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1 BackPropagation

There will be some functions that start with the word "grader" ex: grader_sigmoid(), grader_forwardprop(), grader_backprop() etc, you should not change those function definition.Every Grader function has to return True.

1.1 Loading data

[1]:
```
import pickle
import numpy as np
from tqdm import tqdm
import matplotlib.pyplot as plt

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

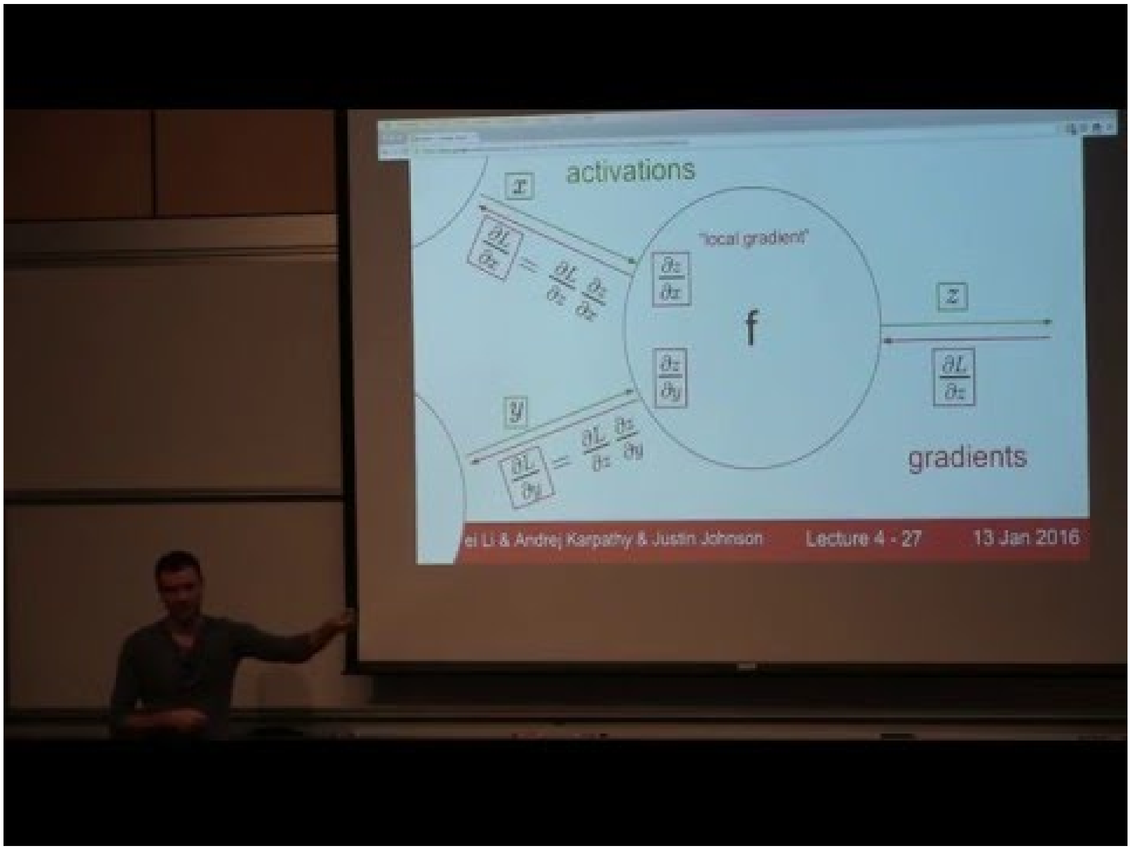
- **If you observe the graph, we are having input features [f1, f2, f3, f4, f5] and 9 weights [w1, w2, w3, w4, w5, w6, w7, w8, w9].**
- **The final output of this graph is a value L which is computed as (Y-Y')^2**

3 Task 1: Implementing backpropagation and Gradient checking

Check this video for better understanding of the computational graphs and back propagation

[2]:
```
from IPython.display import YouTubeVideo
YouTubeVideo('i94OvYb6noo',width="1000",height="500")
```

[2]:



- Write two functions
  - Forward propagation(Write your code in def forward_propagation()) For easy debugging, we will break the computational graph into 3 parts.

  Part 1 Part 2 Part 3

  - Backward propagation(Write your code in def backward_propagation())

Gradient clipping

Check this blog link for more details on Gradient clipping

Algorithm

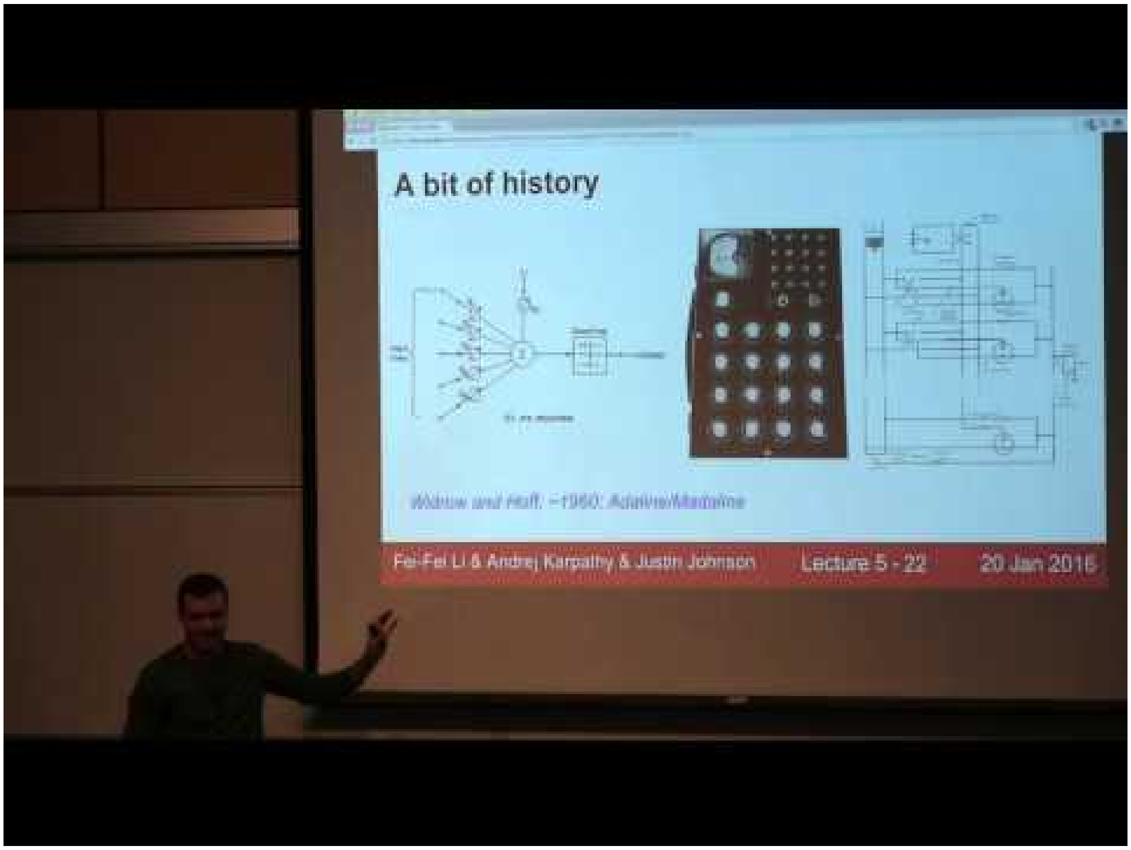
4 Task 2 : Optimizers

- As a part of this task, you will be implementing 3 type of optimizers(methods to update weight)
- Use the same computational graph that was mentioned above to do this task
- Initilze the 9 weights from normal distribution with mean=0 and std=0.01

Check below video and this blog

[3]:
```python
from IPython.display import YouTubeVideo
YouTubeVideo('gYpoJMlgyXA',width="1000",height="500")
```

[3]:



Algorithm

4.1 Implement below tasks

- 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

Note : If you get any assertion error while running grader functions, please print the variables in grader functions and check which variable is returning False .Recheck your logic for that variable .

5 Task 1

5.1 Forward propagation

[4]:
```
def sigmoid(z):
    '''In this function, we will compute the sigmoid(z)'''
    # we can use this function in forward and backward propagation
    return 1 / (1 + np.exp(-z))

