DNN in python from scratch

July 20, 2018

0.0.1 Deep Neural Network For Classification - Python Implementation

```
In [36]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import sklearn
```

General steps to build neural network:

1. Define the neural network structure (# of input units, # of hidden units, etc)
2. Initialize the model's parameters
3. Loop:
   - Implement forward propagation
   - Compute loss
   - Implement backward propagation to get the gradients
   - Update parameters

```
In [2]: def weights_init(layer_dims,init_type='he_normal',seed=0):

            """
            Arguments:
            layer_dims -- python array (list) containing the dimensions of each layer in our net
                          layer_dims lis is like  [ no of input features,# of neurons in hidden
                                                  # of neurons in hidden layer-n shape,output]
            init_type -- he_normal  --> N(0,sqrt(2/fanin))
                         he_uniform --> Uniform(-sqrt(6/fanin),sqrt(6/fanin))
                         xavier_normal --> N(0,2/(fanin+fanout))
                         xavier_uniform --> Uniform(-sqrt(6/fanin+fanout),sqrt(6/fanin+fanout))
            seed -- random seed to generate weights
            Returns:
            parameters -- python dictionary containing your parameters "W1", "b1", ..., "WL", "b
                            Wl -- weight matrix of shape (layer_dims[l], layer_dims[l-1])
                            bl -- bias vector of shape (layer_dims[l], 1)
            """
            np.random.seed(seed)
            parameters = {}
            L = len(layer_dims)            # number of layers in the network
```

```
        if  init_type == 'he_normal':
            for l in range(1, L):
                parameters['W' + str(l)] = np.random.normal(0,np.sqrt(2.0/layer_dims[l-1]),(
                parameters['b' + str(l)] = np.random.normal(0,np.sqrt(2.0/layer_dims[l-1]),(

        elif init_type == 'he_uniform':
            for l in range(1, L):
                parameters['W' + str(l)] = np.random.uniform(-np.sqrt(6.0/layer_dims[l-1]),
                                                            np.sqrt(6.0/layer_dims[l-1]),
                                                            (layer_dims[l], layer_dims[l-1])
                parameters['b' + str(l)] = np.random.uniform(-np.sqrt(6.0/layer_dims[l-1]),
                                                            np.sqrt(6.0/layer_dims[l-1]),
                                                            (layer_dims[l], 1))

        elif init_type == 'xavier_normal':
            for l in range(1, L):
                parameters['W' + str(l)] = np.random.normal(0,2.0/(layer_dims[l]+layer_dims[
                parameters['b' + str(l)] = np.random.normal(0,2.0/(layer_dims[l]+layer_dims[

        elif init_type == 'xavier_uniform':
            for l in range(1, L):
                parameters['W' + str(l)] = np.random.uniform(-(np.sqrt(6.0/(layer_dims[l]+la
                                                            (np.sqrt(6.0/(layer_dims[l]+laye
                                                            (layer_dims[l], layer_dims[l-1])
                parameters['b' + str(l)] = np.random.uniform(-(np.sqrt(6.0/(layer_dims[l]+la
                                                            (np.sqrt(6.0/(layer_dims[l]+laye
                                                            (layer_dims[l], 1))

        return parameters
```

```
In [3]: def sigmoid(X,derivative=False):
            '''Compute Sigmaoid and its derivative'''
            if derivative == False:
                out = 1 / (1 + np.exp(-np.array(X)))
            elif derivative == True:
                s = 1 / (1 + np.exp(-np.array(X)))
                out = s*(1-s)
            return out
        def ReLU(X,alpha=0,derivative=False):
            '''Compute ReLU function and derivative'''
            X = np.array(X,dtype=np.float64)
            if derivative == False:
                return np.where(X<0,alpha*X,X)
            elif derivative == True:
                X_relu = np.ones_like(X,dtype=np.float64)
                X_relu[X < 0] = alpha
                return X_relu
        def Tanh(X,derivative=False):
```

```python
    '''Compute tanh values and derivative of tanh'''
    if derivative == False:
        return np.tanh(X)
    if derivative == True:
        return 1 - (np.tanh(X))**2
def softplus(X,derivative=False):
    '''Compute tanh values and derivative of tanh'''
    if derivative == False:
        return np.log(1+np.exp(X))
    if derivative == True:
        return 1 / (1 + np.exp(-np.array(X)))

def arctan(X,derivative=False):
    '''Compute tan^-1(X) and derivative'''
    if derivative == False:
        return  np.arctan(X)
    if derivative == True:
        return 1/ (1 + np.square(X))

def identity(X,derivative=False):
    '''identity function and derivative f(x) = x'''
    X = np.array(X)
    if derivative ==  False:
        return X
    if derivative == True:
        return np.ones_like(X)
def elu(X,alpha=0,derivative=False):
    '''Exponential Linear Unit'''
    X = np.array(X,dtype=np.float64)
    if derivative == False:
        return np.where(X<0,alpha*(np.exp(X)-1),X)
    elif derivative == True:
        return np.where(X<0,alpha*(np.exp(X)),1)

def softmax(X):
    """Compute softmax values for each sets of scores in x."""
    return np.exp(X) / np.sum(np.exp(X),axis=0)
```

```python
In [6]: def weights_init(layer_dims,init_type='he_normal',seed=None):

            """
            Arguments:
                layer_dims -- python array (list) containing the dimensions of each layer in
                layer_dims lis is like  [ no of input features,# of neurons in hidden layer-
                                          # of neurons in hidden layer-n shape,output]
                init_type -- he_normal  --> N(0,sqrt(2/fanin))
                             he_uniform --> Uniform(-sqrt(6/fanin),sqrt(6/fanin))
```

```
                        xavier_normal --> N(0,2/(fanin+fanout))
                        xavier_uniform --> Uniform(-sqrt(6/fanin+fanout),sqrt(6/fanin+f
                        seed -- random seed to generate weights
    Returns:
        parameters -- python dictionary containing your parameters "W1", "b1", ...,
                    Wl -- weight matrix of shape (layer_dims[l], layer_dims[l-1])
                    bl -- bias vector of shape (layer_dims[l], 1)
    """
    np.random.seed(seed)
    parameters = {}
    opt_parameters = {}
    L = len(layer_dims)             # number of layers in the network
    if  init_type == 'he_normal':
        for l in range(1, L):
            parameters['W' + str(l)] = np.random.normal(0,np.sqrt(2.0/layer_dims[l-1
            parameters['b' + str(l)] = np.random.normal(0,np.sqrt(2.0/layer_dims[l-1

    elif init_type == 'he_uniform':
        for l in range(1, L):
            parameters['W' + str(l)] = np.random.uniform(-np.sqrt(6.0/layer_dims[l-1
                                                        np.sqrt(6.0/layer_dims[l-1]),
                                                        (layer_dims[l], layer_dims[l-1])
            parameters['b' + str(l)] = np.random.uniform(-np.sqrt(6.0/layer_dims[l-1
                                                        np.sqrt(6.0/layer_dims[l-1]),
                                                        (layer_dims[l], 1))

    elif init_type == 'xavier_normal':
        for l in range(1, L):
            parameters['W' + str(l)] = np.random.normal(0,2.0/(layer_dims[l]+layer_d
                                                                (layer_dims[l], layer
            parameters['b' + str(l)] = np.random.normal(0,2.0/(layer_dims[l]+layer_d
                                                                   (layer_dims[l], 1)

    elif init_type == 'xavier_uniform':
        for l in range(1, L):
            parameters['W' + str(l)] = np.random.uniform(-(np.sqrt(6.0/(layer_dims[l
                                                        (np.sqrt(6.0/(layer_dims[l]+laye
                                                        (layer_dims[l], layer_dims[l-1])
            parameters['b' + str(l)] = np.random.uniform(-(np.sqrt(6.0/(layer_dims[l
                                                        (np.sqrt(6.0/(layer_dims[l]+laye
                                                        (layer_dims[l], 1))

    return parameters
```

```
In [4]: def forward_propagation(X, hidden_layers,parameters,keep_proba=1,seed=None):

            """
            Implement forward propagation for the [LINEAR->RELU]*(L-1)->LINEAR->SIGMOID computat
```

```
    Arguments:
    X -- data, numpy array of shape (input size, number of examples)
    hidden_layers -- List of hideden layers
    weights -- Output of weights_init dict (parameters)
    keep_prob -- probability of keeping a neuron active during drop-out, scalar
    Returns:
    AL -- last post-activation value
    caches -- list of caches containing:
                every cache of linear_activation_forward() (there are L-1 of them, index
    """
    if seed != None:
        np.random.seed(seed)
    caches = []
    A = X
    L = len(hidden_layers)
    for l,active_function in enumerate(hidden_layers,start=1):
        A_prev = A

        Z = np.dot(parameters['W' + str(l)],A_prev)+parameters['b' + str(l)]

        if active_function == "sigmoid":
            A = sigmoid(Z)
        elif active_function == "relu":
            A = ReLU(Z)
        elif active_function == "tanh":
            A = Tanh(Z)
        elif active_function == "softmax":
            A = softmax(Z)

        if keep_proba != 1 and l != L and l != 1:
            D = np.random.rand(A.shape[0],A.shape[1])
            D = (D<keep_prob)
            A = np.multiply(A,D)
            A = A / keep_prob
            cache = ((A_prev, parameters['W' + str(l)],parameters['b' + str(l)],D), Z)
            caches.append(cache_temp)
        else:
            cache = ((A_prev, parameters['W' + str(l)],parameters['b' + str(l)]), Z)
            #print(A.shape)
            caches.append(cache)

    return A, caches
```

```
In [5]: def compute_cost(A, Y, parameters, lamda=0,penality=None):
    """
    Implement the cost function with L2 regularization. See formula (2) above.
```

```
    Arguments:
    A -- post-activation, output of forward propagation
    Y -- "true" labels vector, of shape (output size, number of examples)
    parameters -- python dictionary containing parameters of the model

    Returns:
    cost - value of the regularized loss function
    """
    m = Y.shape[1]

    cost = np.squeeze(-np.sum(np.multiply(np.log(A),Y))/m)

    L = len(parameters)//2

    if penality == 'l2' and lamda != 0:
        sum_weights = 0
        for l in range(1, L):
            sum_weights = sum_weights + np.sum(np.square(parameters['W' + str(l)]))
        cost = cost + sum_weights * (lambd/(2*m))
    elif penality == 'l1' and lamda != 0:
        sum_weights = 0
        for l in range(1, L):
            sum_weights = sum_weights + np.sum(np.abs(parameters['W' + str(l)]))
        cost = cost + sum_weights * (lambd/(2*m))

    return cost
```

```
In [6]: def back_propagation(AL, Y, caches, hidden_layers, keep_prob=1, penality=None,lamda=0):
    """
    Implement the backward propagation for the [LINEAR->RELU] * (L-1) -> LINEAR -> SIGMO

    Arguments:
    AL -- probability vector, output of the forward propagation (L_model_forward())
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat)
    caches -- list of caches containing:
    hidden_layers -- hidden layer names
    keep_prob -- probabaility for dropout
    penality -- regularization penality 'l1' or 'l2' or None


    Returns:
    grads -- A dictionary with the gradients
             grads["dA" + str(l)] = ...
             grads["dW" + str(l)] = ...
             grads["db" + str(l)] = ...
    """
    grads = {}
    L = len(caches) # the number of layers
```

```python
m = AL.shape[1]
Y = Y.reshape(AL.shape)

# Initializing the backpropagation
dZL = AL - Y

cache = caches[L-1]
linear_cache, activation_cache = cache
AL, W, b = linear_cache
grads["dW" + str(L)] = np.dot(dZL,AL.T)/m
grads["db" + str(L)] = np.sum(dZL,axis=1,keepdims=True)/m
grads["dA" + str(L-1)] = np.dot(W.T,dZL)


# Loop from l=L-2 to l=0
v_dropout = 0
for l in reversed(range(L-1)):
    cache = caches[l]
    active_function = hidden_layers[l]

    linear_cache, Z = cache
    try:
        A_prev, W, b = linear_cache
    except:
        A_prev, W, b, D = linear_cache
        v_dropout = 1

    m = A_prev.shape[1]

    if keep_prob != 1 and v_dropout == 1:
        dA_prev = np.multiply(grads["dA" + str(l + 1)],D)
        dA_prev = dA_prev/keep_prob
        v_dropout = 0
    else:
        dA_prev = grads["dA" + str(l + 1)]
        v_dropout = 0

    if active_function == "sigmoid":
        dZ = np.multiply(dA_prev,sigmoid(Z,derivative=True))
    elif active_function == "relu":
        dZ = np.multiply(dA_prev,ReLU(Z,derivative=True))
    elif active_function == "tanh":
        dZ = np.multiply(dA_prev,Tanh(Z,derivative=True))


    grads["dA" + str(l)] = np.dot(W.T,dZ)
```

```
            if penality == 'l2':
                grads["dW" + str(l + 1)] = (np.dot(dZ,A_prev.T)/m)  + ((lambd * W)/m)
            elif penality == 'l1':
                grads["dW" + str(l + 1)] = (np.dot(dZ,A_prev.T)/m)  + ((lambd * np.sign(W+10
            else:
                grads["dW" + str(l + 1)] = (np.dot(dZ,A_prev.T)/m)

            grads["db" + str(l + 1)] = np.sum(dZ,axis=1,keepdims=True)/m


        return grads
```

```
In [11]: def update_parameters(parameters, grads,learning_rate,iter_no,method = 'SGD',opt_params
             """
             Update parameters using gradient descent

             Arguments:
             parameters -- python dictionary containing your parameters
             grads -- python dictionary containing your gradients, output of L_model_backward
             method -- method for updation of weights
                       'SGD','SGDM','RMSP','ADAM'
             learning rate -- learning rate alpha value
             beta1 -- weighted avg parameter for SGDM and ADAM
             beta2 -- weighted avg parameter for RMSP and ADAM

             Returns:
             parameters -- python dictionary containing your updated parameters
                           parameters["W" + str(l)] = ...
                           parameters["b" + str(l)] = ...
             """

             L = len(parameters) // 2 # number of layers in the neural network
             if method == 'SGD':
                 for l in range(L):
                     parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - learning_rate*gra
                     parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - learning_rate*gra
             elif method == 'SGDM':
                 for l in range(L):
                     opt_parameters['vdb'+str(l+1)] = beta1*opt_parameters['vdb'+str(l+1)] + (1-
                     opt_parameters['vdw'+str(l+1)] = beta1*opt_parameters['vdw'+str(l+1)] + (1-
                     parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - learning_rate*opt
                     parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - learning_rate*opt
             elif method == 'RMSP':
                 for l in range(L):
                     opt_parameters['sdb'+str(l+1)] = beta2*opt_parameters['sdb'+str(l+1)] + (1-
                     opt_parameters['sdw'+str(l+1)] = beta2*opt_parameters['sdw'+str(l+1)] + (1-
                     parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - \
                                                learning_rate*(grads["dW" + str(l + 1)]/(np.sqrt
```

```
                parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - \
                                             learning_rate*(grads["db" + str(l + 1)]/(np.sqrt
        elif method == 'ADAM':
            for l in range(L):
                opt_parameters['vdb'+str(l+1)] = beta1*opt_parameters['vdb'+str(l+1)] + (1-
                opt_parameters['vdw'+str(l+1)] = beta1*opt_parameters['vdw'+str(l+1)] + (1-
                opt_parameters['sdb'+str(l+1)] = beta2*opt_parameters['sdb'+str(l+1)] + (1-
                opt_parameters['sdw'+str(l+1)] = beta2*opt_parameters['sdw'+str(l+1)] + (1-

                learningrate = learning_rate * np.sqrt((1-beta2**iter_no)/((1-beta1**iter_n
                parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - \
                                             learning_rate*(opt_parameters['vdw'+str(l+1)]/\
                                                            (np.sqrt(opt_parameters['sdw'+str
                parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - \
                                             learning_rate*(opt_parameters['vdb'+str(l+1)]/\
                                                            (np.sqrt(opt_parameters['sdb'+str

        return parameters,opt_parameters
```

```
In [8]: def predict(parameters, X,hidden_layers,return_prob=False):
            """
            Using the learned parameters, predicts a class for each example in X

            Arguments:
            parameters -- python dictionary containing your parameters
            X -- input data of size (n_x, m)

            Returns
            predictions -- vector of predictions of our model (red: 0 / blue: 1)
            """
            A, cache = forward_propagation(X,hidden_layers,parameters,seed=3)
            if return_prob == True:
                return A
            else:
                return np.argmax(A, axis=0)
```

