(self,X,y):
        epoch_loss = []
        N = len(X)
        total_epocs = 100
        each_epoch_weights = np.random.normal(0, 0.01, 9)
        learning_rate = 0.01
        for each_epoch in range(self.total_epocs):
            each_epoch_x, each_epoch_y = X, y
            curr_loss = 0
            for each_point in range(each_epoch_x.shape[0]):
                each_Loss = model.compute_forward_propagation(each_epoch_x[each_poir
                backprop_grads = model.compute_backward_propagation(each_Loss,each_e
                each_epoch_weights += -(self.learning_rate*np.array(backprop_grads))
                curr_loss += each_Loss
            epoch_loss.append(curr_loss/N)
        return epoch_loss

    #function for finding momentum optimization
    def momentum_optimization(self,X,y):
        epoch_loss = []
        N = len(X)
        each_epoch_weights = np.random.normal(0, 0.01, 9)
        for each_epoch in range(self.total_epocs):
            each_epoch_x, each_epoch_y = X, y
            curr_loss = 0
            v = 0
            mu = 0.95
            for each_point in range(each_epoch_x.shape[0]):
                each_Loss = model.compute_forward_propagation(each_epoch_x[each_poir
                backprop_grads = model.compute_backward_propagation(each_Loss,each_e
                v = mu * v -(self.learning_rate*np.array(backprop_grads))
                each_epoch_weights += v
                curr_loss += each_Loss
            epoch_loss.append(curr_loss/N)
        return epoch_loss

    #funciton for doing adam optimization
    def adam_optimization(self,X,y):
        epoch_loss = []
        N = len(X)
        total_epocs = 100
        each_epoch_weights = np.random.normal(0, 0.01, 9)
        eps = 1e-6
```

```
        beta1 = 0.9
        beta2 = 0.999
        m = v = 0
        for each_epoch in range(self.total_epocs):
            curr_loss = 0
            each_epoch_x, each_epoch_y = X, y
            for each_point in range(each_epoch_x.shape[0]):
                each_Loss = model.compute_forward_propagation(each_epoch_x[each_poir
                backprop_grads = model.compute_backward_propagation(each_Loss,each_e
                m = beta1*m + (1-beta1)*np.array(backprop_grads)
                v = beta2*v + (1-beta2)*(np.array(backprop_grads)**2)
                each_epoch_weights += - self.learning_rate * m / (np.sqrt(v) + eps)
                curr_loss += each_Loss
            epoch_loss.append(curr_loss/N)
        return epoch_loss
```

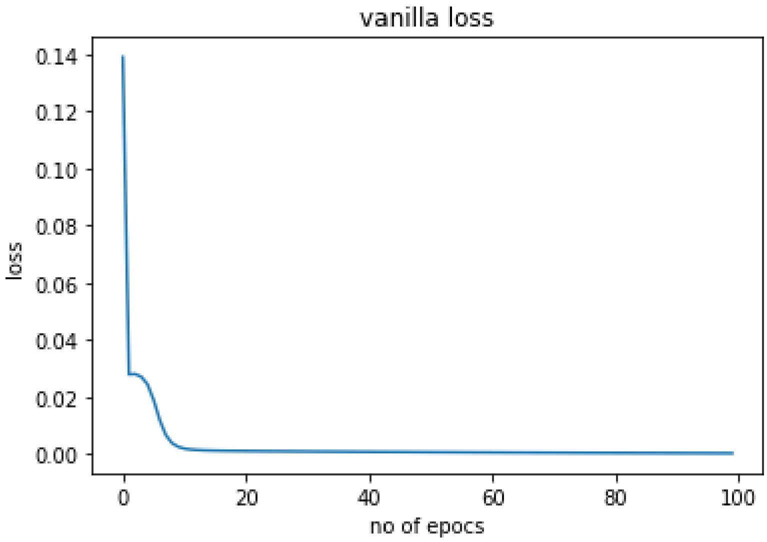
In [13]:

```
opt = Optimizer()
```

task 2.1: you will be implementing the above algorithm with Vanilla update of weights

In [14]:

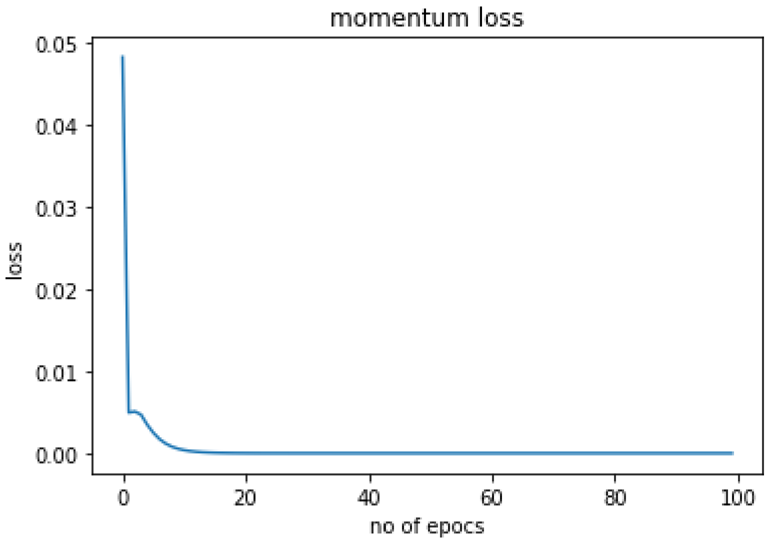
```
get_vanila_loss = opt.vanilla_optimization(X,y)
opt.draw_loss_plot(get_vanila_loss, 'vanilla loss')
```



task 2.2: you will be implementing the above algorithm with Momentum update of weights

In [15]:

```
get_momentum_loss = opt.momentum_optimization(X,y)
opt.draw_loss_plot(get_momentum_loss, 'momentum loss')
```



task 2.3: you will be implementing the above algorithm with Adam update of weights

In [16]:

```
get_adam_loss = opt.adam_optimization(X,y)
opt.draw_loss_plot(get_adam_loss, 'adam loss')
```