def forward_propagation(x, y, w):
    '''In this function, we will compute the forward propagation '''
    # 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.
    # you have to return the following variables
    # exp= part1 (compute the forward propagation until exp and then store the␣
 ↪values in exp)
    # tanh =part2(compute the forward propagation until tanh and then store the␣
 ↪values in tanh)
    # sig = part3(compute the forward propagation until sigmoid and then store␣
 ↪the values in sig)
    # now compute remaining values from computional graph and get y'
    # write code to compute the value of L=(y-y')^2
    # compute derivative of L  w.r.to Y' and store it in dl
    # Create a dictionary to store all the intermediate values
    # store L, exp,tanh,sig variables
    t     = np.dot(w[0], x[ 0]) +  np.dot(w[1], x[ 1])
    exp   = np.exp(np.dot(t,t) + w[5])
    tanh  = np.tanh(exp + w[6])
    sig   = sigmoid(w[7] + (np.dot(np.sin(np.dot(w[2], x[ 2])) , np.dot(w[3],␣
 ↪x[ 3]) + np.dot(w[4], x[ 4]) )))
    y_hat = np.dot(sig, w[8]) + tanh
    l     = (y-y_hat) ** 2
    dl    =  -2 * (y - y_hat)
    return {'dl':dl,'loss':l, 'exp':exp, 'tanh':tanh, 'sigmoid':sig, 'x':x}
```

Grader function - 1

[5]:
```
def grader_sigmoid(z):
    val=sigmoid(z)
    assert(val==0.8807970779778823)
    return True
grader_sigmoid(2)
```

[5]: True

Grader function - 2