Merging into one class `DNNClassifier`

```
In [238]: class DNNClassifier(object):
              '''
              Parameters: layer_dims -- List Dimensions of layers including input and output lay
                          hidden_layers -- List of hidden layers
                                           'relu','sigmoid','tanh','softplus','arctan','elu','id
                                           Note: 1. last layer must be softmax
                                                 2. For relu and elu need to mention alpha value
                                                  ['tanh',('relu',alpha1),('elu',alpha2),('relu'
                                                  need to give a tuple for relu and elu if you u
                                                  if not default alpha is 0
```

```
            init_type -- init_type -- he_normal  --> N(0,sqrt(2/fanin))
                         he_uniform --> Uniform(-sqrt(6/fanin),sqrt(6/fanin))
                         xavier_normal --> N(0,2/(fanin+fanout))
                         xavier_uniform --> Uniform(-sqrt(6/fanin+fanout),sqrt(6/f

            learning_rate -- Learning rate
            optimization_method -- optimization method 'SGD','SGDM','RMSP','ADAM'
            batch_size -- Batch size to update weights
            max_epoch -- Max epoch number
                         Note : Max_iter  = max_epoch * (size of traing / batch si
            tolarance -- if abs(previous cost  - current cost ) < tol training wil
                         if None -- No check will be performed
            keep_proba -- probability for dropout
                          if 1 then there is no dropout
            penality -- regularization penality
                        values taken 'l1','l2',None(default)
            lamda -- l1 or l2 regularization value
            beta1 -- SGDM and adam optimization param
            beta2 -- RMSP and adam optimization value
            seed -- Random seed to generate randomness
            verbose -- takes 0  or 1
'''

def __init__(self,layer_dims,hidden_layers,init_type='he_normal',learning_rate=0.1
             optimization_method = 'SGD',batch_size=64,max_epoch=100,tolarance = 0
             keep_proba=1,penality=None,lamda=0,beta1=0.9,
             beta2=0.999,seed=None,verbose=0):
    self.layer_dims = layer_dims
    self.hidden_layers = hidden_layers
    self.init_type = init_type
    self.learning_rate = learning_rate
    self.optimization_method = optimization_method
    self.batch_size = batch_size
    self.keep_proba = keep_proba
    self.penality = penality
    self.lamda = lamda
    self.beta1 = beta1
    self.beta2 = beta2
    self.seed = seed
    self.max_epoch = max_epoch
    self.tol = tolarance
    self.verbose = verbose
@staticmethod
def weights_init(layer_dims,init_type='he_normal',seed=None):

    """
    Arguments:
        layer_dims -- python array (list) containing the dimensions of each layer
```

```python
    layer_dims lis is like  [ no of input features,# of neurons in hidden laye
                             # of neurons in hidden layer-n shape,output]
    init_type -- he_normal  --> N(0,sqrt(2/fanin))
                 he_uniform --> Uniform(-sqrt(6/fanin),sqrt(6/fanin))
                 xavier_normal --> N(0,2/(fanin+fanout))
                 xavier_uniform --> Uniform(-sqrt(6/fanin+fanout),sqrt(6/fanin
                 seed -- random seed to generate weights
Returns:
    parameters -- python dictionary containing your parameters "W1", "b1", ...
            Wl -- weight matrix of shape (layer_dims[l], layer_dims[l-1])
            bl -- bias vector of shape (layer_dims[l], 1)
"""
np.random.seed(seed)
parameters = {}
opt_parameters = {}
L = len(layer_dims)            # number of layers in the network
if  init_type == 'he_normal':
    for l in range(1, L):
        parameters['W' + str(l)] = np.random.normal(0,np.sqrt(2.0/layer_dims[l
        parameters['b' + str(l)] = np.random.normal(0,np.sqrt(2.0/layer_dims[l

elif init_type == 'he_uniform':
    for l in range(1, L):
        parameters['W' + str(l)] = np.random.uniform(-np.sqrt(6.0/layer_dims[l
                                        np.sqrt(6.0/layer_dims[l-1]),
                                        (layer_dims[l], layer_dims[l-1
        parameters['b' + str(l)] = np.random.uniform(-np.sqrt(6.0/layer_dims[l
                                        np.sqrt(6.0/layer_dims[l-1]),
                                        (layer_dims[l], 1))


elif init_type == 'xavier_normal':
    for l in range(1, L):
        parameters['W' + str(l)] = np.random.normal(0,2.0/(layer_dims[l]+layer
                                                   (layer_dims[l], lay
        parameters['b' + str(l)] = np.random.normal(0,2.0/(layer_dims[l]+layer
                                                      (layer_dims[l],


elif init_type == 'xavier_uniform':
    for l in range(1, L):
        parameters['W' + str(l)] = np.random.uniform(-(np.sqrt(6.0/(layer_dims
                                        (np.sqrt(6.0/(layer_dims[l]+la
                                        (layer_dims[l], layer_dims[l-1
        parameters['b' + str(l)] = np.random.uniform(-(np.sqrt(6.0/(layer_dims
                                        (np.sqrt(6.0/(layer_dims[l]+la
                                        (layer_dims[l], 1))

return parameters
```

```python
@staticmethod
def sigmoid(X,derivative=False):
    '''Compute Sigmaoid and its derivative'''
    if derivative == False:
        out = 1 / (1 + np.exp(-np.array(X)))
    elif derivative == True:
        s = 1 / (1 + np.exp(-np.array(X)))
        out = s*(1-s)
    return out
@staticmethod
def ReLU(X,alpha=0,derivative=False):
    '''Compute ReLU function and derivative'''
    X = np.array(X,dtype=np.float64)
    if derivative == False:
        return np.where(X<0,alpha*X,X)
    elif derivative == True:
        X_relu = np.ones_like(X,dtype=np.float64)
        X_relu[X < 0] = alpha
        return X_relu
@staticmethod
def Tanh(X,derivative=False):
    '''Compute tanh values and derivative of tanh'''
    X = np.array(X)
    if derivative == False:
        return np.tanh(X)
    if derivative == True:
        return 1 - (np.tanh(X))**2
@staticmethod
def softplus(X,derivative=False):
    '''Compute tanh values and derivative of tanh'''
    X = np.array(X)
    if derivative == False:
        return np.log(1+np.exp(X))
    if derivative == True:
        return 1 / (1 + np.exp(-np.array(X)))
@staticmethod
def arctan(X,derivative=False):
    '''Compute tan^-1(X) and derivative'''
    if derivative == False:
        return  np.arctan(X)
    if derivative == True:
        return 1/ (1 + np.square(X))
@staticmethod
def identity(X,derivative=False):
    '''identity function and derivative f(x) = x'''
    X = np.array(X)
    if derivative ==  False:
        return X
```

```
        if derivative == True:
            return np.ones_like(X)
    @staticmethod
    def elu(X,alpha=0,derivative=False):
        '''Exponential Linear Unit'''
        X = np.array(X,dtype=np.float64)
        if derivative == False:
            return np.where(X<0,alpha*(np.exp(X)-1),X)
        elif derivative == True:
            return np.where(X<0,alpha*(np.exp(X)),1)
    @staticmethod
    def softmax(X):
        """Compute softmax values for each sets of scores in x."""
        return np.exp(X) / np.sum(np.exp(X),axis=0)
    @staticmethod
    def forward_propagation(X, hidden_layers,parameters,keep_prob=1,seed=None):

        """"
        Arguments:
            X -- data, numpy array of shape (input size, number of examples)
            hidden_layers -- List of hideden layers
            weights -- Output of weights_init dict (parameters)
            keep_prob -- probability of keeping a neuron active during drop-out, scala
        Returns:
            AL -- last post-activation value
            caches -- list of caches containing:
                every cache of linear_activation_forward() (there are L-1 of them, ind
        """
        if seed != None:
            np.random.seed(seed)
        caches = []
        A = X
        L = len(hidden_layers)
        for l,active_function in enumerate(hidden_layers,start=1):
            A_prev = A

            Z = np.dot(parameters['W' + str(l)],A_prev)+parameters['b' + str(l)]

            if type(active_function) is tuple:

                if  active_function[0] == "relu":
                    A = DNNClassifier.ReLU(Z,active_function[1])
                elif active_function[0] == 'elu':
                    A = DNNClassifier.elu(Z,active_function[1])
            else:
                if active_function == "sigmoid":
                    A = DNNClassifier.sigmoid(Z)
                elif active_function == "identity":
```

```
                A = DNNClassifier.identity(Z)
            elif active_function == "arctan":
                A = DNNClassifier.arctan(Z)
            elif active_function == "softplus":
                A = DNNClassifier.softplus(Z)
            elif active_function == "tanh":
                A = DNNClassifier.Tanh(Z)
            elif active_function == "softmax":
                A = DNNClassifier.softmax(Z)
            elif  active_function == "relu":
                A = DNNClassifier.ReLU(Z)
            elif active_function == 'elu':
                A = DNNClassifier.elu(Z)

        if keep_prob != 1 and l != L and l != 1:
            D = np.random.rand(A.shape[0],A.shape[1])
            D = (D<keep_prob)
            A = np.multiply(A,D)
            A = A / keep_prob
            cache = ((A_prev, parameters['W' + str(l)],parameters['b' + str(l)],D)
            caches.append(cache)
        else:
            cache = ((A_prev, parameters['W' + str(l)],parameters['b' + str(l)]),
            #print(A.shape)
            caches.append(cache)
    return A, caches
@staticmethod
def compute_cost(A, Y, parameters, lamda=0,penality=None):
    """
    Implement the cost function with L2 regularization. See formula (2) above.

    Arguments:
        A -- post-activation, output of forward propagation
        Y -- "true" labels vector, of shape (output size, number of examples)