```
[8]: def grader_forwardprop(data):
         dl = (np.round(data['dl'],4)==-1.9285)
         loss=(np.round(data['loss'],4)==0.9298)
         part1=(np.round(data['exp'],4)==1.1273)
         part2=(np.round(data['tanh'],4)==0.8418)
         part3=(np.round(data['sigmoid'],4)==0.5279)
         assert(dl and loss and part1 and part2 and part3)
         return True
     w=np.ones(9)*0.1
     d1=forward_propagation(X[0],y[0],w)
     grader_forwardprop(d1)
```

```
[8]: True
```

5.2 Backward propagation

```
[9]: def backward_propagation(L,W,dicts):
         '''In this function, we will compute the backward propagation '''
         # L: the loss we calculated for the current point
         # dictionary: the outputs of the forward_propagation() function
         # write code to compute the gradients of each weight [w1,w2,w3,...,w9]
         # Hint: you can use dict type to store the required variables
         # dw1 = # in dw1 compute derivative of L w.r.to w1
         # dw2 = # in dw2 compute derivative of L w.r.to w2
         # dw3 = # in dw3 compute derivative of L w.r.to w3
         # dw4 = # in dw4 compute derivative of L w.r.to w4
         # dw5 = # in dw5 compute derivative of L w.r.to w5
         # dw6 = # in dw6 compute derivative of L w.r.to w6
         # dw7 = # in dw7 compute derivative of L w.r.to w7
         # dw8 = # in dw8 compute derivative of L w.r.to w8
         # dw9 = # in dw9 compute derivative of L w.r.to w9

         dw = {}
         dw['dw1'] = dicts['dl'] * 2 * dicts['x'][0] * dicts['exp'] * (np.dot(W[0],
     ↪dicts['x'][0]) + np.dot(W[1], dicts['x'][1])) * (1 - (dicts['tanh']**2))
         dw['dw2'] = dicts['dl'] * 2 * dicts['x'][1] * dicts['exp'] * (np.dot(W[0],
     ↪dicts['x'][0]) + np.dot(W[1], dicts['x'][1])) * (1 - (dicts['tanh']**2))
         dw['dw3'] = dicts['dl'] * dicts['x'][2] * W[8] * np.cos(np.dot(W[2],
     ↪dicts['x'][2])) * (np.dot(W[4], dicts['x'][4]) + np.dot(W[3],
     ↪dicts['x'][3])) * dicts['sigmoid'] * (1 - dicts['sigmoid'])
         dw['dw4'] = dicts['dl'] * dicts['x'][3] * W[8] * np.sin(np.dot(W[2],
     ↪dicts['x'][2])) * dicts['sigmoid'] * (1 - dicts['sigmoid'])
         dw['dw5'] = dicts['dl'] * dicts['x'][4] * W[8] * np.sin(np.dot(W[2],
     ↪dicts['x'][2])) * dicts['sigmoid'] * (1 - dicts['sigmoid'])
         dw['dw6'] = dicts['dl'] * dicts['exp'] * (1 - (dicts['tanh']**2))
```