        parameters -- python dictionary containing parameters of the model

    Returns:
        cost - value of the regularized loss function
    """
    m = Y.shape[1]

    cost = np.squeeze(-np.sum(np.multiply(np.log(A),Y))/m)

    L = len(parameters)//2

    if penality == 'l2' and lamda != 0:
        sum_weights = 0
        for l in range(1, L):
```

```
            sum_weights = sum_weights + np.sum(np.square(parameters['W' + str(l)])
        cost = cost + sum_weights * (lamda/(2*m))
    elif penality == 'l1' and lamda != 0:
        sum_weights = 0
        for l in range(1, L):
            sum_weights = sum_weights + np.sum(np.abs(parameters['W' + str(l)]))
        cost = cost + sum_weights * (lamda/(2*m))
    return cost
@staticmethod
def back_propagation(AL, Y, caches, hidden_layers, keep_prob=1, penality=None,lamd
    """
    Implement the backward propagation

    Arguments:
        AL -- probability vector, output of the forward propagation (L_model_forwa
        Y -- true "label" vector (containing 0 if non-cat, 1 if cat)
        caches -- list of caches containing:
        hidden_layers -- hidden layer names
        keep_prob -- probabaility for dropout
        penality -- regularization penality 'l1' or 'l2' or None

    Returns:
         grads -- A dictionary with the gradients
         grads["dA" + str(l)] = ...
         grads["dW" + str(l)] = ...
         grads["db" + str(l)] = ...
    """
    grads = {}
    L = len(caches) # the number of layers

    m = AL.shape[1]
    Y = Y.reshape(AL.shape)

    # Initializing the backpropagation
    dZL = AL - Y

    cache = caches[L-1]
    linear_cache, activation_cache = cache
    AL, W, b = linear_cache
    grads["dW" + str(L)] = np.dot(dZL,AL.T)/m
    grads["db" + str(L)] = np.sum(dZL,axis=1,keepdims=True)/m
    grads["dA" + str(L-1)] = np.dot(W.T,dZL)


    # Loop from l=L-2 to l=0
    v_dropout = 0
    for l in reversed(range(L-1)):
        cache = caches[l]
```

```
active_function = hidden_layers[l]

linear_cache, Z = cache
try:
    A_prev, W, b = linear_cache
except:
    A_prev, W, b, D = linear_cache
    v_dropout = 1

m = A_prev.shape[1]

if keep_prob != 1 and v_dropout == 1:
    dA_prev = np.multiply(grads["dA" + str(l + 1)],D)
    dA_prev = dA_prev/keep_prob
    v_dropout = 0
else:
    dA_prev = grads["dA" + str(l + 1)]
    v_dropout = 0


if type(active_function) is tuple:

    if  active_function[0] == "relu":
        dZ = np.multiply(dA_prev,DNNClassifier.ReLU(Z,active_function[1],d
    elif active_function[0] == 'elu':
        dZ = np.multiply(dA_prev,DNNClassifier.elu(Z,active_function[1],de
else:
    if active_function == "sigmoid":
        dZ = np.multiply(dA_prev,DNNClassifier.sigmoid(Z,derivative=True))
    elif active_function == "relu":
        dZ = np.multiply(dA_prev,DNNClassifier.ReLU(Z,derivative=True))
    elif active_function == "tanh":
        dZ = np.multiply(dA_prev,DNNClassifier.Tanh(Z,derivative=True))
    elif active_function == "identity":
        dZ = np.multiply(dA_prev,DNNClassifier.identity(Z,derivative=True)
    elif active_function == "arctan":
        dZ = np.multiply(dA_prev,DNNClassifier.arctan(Z,derivative=True))
    elif active_function == "softplus":
        dZ = np.multiply(dA_prev,DNNClassifier.softplus(Z,derivative=True)
    elif active_function == 'elu':
        dZ = np.multiply(dA_prev,DNNClassifier.elu(Z,derivative=True))

grads["dA" + str(l)] = np.dot(W.T,dZ)

if penality == 'l2':
    grads["dW" + str(l + 1)] = (np.dot(dZ,A_prev.T)/m)  + ((lamda * W)/m)
elif penality == 'l1':
    grads["dW" + str(l + 1)] = (np.dot(dZ,A_prev.T)/m)  + ((lamda * np.sig
```

```python
        else:
            grads["dW" + str(l + 1)] = (np.dot(dZ,A_prev.T)/m)

        grads["db" + str(l + 1)] = np.sum(dZ,axis=1,keepdims=True)/m
    return grads

@staticmethod
def update_parameters(parameters, grads,learning_rate,iter_no,method = 'SGD',opt_p
    """
    Update parameters using gradient descent

    Arguments:
    parameters -- python dictionary containing your parameters
    grads -- python dictionary containing your gradients, output of L_model_backwa
    method -- method for updation of weights
              'SGD','SGDM','RMSP','ADAM'
    learning rate -- learning rate alpha value
    beta1 -- weighted avg parameter for SGDM and ADAM
    beta2 -- weighted avg parameter for RMSP and ADAM

    Returns:
    parameters -- python dictionary containing your updated parameters
                  parameters["W" + str(l)] = ...
                  parameters["b" + str(l)] = ...
                  opt_parameters
    """

    L = len(parameters) // 2 # number of layers in the neural network
    if method == 'SGD':
        for l in range(L):
            parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - learning_rat
            parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - learning_rat
        opt_parameters = None
    elif method == 'SGDM':
        for l in range(L):
            opt_parameters['vdb'+str(l+1)] = beta1*opt_parameters['vdb'+str(l+1)]
            opt_parameters['vdw'+str(l+1)] = beta1*opt_parameters['vdw'+str(l+1)]
            parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - learning_rat
            parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - learning_rat
    elif method == 'RMSP':
        for l in range(L):
            opt_parameters['sdb'+str(l+1)] = beta2*opt_parameters['sdb'+str(l+1)]
                                            (1-beta2)*np.square(grads["db" +
            opt_parameters['sdw'+str(l+1)] = beta2*opt_parameters['sdw'+str(l+1)]
                                                  (1-beta2)*np.square(grads["
            parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - \
                                    learning_rate*(grads["dW" + str(l + 1)]/(np.sqr
            parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - \
```

```
                                    learning_rate*(grads["db" + str(l + 1)]/(np.sqr
        elif method == 'ADAM':
            for l in range(L):
                opt_parameters['vdb'+str(l+1)] = beta1*opt_parameters['vdb'+str(l+1)]
                opt_parameters['vdw'+str(l+1)] = beta1*opt_parameters['vdw'+str(l+1)]
                opt_parameters['sdb'+str(l+1)] = beta2*opt_parameters['sdb'+str(l+1)]
                                                  (1-beta2)*np.square(
                opt_parameters['sdw'+str(l+1)] = beta2*opt_parameters['sdw'+str(l+1)]
                                                   (1-beta2)*np.square

                learning_rate = learning_rate * np.sqrt((1-beta2**iter_no)/((1-beta1**
                parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - \
                                    learning_rate*(opt_parameters['vdw'+str(l+1)]/\
                                                   (np.sqrt(opt_parameters['sdw'+st
                parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - \
                                    learning_rate*(opt_parameters['vdb'+str(l+1)]/\
                                                   (np.sqrt(opt_parameters['sdb'+st

        return parameters,opt_parameters

    def fit(self,X,y):
        '''
        X -- data, numpy array of shape (input size, number of examples)
        y -- lables, numpy array of shape (no of classes,n)

        '''

        np.random.seed(self.seed)
        self.grads = {}
        self.costs = []
        M = X.shape[1]
        opt_parameters = {}

        if self.verbose == 1:
            print('Initilizing Weights...')
        self.parameters = self.weights_init(self.layer_dims,self.init_type,self.seed)
        self.iter_no = 0
        idx = np.arange(0,M)

        if self.optimization_method != 'SGD':
            for l in range(1, len(self.layer_dims)):
                opt_parameters['vdw' + str(l)] = np.zeros((self.layer_dims[l], self.la
                opt_parameters['vdb' + str(l)] = np.zeros((self.layer_dims[l], 1))
                opt_parameters['sdw' + str(l)] = np.zeros((self.layer_dims[l], self.la
                opt_parameters['sdb' + str(l)] = np.zeros((self.layer_dims[l], 1))

        if self.verbose == 1:
            print('Starting Training...')
```

```
        for epoch_no in range(1,self.max_epoch+1):
            np.random.shuffle(idx)
            X = X[:,idx]
            y = y[:,idx]
            for i in range(0,M, self.batch_size):
                self.iter_no = self.iter_no + 1
                X_batch = X[:,i:i + self.batch_size]
                y_batch = y[:,i:i + self.batch_size]
                # Forward propagation:
                AL, cache = self.forward_propagation(X_batch,self.hidden_layers,self.p
                #cost
                cost = self.compute_cost(AL, y_batch, self.parameters,self.lamda,self.
                self.costs.append(cost)

                if self.tol != None:
                    try:
                        if abs(cost - self.costs[-2]) < self.tol:
                            return self
                    except:
                        pass
                #back prop
                grads = self.back_propagation(AL, y_batch, cache,self.hidden_layers,se

                #update params
                self.parameters,opt_parameters = self.update_parameters(self.parameter
                                                                        self.iter_no-1
                                                                        opt_parameters


                if self.verbose == 1:
                    if self.iter_no % 100 == 0:
                        print("Cost after iteration {}: {}".format(self.iter_no, cost)

        return self
    def predict(self,X,proba=False):
        '''predicting values
           arguments: X - iput data
                      proba -- False then return value
                               True then return probabaility
        '''

        out, _ = self.forward_propagation(X,self.hidden_layers,self.parameters,self.ke
        if proba == True:
            return out.T
        else:
            return np.argmax(out, axis=0)
```

Testing With some Datasets:

Iris Data:

```
In [75]: from sklearn.datasets import load_iris
         data = load_iris()
         X = data.data[:,[0,2]].T
         y = data.target
         from sklearn import preprocessing
         lb = preprocessing.LabelBinarizer()
         Y = lb.fit_transform(y)
         Y = Y.T
```

```
In [76]: print(X.shape)
         print(Y.shape)
```

```
(2, 150)
(3, 150)
```

SGD with Momentum optimization with layers 'relu','relu','softmax'

```
In [80]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4, 3],hidden_layers=[('relu',0),('relu
                                    optimization_method='SGDM',tolarance=None,max_epoch=1000,verbose=
         model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.5198108710634975
Cost after iteration 200: 0.3350581601078205
Cost after iteration 300: 0.24724196512064792
Cost after iteration 400: 0.18890671914773782
Cost after iteration 500: 0.19854223111129288
Cost after iteration 600: 0.18061499868242695
Cost after iteration 700: 0.12660638571109112
Cost after iteration 800: 0.09670201792713956
Cost after iteration 900: 0.09193751648505266
Cost after iteration 1000: 0.2892882109708265
Cost after iteration 1100: 0.15207116857830852
Cost after iteration 1200: 0.15650933122352076
Cost after iteration 1300: 0.24324968840019756
Cost after iteration 1400: 0.06982186948377132
Cost after iteration 1500: 0.07107804853883976
Cost after iteration 1600: 0.15665737484251224
Cost after iteration 1700: 0.1908301179306225
Cost after iteration 1800: 0.12216070062084422
Cost after iteration 1900: 0.10397679102871141
Cost after iteration 2000: 0.1561301393626421
Cost after iteration 2100: 0.07481075025142646
```

```
Cost after iteration 2200: 0.16942260474885362
Cost after iteration 2300: 0.10229128965819373
Cost after iteration 2400: 0.19292215139705035
Cost after iteration 2500: 0.11314947820866474
Cost after iteration 2600: 0.09353431104844842
Cost after iteration 2700: 0.3184685711904773
Cost after iteration 2800: 0.14983129470829432
Cost after iteration 2900: 0.34749723946637356
Cost after iteration 3000: 0.030838112829122657
```

```
Out[80]: <__main__.DNNClassifier at 0x152ca95cb0b8>
```

```
In [81]: y_pred = model.predict(X,proba=False)
         y_pred
```

```
Out[81]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 2, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

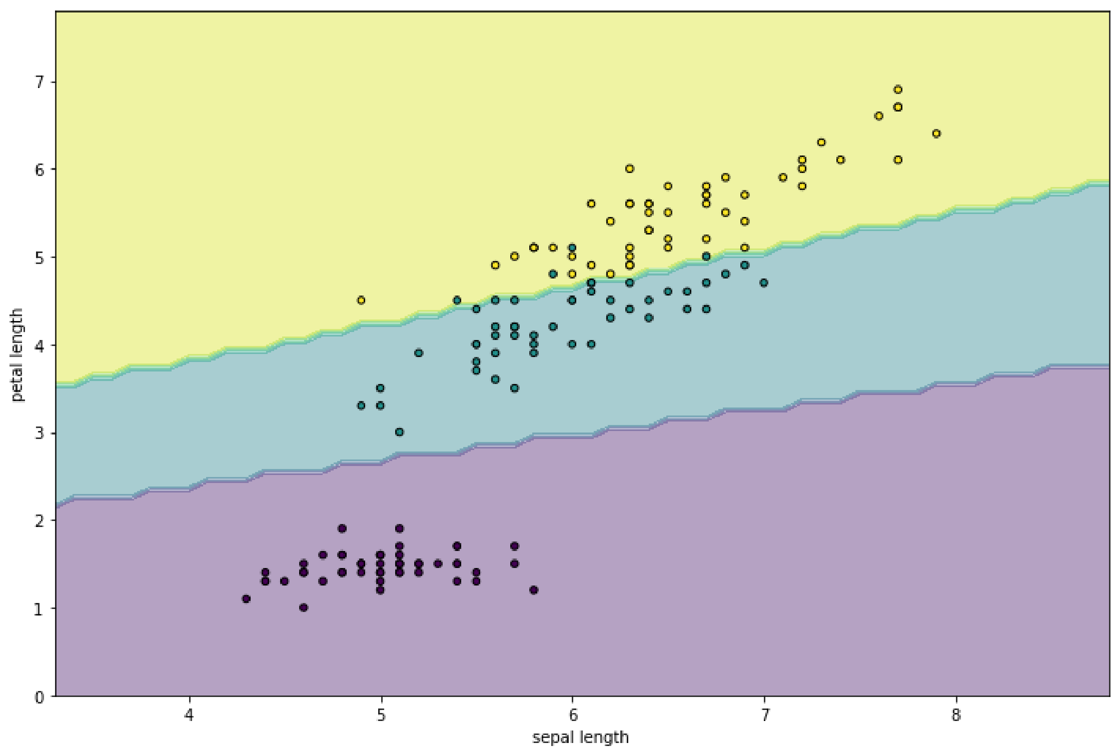
Plotting Decision Boundaries

```
In [122]: %matplotlib inline
          import matplotlib.pyplot as plt
          dt = data.data[:,[0,2]]
          x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
          y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                               np.arange(y_min, y_max, 0.1))

          # here "model" is your model's prediction (classification) function
          Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure(figsize=(12,8))
          plt.contourf(xx, yy, Z,alpha=0.4)
          #plt.axis('off')
          plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
          plt.xlabel('sepal length')
          plt.ylabel('petal length')
```

```
Out[122]: Text(0,0.5,'petal length')
```



Optimization using adam

```
In [128]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4, 3],hidden_layers=[('relu',0),('rel
                              optimization_method='ADAM',tolarance=None,max_epoch=900,verbose=
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.2410524910881379
Cost after iteration 200: 0.156933182530525
Cost after iteration 300: 0.4761735247293429
Cost after iteration 400: 0.07214152730963741
Cost after iteration 500: 0.05967539457093406
Cost after iteration 600: 0.18715592303547562
Cost after iteration 700: 0.14981032092268548
Cost after iteration 800: 0.0827908281308122
Cost after iteration 900: 0.036099842961624516
Cost after iteration 1000: 0.11922918395829907
Cost after iteration 1100: 0.06045911527459521
Cost after iteration 1200: 0.16172553441807452
Cost after iteration 1300: 0.06256067453485452
Cost after iteration 1400: 0.12874850080531294
Cost after iteration 1500: 0.07305011781964871
```