```
    dw['dw7'] = dicts['dl'] * (1 - (dicts['tanh']**2))
    dw['dw8'] = dicts['dl'] * W[8] * dicts['sigmoid'] * (1 - dicts['sigmoid'])
    dw['dw9'] = dicts['dl'] * dicts['sigmoid']

    return dw
    # return dW, dW is a dictionary with gradients of all the weights
```

Grader function - 3

[10]:
```
def grader_backprop(data):
    dw1=(np.round(data['dw1'],8)==-0.22973323)
    dw2=(np.round(data['dw2'],8)==-0.02140761)
    dw3=(np.round(data['dw3'],8)==-0.00562541)
    dw4=(np.round(data['dw4'],8)==-0.00465794)
    dw5=(np.round(data['dw5'],8)==-0.00100772)
    dw6=(np.round(data['dw6'],8)==-0.63347519)
    dw7=(np.round(data['dw7'],8)==-0.56194184)
    dw8=(np.round(data['dw8'],8)==-0.04806288)
    dw9=(np.round(data['dw9'],8)==-1.01810444)
    assert(dw1 and dw2 and dw3 and dw4 and dw5 and dw6 and dw7 and dw8 and dw9)
    return True
w=np.ones(9)*0.1
d1=forward_propagation(X[0],y[0],w)
d1=backward_propagation(X[0],w,d1)
grader_backprop(d1)
```

[10]: True

5.3 Implement gradient checking

[18]:
```
W = np.ones(9)*0.1
def gradient_checking(data_point, W):
    x_train = data_point[:5]
    y_train = data_point[-1]

    forward_result = forward_propagation(x_train, y_train, W)
    backward_result = backward_propagation(x_train, W, forward_result)
    delta = 10 ** -7

    approx_gradient = {}
    gradient_checking = {}
    for ind in range(W.shape[0]):
        temp_w_i = temp_w_ii = W
        temp = W[ind]
        temp_w_i[ind] = temp  + delta
        forward_result_i  = forward_propagation(x_train, y_train, temp_w_i)
```

```
        backward_result_i = backward_propagation(x_train, temp_w_i,␣
↪forward_result_i)

        temp_w_ii[ind] = temp  - delta
        forward_result_ii  = forward_propagation(x_train, y_train, temp_w_ii)
        backward_result_ii = backward_propagation(x_train, temp_w_i,␣
↪forward_result_ii)
        approx_gradient['dw{}'.format(ind+1)] = (forward_result_i['loss'] -␣
↪forward_result_ii['loss'])/( 2 * delta)
    for key in backward_result.keys():
        gradient_checking[key] = (backward_result[key] - approx_gradient[key]) /
↪ (backward_result[key] + approx_gradient[key])
    return gradient_checking



grad = gradient_checking(data[0], W)
print(grad)
```

```
{'dw1': -4.918867403857781e-10, 'dw2': 4.313072065448279e-07, 'dw3':
-5.96991379072821e-08, 'dw4': 5.328311462684123e-07, 'dw5':
5.785228848348613e-07, 'dw6': -2.4944672635960616e-08, 'dw7':
-1.5675493248917714e-07, 'dw8': -3.6260816099250785e-08, 'dw9':
-1.1321577367826861e-08}
```

6 Task 2: Optimizers

6.0.1 Algorithm with Vanilla update of weights

[67]:
```
# Setting Up Constants
# Setting Fixed Seeding for better and replicable results
np.random.seed(42)

# Mean of Normal Distribution of weights
mu = 0

# Variance of Normal Distribution of weights
sigma = 0.1

# Learning Rate
eta = 0.1

# Creating a Normal Distribution of Weights
W = sigma * np.random.randn(9) + mu

# Creating list to capture loss
loss = []
```

```python
# For Each Epoch
for epoch in range(0,100):

    # Copying Weights to calculate convergence
    temp = np.copy(W)
    # Creating list to capture at each datapoint loss
    temp_loss = []

    print('Executing Epoch {}'.format(epoch))

    # Looping over each datapoint
    for x_train, y_train in zip(data[:, :5], data[:, -1]):
        # Calculate Forward Propagation
        forward_result  = forward_propagation(x_train, y_train, W)
        # Calculate Backward Propagation
        backward_result = backward_propagation(x_train, W, forward_result)
        # Capturing Loss
        temp_loss.append(forward_result['loss'])

        # Updating Each Set of Weights
        for ind, key in enumerate(backward_result.keys()):
            W[ind] = W[ind] - eta * backward_result[key]