```
Cost after iteration 1600: 0.06243921009966007
Cost after iteration 1700: 0.08108399200652769
Cost after iteration 1800: 0.03237463795372483
Cost after iteration 1900: 0.11286957459033613
Cost after iteration 2000: 0.027619164456255337
Cost after iteration 2100: 0.06070563698015665
Cost after iteration 2200: 0.07938127864818988
Cost after iteration 2300: 0.07858317488644868
Cost after iteration 2400: 0.1123352927395408
Cost after iteration 2500: 0.10150951195641762
Cost after iteration 2600: 0.10453249850378561
Cost after iteration 2700: 0.01809885284854305
```

```
Out[128]: <__main__.DNNClassifier at 0x152ca41afa58>
```

```
In [129]: y_pred = model.predict(X,proba=False)
          y_pred
```

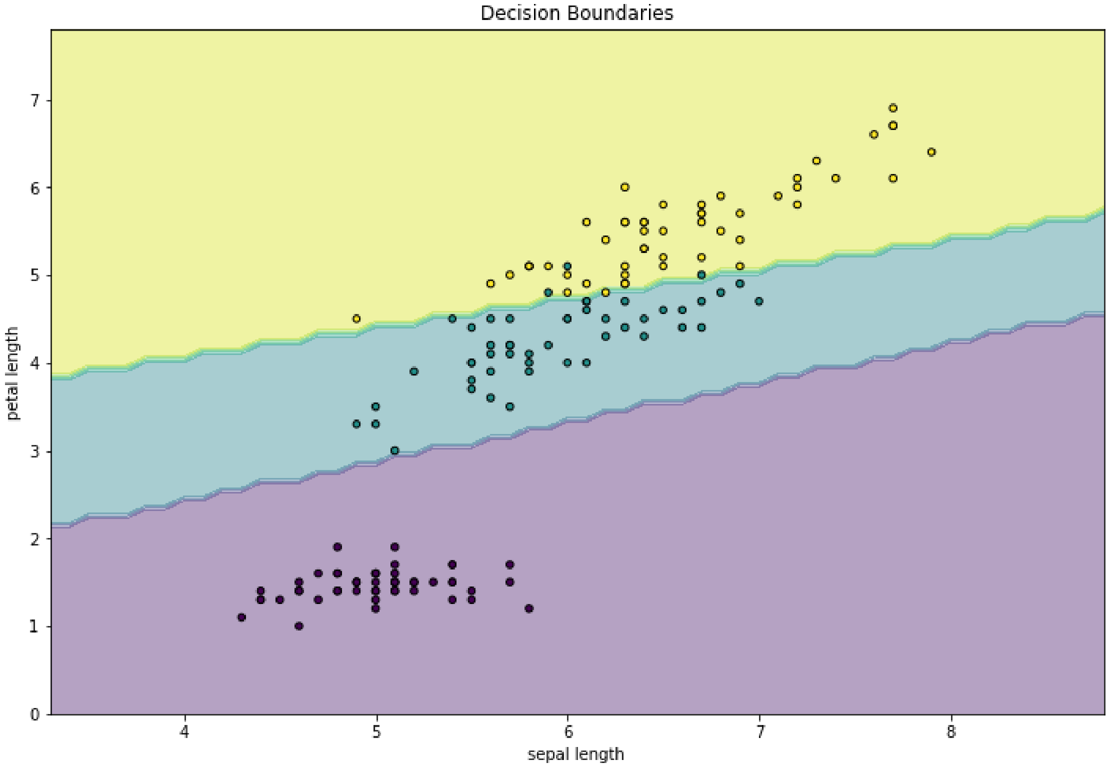
```
Out[129]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                 1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2,
                 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

```
In [130]: ### Decision Boundaries
          %matplotlib inline
          import matplotlib.pyplot as plt
          dt = data.data[:,[0,2]]
          x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
          y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                               np.arange(y_min, y_max, 0.1))

          # here "model" is your model's prediction (classification) function
          Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure(figsize=(12,8))
          plt.contourf(xx, yy, Z,alpha=0.4)
          #plt.axis('off')
          plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
          plt.xlabel('sepal length')
          plt.ylabel('petal length')
          plt.title('Decision Boundaries')
```

```
Out[130]: Text(0.5,1,'Decision Boundaries')
```



Moon Curves:

```
In [161]: from sklearn.datasets import make_moons

In [190]: x,y =make_moons(n_samples=1500, noise=.05)
          X = x.T
          lb = preprocessing.LabelBinarizer()
          Y = lb.fit_transform(y)
          y_next = np.where(y==0,1,0)
          Y = Y.T
          Y = list(Y)
          Y.append(y_next)
          Y = np.array(Y)

In [192]: Y.shape

Out[192]: (2, 1500)

In [204]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4,3, 2],hidden_layers=[('relu',0),('r
                                optimization_method='ADAM',tolarance=None,batch_size=512,max_epo
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.3621104058351161
Cost after iteration 200: 0.12213695696079738
Cost after iteration 300: 0.03338506361379205
Cost after iteration 400: 0.014662242229828303
Cost after iteration 500: 0.007697555099209768
Cost after iteration 600: 0.0046203951192425935
Cost after iteration 700: 0.0030145995218986876
Cost after iteration 800: 0.0021057294721802894
Cost after iteration 900: 0.0015219705690779476
Cost after iteration 1000: 0.0011528026448003074
Cost after iteration 1100: 0.0008815357076611342
Cost after iteration 1200: 0.0007046679789013923
Cost after iteration 1300: 0.0005789409917109167
Cost after iteration 1400: 0.00046502519675507885
Cost after iteration 1500: 0.00039321669343281377
Cost after iteration 1600: 0.000328993674825817 7
Cost after iteration 1700: 0.00028169521217718727
Cost after iteration 1800: 0.00023916938949804847
Cost after iteration 1900: 0.00020995242501015122
Cost after iteration 2000: 0.00018237646273787432
Cost after iteration 2100: 0.00016031670288039137
```

Out[204]: <__main__.DNNClassifier at 0x152ca9dd0668>

In [205]:
```
model.predict(X)
```

Out[205]: array([0, 1, 0, ..., 1, 1, 0])

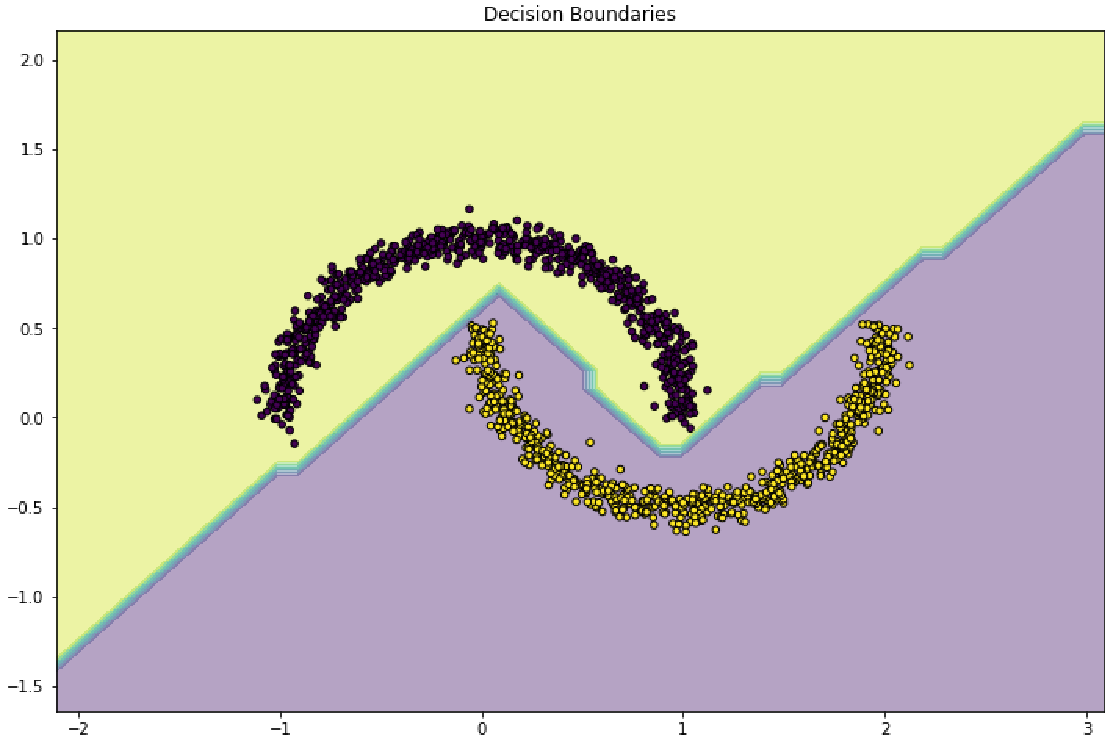
In [207]:
```
### Decision Boundaries
%matplotlib inline
import matplotlib.pyplot as plt
dt = x
x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))

# here "model" is your model's prediction (classification) function
Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.figure(figsize=(12,8))
plt.contourf(xx, yy, Z,alpha=0.4)
#plt.axis('off')
```

```
        plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
        plt.title('Decision Boundaries')
```

Out[207]: Text(0.5,1,'Decision Boundaries')



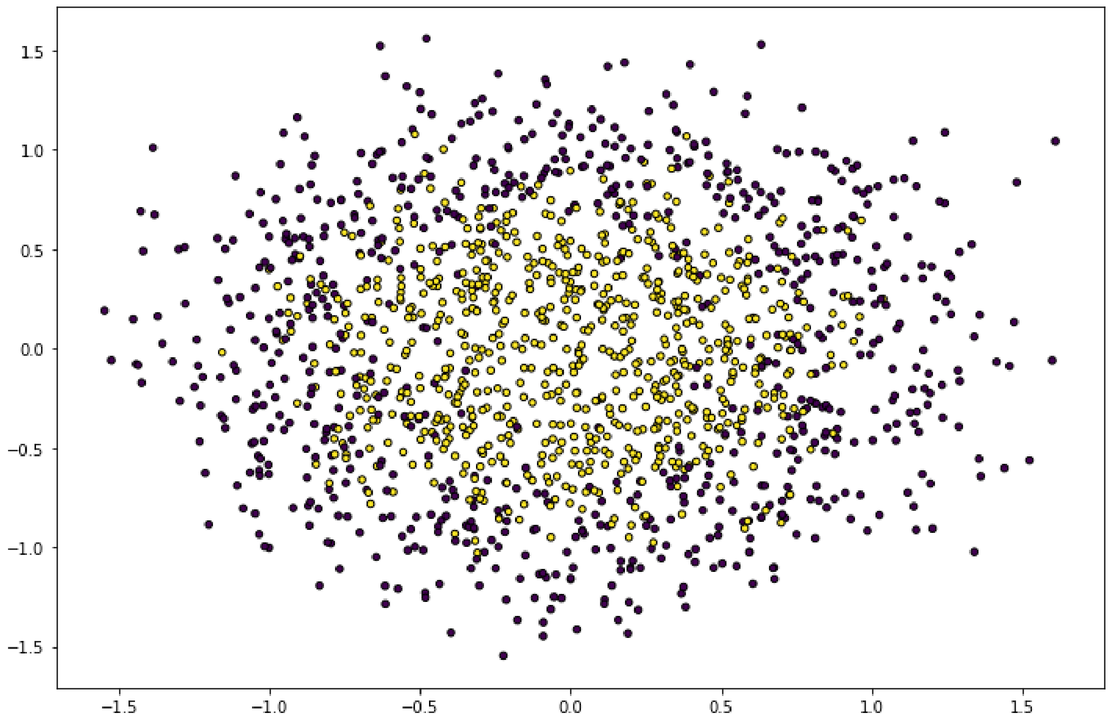
Some Noise data

```
In [208]: from sklearn.datasets import make_moons, make_circles, make_classification
```

```
In [219]: x,y = make_circles(n_samples=1500,noise=0.25, factor=0.5, random_state=1)
```

```
In [220]: plt.figure(figsize=(12,8))
          plt.scatter(x[:, 0], x[:, 1], c=y,s=20, edgecolor='k')
```

Out[220]: <matplotlib.collections.PathCollection at 0x152c82b1d198>




```
In [221]: X = x.T
          lb = preprocessing.LabelBinarizer()
          Y = lb.fit_transform(y)
          y_next = np.where(y==0,1,0)
          Y = Y.T
          Y = list(Y)
          Y.append(y_next)
          Y = np.array(Y)
```

```
In [226]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4,3, 2],hidden_layers=[('relu',0),('r
                                optimization_method='ADAM',tolarance=None,batch_size=512,max_epo
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.45720467395194553
Cost after iteration 200: 0.405379316535335
Cost after iteration 300: 0.3869594502913372
Cost after iteration 400: 0.3772658512063516
Cost after iteration 500: 0.3779936532090616
Cost after iteration 600: 0.31271739773971713
Cost after iteration 700: 0.3426347841044403
Cost after iteration 800: 0.3915129531097433
Cost after iteration 900: 0.3555932346136275
```

```
Cost after iteration 1000: 0.3835513814261377
Cost after iteration 1100: 0.3572449192481134
Cost after iteration 1200: 0.34773344818683366
Cost after iteration 1300: 0.3427315993713393
Cost after iteration 1400: 0.35526492617368904
Cost after iteration 1500: 0.3427916397480477
Cost after iteration 1600: 0.38698530968706796
Cost after iteration 1700: 0.34460680291127704
Cost after iteration 1800: 0.3281842154819242
Cost after iteration 1900: 0.362553112032135
Cost after iteration 2000: 0.37608659798233757
Cost after iteration 2100: 0.32291330367751997
```

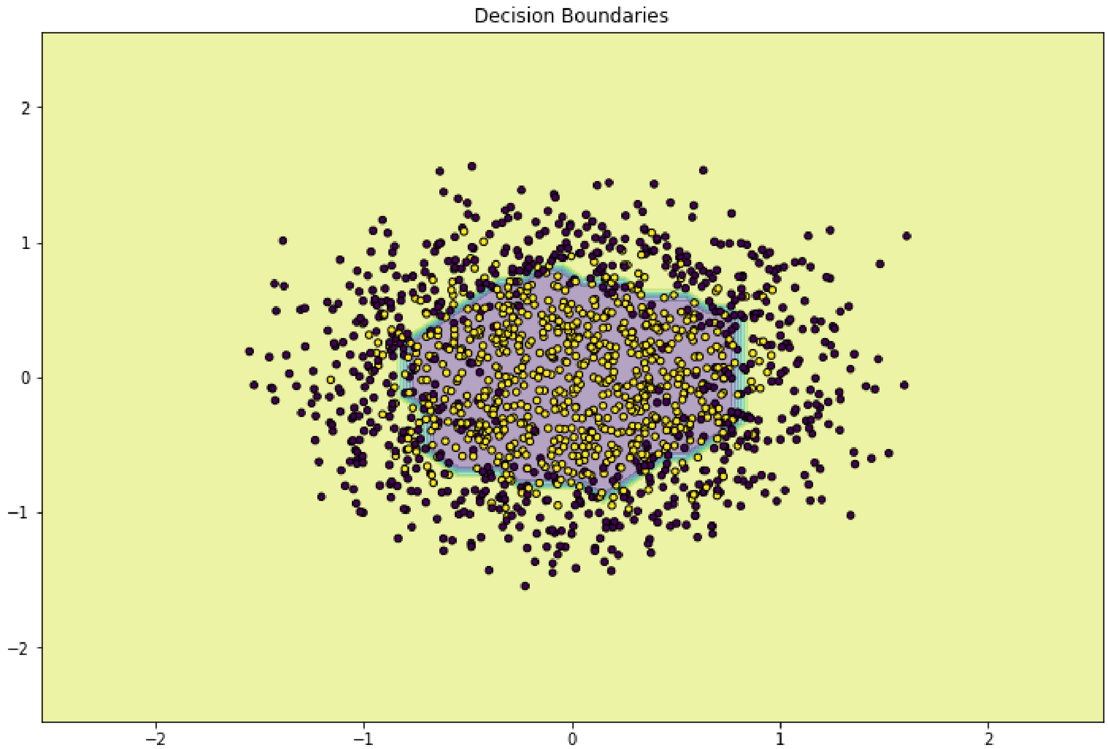
```
Out[226]: <__main__.DNNClassifier at 0x152c82cbb080>
```

```
In [227]: ### Decision Boundaries
          %matplotlib inline
          import matplotlib.pyplot as plt
          dt = x
          x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
          y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                               np.arange(y_min, y_max, 0.1))

          # here "model" is your model's prediction (classification) function
          Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure(figsize=(12,8))
          plt.contourf(xx, yy, Z,alpha=0.4)
          #plt.axis('off')
          plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
          plt.title('Decision Boundaries')
```

```
Out[227]: Text(0.5,1,'Decision Boundaries')
```




```
In [235]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 5,4, 2],hidden_layers=[('relu',0),('r
                                optimization_method='ADAM',keep_proba=0.85,tolarance=None,batch_
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.788188134256454
Cost after iteration 200: 0.7019137303780809
Cost after iteration 300: 0.6898942771688221
Cost after iteration 400: 0.6783332381538787
Cost after iteration 500: 0.6817545656079715
Cost after iteration 600: 0.6771002236671971
Cost after iteration 700: 0.5683667278910918
Cost after iteration 800: 0.5125143762758825
Cost after iteration 900: 0.5220465692907031
Cost after iteration 1000: 0.5063157270635141
Cost after iteration 1100: 0.4360049590512598
Cost after iteration 1200: 0.48342245988515187
Cost after iteration 1300: 0.47680778908862786
Cost after iteration 1400: 0.4821902764632856
Cost after iteration 1500: 0.4993909442888387
Cost after iteration 1600: 0.5031331698286605
Cost after iteration 1700: 0.41235219429375114
```

```
Cost after iteration 1800: 0.4409391440104965
Cost after iteration 1900: 0.4897770330836313
Cost after iteration 2000: 0.44360422325161886
Cost after iteration 2100: 0.4279769330913007
Cost after iteration 2200: 0.41143385779812636
Cost after iteration 2300: 0.4337755699295872
Cost after iteration 2400: 0.434719354306776
Cost after iteration 2500: 0.4213856313375228
Cost after iteration 2600: 0.4524526382057342
Cost after iteration 2700: 0.43121838319513817
Cost after iteration 2800: 0.44604008758319436
Cost after iteration 2900: 0.44317105239311755
Cost after iteration 3000: 0.4523862885324596
```

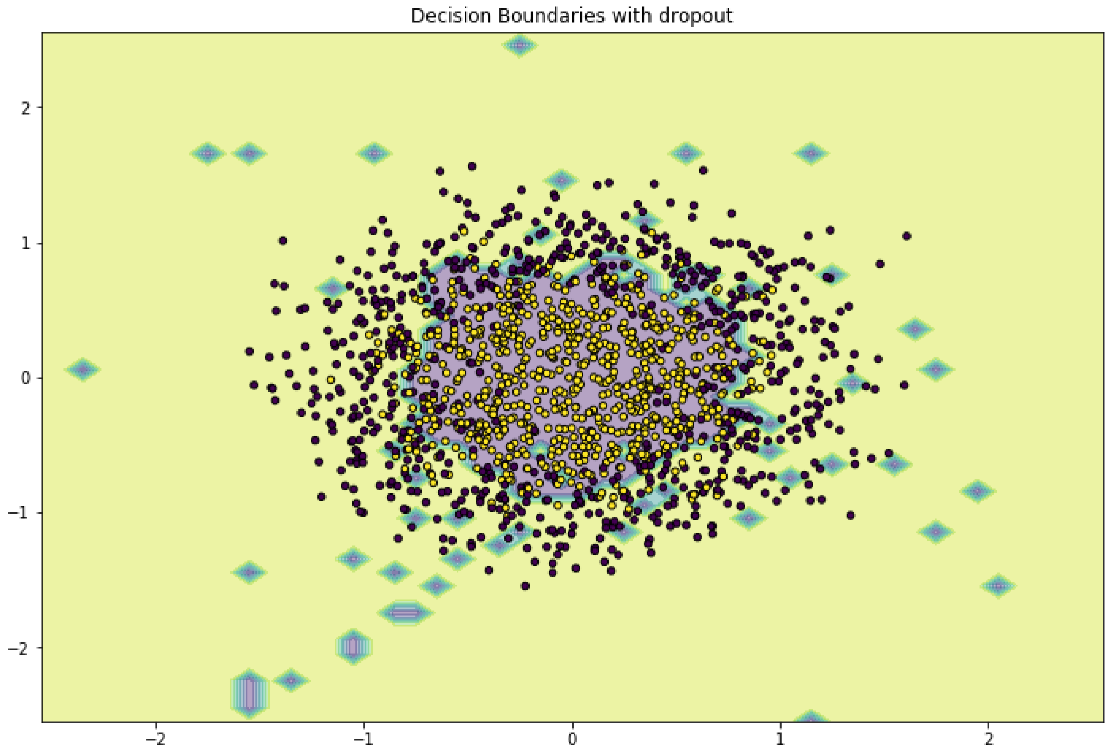
Out[235]: `<__main__.DNNClassifier at 0x152c82b41940>`