    # Checking for convergence
    if np.where(W - temp > 10 ** -3)[0].shape[0] == 0:
        print('\n')
        print("-"*100)
        print('Weigths Have Converged')
        print("-"*100)
        break

    # Calculating mean loss for each epoch
    loss.append(np.mean(temp_loss))
```

```
Executing Epoch 0
Executing Epoch 1
Executing Epoch 2
Executing Epoch 3
Executing Epoch 4
Executing Epoch 5
Executing Epoch 6
Executing Epoch 7
Executing Epoch 8
Executing Epoch 9
Executing Epoch 10
Executing Epoch 11
```

```
Executing Epoch 12
Executing Epoch 13
Executing Epoch 14
Executing Epoch 15
Executing Epoch 16
Executing Epoch 17
Executing Epoch 18
Executing Epoch 19
Executing Epoch 20
Executing Epoch 21
Executing Epoch 22
Executing Epoch 23
Executing Epoch 24
Executing Epoch 25
Executing Epoch 26
Executing Epoch 27
Executing Epoch 28
Executing Epoch 29
Executing Epoch 30
Executing Epoch 31
Executing Epoch 32
Executing Epoch 33
Executing Epoch 34
Executing Epoch 35
Executing Epoch 36
Executing Epoch 37
Executing Epoch 38
Executing Epoch 39
Executing Epoch 40
Executing Epoch 41
Executing Epoch 42
Executing Epoch 43
Executing Epoch 44
Executing Epoch 45
Executing Epoch 46
Executing Epoch 47
Executing Epoch 48
Executing Epoch 49
Executing Epoch 50
Executing Epoch 51
Executing Epoch 52
Executing Epoch 53
Executing Epoch 54
Executing Epoch 55
Executing Epoch 56
Executing Epoch 57
Executing Epoch 58
Executing Epoch 59
```

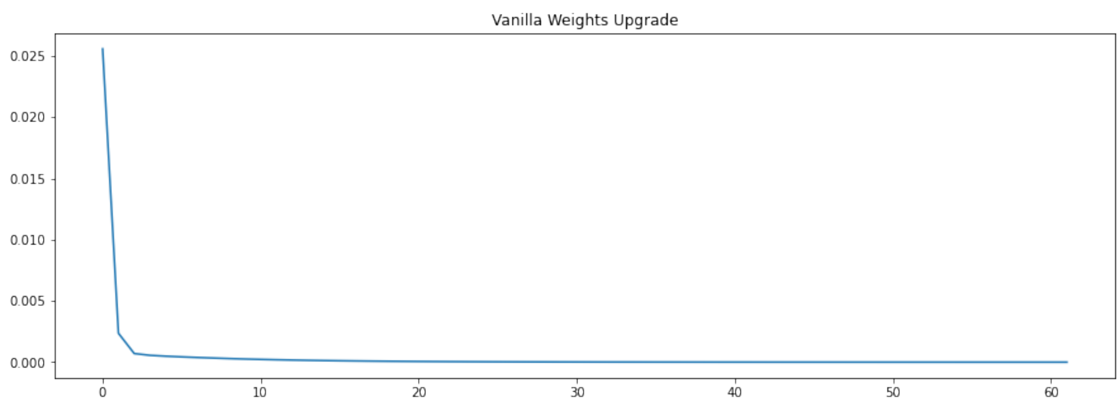
```
Executing Epoch 60
Executing Epoch 61
Executing Epoch 62


--------------------------------------------------------------------------------
--------------------
Weigths Have Converged
--------------------------------------------------------------------------------
--------------------
```

Plot between epochs and loss

[68]:
```
_, ax = plt.subplots(1, 1, figsize=(15,5))
ax.plot(loss)
ax.set_title('Vanilla Weights Upgrade')
plt.show()

vanilla_loss = loss
```



6.0.2 Algorithm with Momrentum update of weights

[69]:
```
# Setting Up Constants
# Setting Fixed Seeding for better and replicable results
np.random.seed(42)
# Mean
mu = 0

#  Standard Deviation
sigma = 0.1

# Learning Rate
eta = 0.1
```

```python
# Gamma for momentum
gamma = 0.9

# Calculating weighs from a Normal Distribution
W = sigma * np.random.randn(9) + mu

loss = []

for epoch in range(0,100):
    # Copy Weigts for convergence evaluation
    temp = np.copy(W)
    temp_loss = []
    print('Executing Epoch {}'.format(epoch))