In [236]:
```
### Decision Boundaries
%matplotlib inline
import matplotlib.pyplot as plt
dt = x
x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))

# here "model" is your model's prediction (classification) function
Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.figure(figsize=(12,8))
plt.contourf(xx, yy, Z,alpha=0.4)
#plt.axis('off')
plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
plt.title('Decision Boundaries with dropout')
```

Out[236]: `Text(0.5,1,'Decision Boundaries with dropout')`



With l2 regularization: With small lambda

```
In [251]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4,3, 2],hidden_layers=[('relu',0),('r
                                optimization_method='ADAM',penality='l2',lamda=0.35,
                                tolarance=None,batch_size=512,max_epoch=1000,verbose=1,seed=25)
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.5806166689724982
Cost after iteration 200: 0.45974908548940446
Cost after iteration 300: 0.4352750468782838
Cost after iteration 400: 0.4100871900132933
Cost after iteration 500: 0.4072215489720923
Cost after iteration 600: 0.3474795736890927
Cost after iteration 700: 0.38918413031656
Cost after iteration 800: 0.3954144399690004
Cost after iteration 900: 0.37744517763552976
Cost after iteration 1000: 0.4106163947286747
Cost after iteration 1100: 0.3949461838404195
Cost after iteration 1200: 0.3607784478023016
Cost after iteration 1300: 0.35741376846518674
Cost after iteration 1400: 0.35755798049644594
```

```
Cost after iteration 1500: 0.37328545889459613
Cost after iteration 1600: 0.3983437120495418
Cost after iteration 1700: 0.3776207638259863
Cost after iteration 1800: 0.34347732425351896
Cost after iteration 1900: 0.38361435332967153
Cost after iteration 2000: 0.39826276937478966
Cost after iteration 2100: 0.34273338828175337
Cost after iteration 2200: 0.3708299072754191
Cost after iteration 2300: 0.3777566913647341
Cost after iteration 2400: 0.3624104992392394
Cost after iteration 2500: 0.3995656396062371
Cost after iteration 2600: 0.3888233959812816
Cost after iteration 2700: 0.37597139770981974
Cost after iteration 2800: 0.3619042423641757
Cost after iteration 2900: 0.39978460260196197
Cost after iteration 3000: 0.3836822591508139
```

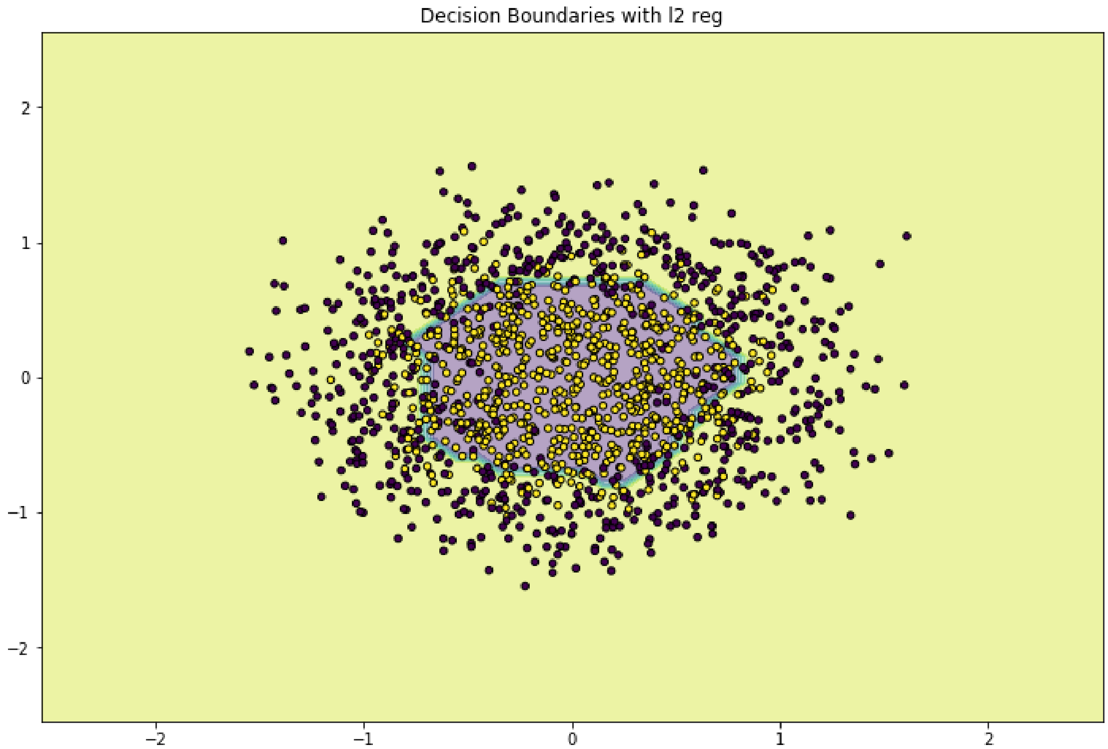
Out[251]: <__main__.DNNClassifier at 0x152c82b1d668>

In [252]:
```
### Decision Boundaries
%matplotlib inline
import matplotlib.pyplot as plt
dt = x
x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))

# here "model" is your model's prediction (classification) function
Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.figure(figsize=(12,8))
plt.contourf(xx, yy, Z,alpha=0.4)
#plt.axis('off')
plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
plt.title('Decision Boundaries with l2 reg')
```

Out[252]: Text(0.5,1,'Decision Boundaries with l2 reg')



With High lambda

```
In [255]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4,3, 2],hidden_layers=[('relu',0),('r
                                 optimization_method='ADAM',penality='l2',lamda=3,
                                 tolarance=None,batch_size=512,max_epoch=1000,verbose=1,seed=25)
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.7036416575379517
Cost after iteration 200: 0.6902162747614012
Cost after iteration 300: 0.6671797152597352
Cost after iteration 400: 0.6365139075412387
Cost after iteration 500: 0.6099057595332051
Cost after iteration 600: 0.6121004325210112
Cost after iteration 700: 0.5933699400088326
Cost after iteration 800: 0.6234754556784149
Cost after iteration 900: 0.5865937347819079
Cost after iteration 1000: 0.6296352093897949
Cost after iteration 1100: 0.6073494260910217
Cost after iteration 1200: 0.5745560242945857
Cost after iteration 1300: 0.6085452377640669
Cost after iteration 1400: 0.5760010281668105
Cost after iteration 1500: 0.5864934730892997
```

```
Cost after iteration 1600: 0.6011090834059049
Cost after iteration 1700: 0.6142769590843096
Cost after iteration 1800: 0.6154664076402668
Cost after iteration 1900: 0.5884989759002314
Cost after iteration 2000: 0.6200659142833614
Cost after iteration 2100: 0.587044090638867
Cost after iteration 2200: 0.593158806467417
Cost after iteration 2300: 0.5855981812306138
Cost after iteration 2400: 0.5983866822266155
Cost after iteration 2500: 0.6108713636197524
Cost after iteration 2600: 0.6000967685304033
Cost after iteration 2700: 0.5961853059299012
Cost after iteration 2800: 0.6114256593706265
Cost after iteration 2900: 0.5863387339537713
Cost after iteration 3000: 0.6065206533650478
```

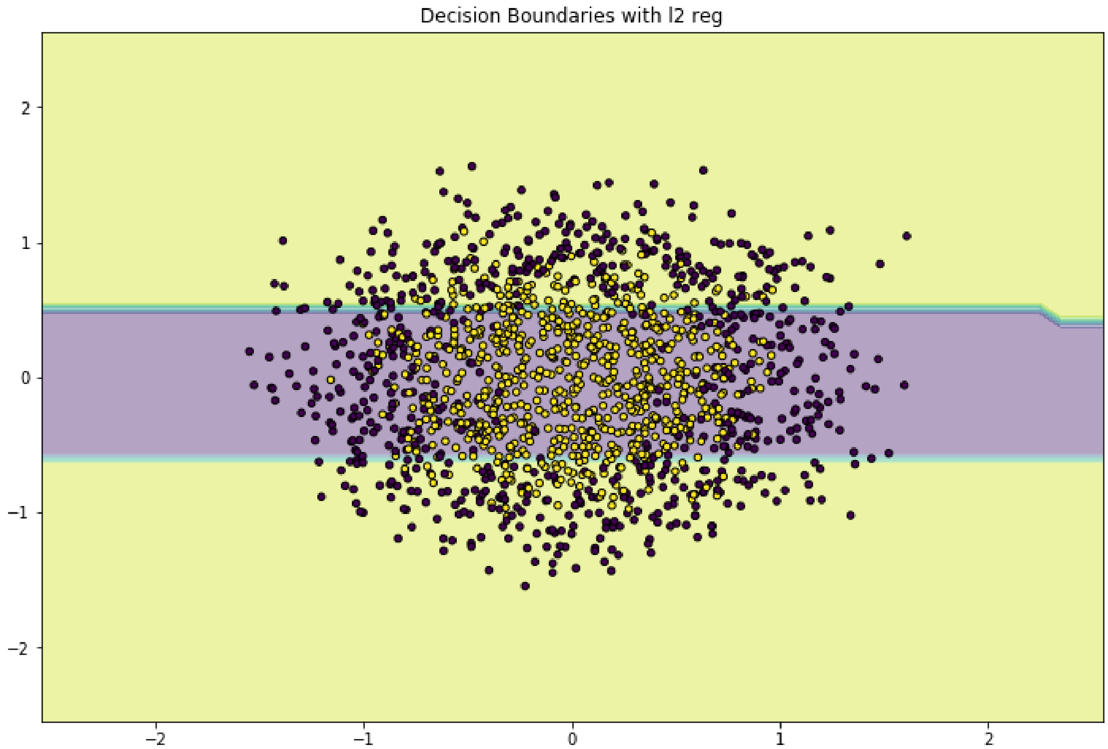
```
Out[255]: <__main__.DNNClassifier at 0x152c825c0dd8>
```

```
In [256]: ### Decision Boundaries
          %matplotlib inline
          import matplotlib.pyplot as plt
          dt = x
          x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
          y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                               np.arange(y_min, y_max, 0.1))

          # here "model" is your model's prediction (classification) function
          Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure(figsize=(12,8))
          plt.contourf(xx, yy, Z,alpha=0.4)
          #plt.axis('off')
          plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
          plt.title('Decision Boundaries with l2 reg')
```

```
Out[256]: Text(0.5,1,'Decision Boundaries with l2 reg')
```