    # Place holder for capturing all the momentum values
    v = {}
    for t, points in enumerate(zip(data[:, :5], data[:, -1])):
        x_train = points[0]
        y_train = points[1]
        # Forward Propagation
        forward_result  = forward_propagation(x_train, y_train, W)
        # Backward Propagation
        backward_result = backward_propagation(x_train, W, forward_result)
        # Calculating loss for each data point
        temp_loss.append(forward_result['loss'])
        # Weights Updation
        for ind, key in enumerate(backward_result.keys()):
            if t not in v.keys():
                v[t] = {}
            if t == 0:
                # Storing values of momentum to be used for the next iteration
                v[t][key] = eta * backward_result[key]
            else:
                # Storing values of momentum to be used for the next iteration
                v[t][key] = gamma * v[t-1][key] + eta * backward_result[key]

            # Updating Weights Using Momentum
            W[ind] = W[ind] - v[t][key]
    # Checking for convergence
    if np.where(W - temp > 10 ** -3)[0].shape[0] == 0:
        print('\n')
        print("-"*100)
        print('Weigths Have Converged')
        print("-"*100)
        break
    loss.append(np.mean(temp_loss))
```

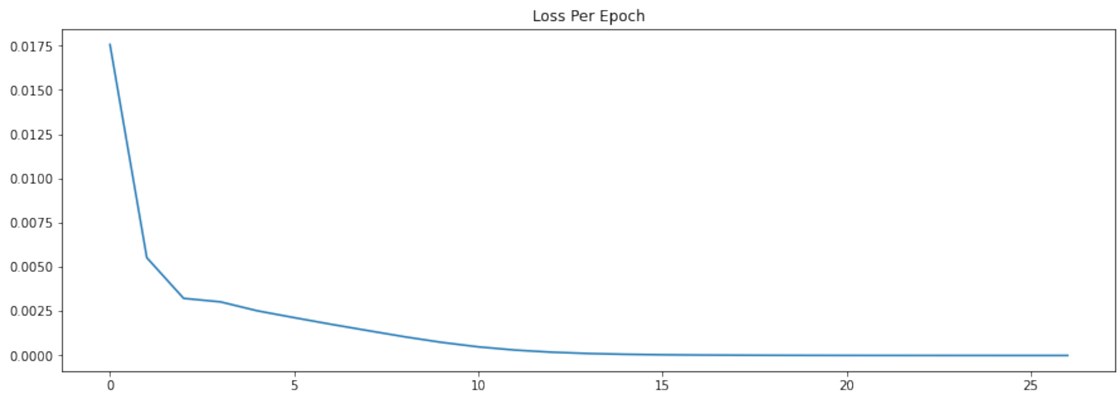
```
Executing Epoch 0
Executing Epoch 1
Executing Epoch 2
Executing Epoch 3
Executing Epoch 4
Executing Epoch 5
Executing Epoch 6
Executing Epoch 7
Executing Epoch 8
Executing Epoch 9
Executing Epoch 10
Executing Epoch 11
Executing Epoch 12
Executing Epoch 13
Executing Epoch 14
Executing Epoch 15
Executing Epoch 16
Executing Epoch 17
Executing Epoch 18
Executing Epoch 19
Executing Epoch 20
Executing Epoch 21
Executing Epoch 22
Executing Epoch 23
Executing Epoch 24
Executing Epoch 25
Executing Epoch 26
Executing Epoch 27


--------------------------------------------------------------------------------
--------------------
Weigths Have Converged
--------------------------------------------------------------------------------
--------------------
```

Plot between epochs and loss

[70]:
```
_, ax = plt.subplots(1, 1, figsize=(15,5))
ax.plot(loss)
ax.set_title('Loss Per Epoch')
plt.show()

momentum_loss = loss
```



6.0.3 Algorithm with Adam update of weights

[100]:
```
# Setting Up Constants
# Setting Fixed Seeding for better and replicable results
np.random.seed(42)
# Mean
mu = 0

#  Standard Deviation
sigma = 0.1

# Learning Rate
eta = 0.1

# Calculating weights from a Normal Distribution
W = sigma * np.random.randn(9) + mu

loss = []

beta={1:0.9, 2:0.99}

alpha = 0.001
epsilon = 10 ** -7

for epoch in range(0,100):
    # Copy Weigts for convergence evaluation
    temp = np.copy(W)
    temp_loss = []
    print('Executing Epoch {}'.format(epoch))
    print(W)
    # Place holder for capturing all the momentum values
    v = {}
    m = {}
```

```python
    for t, points in enumerate(zip(data[:, :5], data[:, -1])):
        x_train = points[0]
        y_train = points[1]
        # Forward Propagation
        forward_result  = forward_propagation(x_train, y_train, W)
        # Backward Propagation
        backward_result = backward_propagation(x_train, W, forward_result)
        # Calculating loss for each data point
        temp_loss.append(forward_result['loss'])
        # Weights Updation
        m_cap = {}
        v_cap = {}
        m[t] = {}
        v[t] = {}
        for ind, key in enumerate(backward_result.keys()):

            if key not in m.keys():
                m[t][key] = {}
                v[t][key] = {}
            # Exponential Decaying Average
            if t == 0:
                m[t][key] = (1-beta[1]) * backward_result[key]
                v[t][key] = (1-beta[2]) * (backward_result[key] ** 2)

            else:
                m[t][key] = (beta[1] * m[t-1][key]) + ((1-beta[1]) * backward_result[key])
                v[t][key] = (beta[2] * v[t-1][key]) + ((1-beta[2]) * (backward_result[key] ** 2))

            # Bias Correction
            m_cap[key] = m[t][key]/(1-(beta[1] ** 2))
            v_cap[key] = v[t][key]/(1-(beta[1] ** 2))

            # Updating Weights Using Momentum

            W[ind] = W[ind] - ((alpha * m_cap[key])/((np.sqrt(v_cap[key]))+epsilon))

    # Checking for convergence
    if np.where(W - temp > 10 ** -2)[0].shape[0] == 0:
        print('\n')
        print("-"*100)
        print('Weigths Have Converged')
        print("-"*100)
        break
```

```
    loss.append(np.mean(temp_loss))
```

```
Executing Epoch 0
[ 0.04967142 -0.01382643  0.06476885  0.15230299 -0.02341534 -0.0234137
  0.15792128  0.07674347 -0.04694744]
Executing Epoch 1
[ 0.67253833  0.26039121 -0.75599003 -0.71208851 -0.68629166  0.45414311
  0.55713967  1.14462593  0.99733857]
Executing Epoch 2
[ 0.71668682  0.17841498 -1.02483006 -0.99369323 -1.02768891  0.56922
  0.67514454  1.05145805  1.00588215]
Executing Epoch 3
[ 0.7550966   0.02637095 -0.99341282 -1.00774675 -1.02183591  0.70730048
  0.81646929  1.02196702  1.00079792]
Executing Epoch 4
[ 0.77917404  0.04504284 -1.00756625 -1.0060123  -1.00276255  0.76285014
  0.87641409  1.01920124  1.0039031 ]
Executing Epoch 5
[ 0.78590844  0.0109296  -0.99752301 -1.00920052 -1.00810754  0.81650671
  0.9364778   1.00893415  1.00518362]
Executing Epoch 6
[ 0.83864996 -0.02488791 -1.00604472 -1.00327221 -1.01813819  0.86066361
  0.9801075   0.99788298  1.00469309]
Executing Epoch 7
[ 0.76945744  0.09907162 -1.0015239  -0.97801338 -0.99057862  0.84961851
  0.97591525  0.99822687  0.99491219]
Executing Epoch 8
[ 0.78804747  0.05971815 -0.9954287  -0.98496291 -0.99042389  0.93409867
  1.06430289  1.00797372  0.99303475]
Executing Epoch 9
[ 0.83044854  0.00498609 -0.98802779 -0.99203005 -0.98973555  1.00405851
  1.13621376  1.0081935   0.99321198]
Executing Epoch 10
[ 0.84444874 -0.08258764 -0.99111715 -1.01333547 -1.00622727  1.07466253
  1.21035964  1.00168986  1.00513244]
Executing Epoch 11
[ 0.86169512 -0.00676612 -1.00983749 -0.99743721 -1.01252626  1.07432873
  1.21170406  0.9945281   1.00506031]
Executing Epoch 12
[ 0.77033157  0.12153459 -0.99978128 -0.97937329 -0.98369266  1.00213066
  1.14647618  0.99626377  0.99457395]
Executing Epoch 13
[ 0.77084417  0.13924806 -0.99634589 -0.98611454 -0.99775518  1.07109095
  1.21797124  0.99729933  0.99587703]
Executing Epoch 14
[ 0.82173543  0.05704928 -0.99703526 -1.00887589 -1.00844963  1.15469229
  1.30100296  0.99852061  1.00523302]
```

```
Executing Epoch 15
[ 0.74931144  0.17215015 -1.0016885  -0.98738652 -1.00938991  1.07021286
  1.2218226   0.98918239  1.00024171]
Executing Epoch 16
[ 0.67383647  0.23124916 -1.00147594 -0.97676052 -1.00144209  1.08360021
  1.24359972  0.99854341  0.99046523]
Executing Epoch 17
[ 0.68000747  0.2736527  -0.99784945 -0.98954408 -0.98758955  1.01216643
  1.17207433  1.00225757  0.99728205]
Executing Epoch 18
[ 0.77085062  0.27078706 -0.9891589  -1.03216815 -1.00572212  0.98663016
  1.14020926  0.99583706  1.01323832]
Executing Epoch 19
[ 0.75729412  0.22981133 -0.99967699 -1.00246993 -1.00516742  1.08804358
  1.24445934  1.00092418  1.00279731]
Executing Epoch 20
[ 0.65149453  0.33777049 -0.99749012 -0.97903998 -0.99352689  1.05879668
  1.22092954  1.00438909  0.98912044]
Executing Epoch 21
[ 0.67197697  0.32703883 -0.99760148 -0.99064119 -0.98876448  0.99431126
  1.15634226  1.00444471  0.99665757]
Executing Epoch 22
[ 0.73066255  0.29802711 -1.00054944 -1.01525391 -1.00898512  1.03315039
  1.19296808  0.99718589  1.00841679]
Executing Epoch 23
[ 0.70153758  0.3237949  -1.00238696 -0.99941285 -1.01068756  1.05289133
  1.21580877  0.9921103   1.00252318]
Executing Epoch 24
[ 0.75061486  0.35352831 -0.99195797 -1.01200741 -1.00214524  1.15048566
  1.30734705  0.99751855  1.00657222]
Executing Epoch 25
[ 0.74244418  0.37994618 -1.01306386 -1.00514252 -1.0159127   1.10347808
  1.26130887  0.98980567  1.00815956]


--------------------------------------------------------------------------------
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Weigths Have Converged
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```
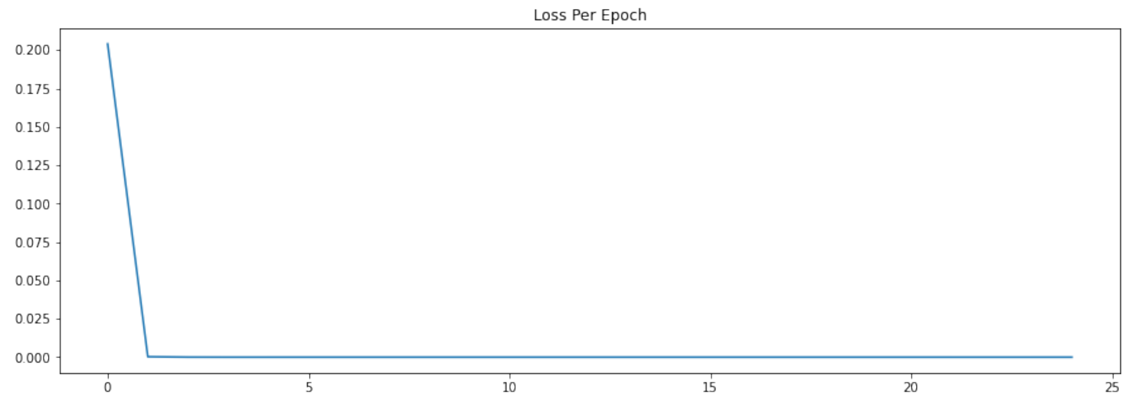

Plot between epochs and loss

[101]:
```
_, ax = plt.subplots(1, 1, figsize=(15,5))
ax.plot(loss)
ax.set_title('Loss Per Epoch')
plt.show()
```

```
adam_loss = loss
```



Comparision plot between epochs and loss with different optimizers

[102]:
```
_, ax = plt.subplots(1, 1, figsize=(20,10))
ax.plot(vanilla_loss, label='Vanilla',color='Green', alpha=0.7)
ax.plot(momentum_loss, label='Momentum',color='Blue', alpha=0.9)
ax.plot(adam_loss, label='Adam',color='Red')
ax.set_title('Loss Comparison')
ax.legend()
plt.show()
```