With L1 Regularization With Low Lambda

```
In [259]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4,3, 2],hidden_layers=[('relu',0),('r
                                 optimization_method='ADAM',penality='l1',lamda=0.4,
                                 tolarance=None,batch_size=512,max_epoch=1000,verbose=1,seed=25)
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.5225446366680638
Cost after iteration 200: 0.4099718597190881
Cost after iteration 300: 0.4049840523488595
Cost after iteration 400: 0.3835680407577898
Cost after iteration 500: 0.38942437251658774
Cost after iteration 600: 0.3332954592810706
Cost after iteration 700: 0.3596084492732947
Cost after iteration 800: 0.3735684884413414
Cost after iteration 900: 0.3648458498978709
Cost after iteration 1000: 0.4008201838393185
Cost after iteration 1100: 0.35608614726068316
Cost after iteration 1200: 0.3575552859331963
Cost after iteration 1300: 0.3535500848097046
Cost after iteration 1400: 0.3603667514893773
```

```
Cost after iteration 1500: 0.3632277006835128
Cost after iteration 1600: 0.4052922377488472
Cost after iteration 1700: 0.3645443690074442
Cost after iteration 1800: 0.34379414468741054
Cost after iteration 1900: 0.38598583710609363
Cost after iteration 2000: 0.393730363195893
Cost after iteration 2100: 0.3380342528033145
Cost after iteration 2200: 0.3709844279824385
Cost after iteration 2300: 0.39545670715581893
Cost after iteration 2400: 0.36428261717696625
Cost after iteration 2500: 0.3893998146919035
Cost after iteration 2600: 0.3723866106746444
Cost after iteration 2700: 0.36340565200298575
Cost after iteration 2800: 0.36292220575816514
Cost after iteration 2900: 0.3853528407790814
Cost after iteration 3000: 0.3778348091123351
```

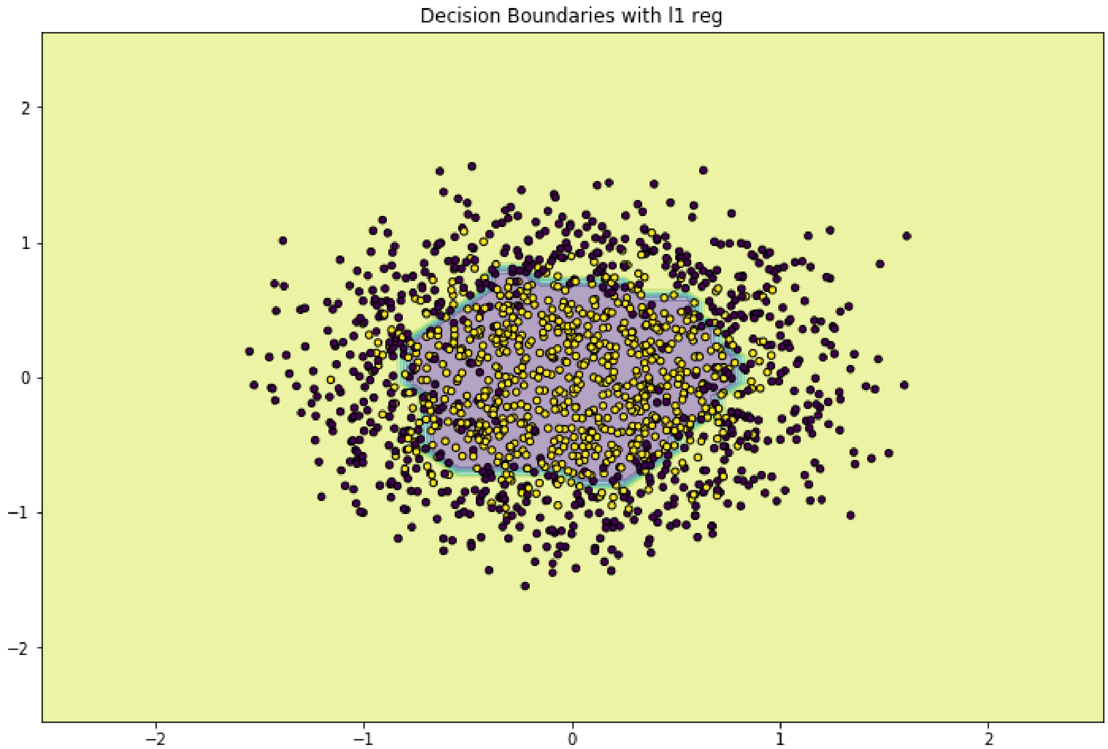
```
Out[259]: <__main__.DNNClassifier at 0x152c82546278>
```

```
In [261]: ### Decision Boundaries
          %matplotlib inline
          import matplotlib.pyplot as plt
          dt = x
          x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
          y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                               np.arange(y_min, y_max, 0.1))

          # here "model" is your model's prediction (classification) function
          Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure(figsize=(12,8))
          plt.contourf(xx, yy, Z,alpha=0.4)
          #plt.axis('off')
          plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
          plt.title('Decision Boundaries with l1 reg')
```

```
Out[261]: Text(0.5,1,'Decision Boundaries with l1 reg')
```



With High Lambda

```
In [266]: model = DNNClassifier(layer_dims=[X.shape[0], 6, 4,3, 2],hidden_layers=[('relu',0),('r
                              optimization_method='ADAM',penality='l1',lamda=3.5,
                              tolarance=None,batch_size=512,max_epoch=1000,verbose=1,seed=15)
          model.fit(X,Y)
```

```
Initilizing Weights...
Starting Training...
Cost after iteration 100: 0.6947741144756275
Cost after iteration 200: 0.6865100179447006
Cost after iteration 300: 0.6808774991172852
Cost after iteration 400: 0.6759591840050962
Cost after iteration 500: 0.6711090270403037
Cost after iteration 600: 0.6641226487315927
Cost after iteration 700: 0.6670957848437121
Cost after iteration 800: 0.6674261910405109
Cost after iteration 900: 0.6459777825521165
Cost after iteration 1000: 0.652011044063832
Cost after iteration 1100: 0.6552505487826152
Cost after iteration 1200: 0.6573969102569003
Cost after iteration 1300: 0.6702285365506423
Cost after iteration 1400: 0.6707962869430603
Cost after iteration 1500: 0.6625238585966345
```

```
Cost after iteration 1600: 0.6533984172565822
Cost after iteration 1700: 0.6744558831868294
Cost after iteration 1800: 0.6673310796279402
Cost after iteration 1900: 0.6621421246292215
Cost after iteration 2000: 0.6719771410552794
Cost after iteration 2100: 0.6725542786587769
Cost after iteration 2200: 0.6710493704397011
Cost after iteration 2300: 0.6689693451955543
Cost after iteration 2400: 0.6697825960307424
Cost after iteration 2500: 0.6732499019381561
Cost after iteration 2600: 0.6589084080836509
Cost after iteration 2700: 0.6736168078650121
Cost after iteration 2800: 0.6610252039992268
Cost after iteration 2900: 0.6574637008822438
Cost after iteration 3000: 0.6747279931159607
```

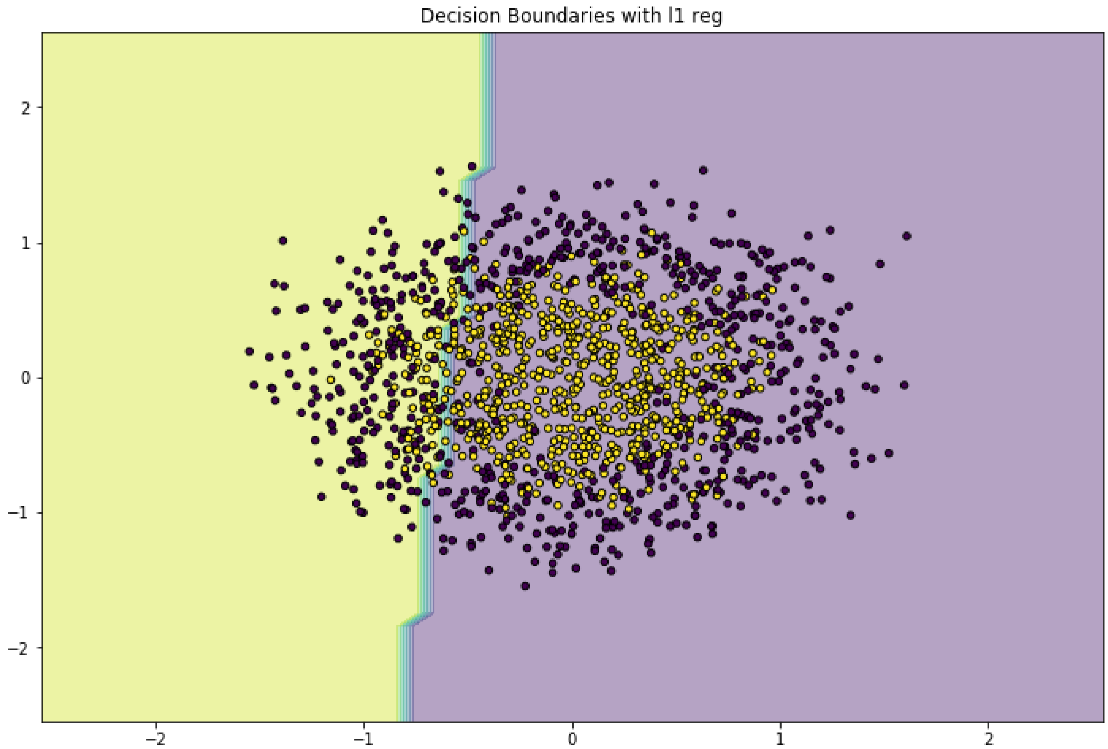
```
Out[266]: <__main__.DNNClassifier at 0x152c822e18d0>
```

```
In [267]: ### Decision Boundaries
          %matplotlib inline
          import matplotlib.pyplot as plt
          dt = x
          x_min, x_max = dt[:, 0].min() - 1, dt[:, 0].max() + 1
          y_min, y_max = dt[:, 1].min() - 1, dt[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                               np.arange(y_min, y_max, 0.1))

          # here "model" is your model's prediction (classification) function
          Z = model.predict(np.c_[xx.ravel(), yy.ravel()].T)

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure(figsize=(12,8))
          plt.contourf(xx, yy, Z,alpha=0.4)
          #plt.axis('off')
          plt.scatter(dt[:, 0], dt[:, 1], c=y,s=20, edgecolor='k')
          plt.title('Decision Boundaries with l1 reg')
```

```
Out[267]: Text(0.5,1,'Decision Boundaries with l1 reg')
```



References: 1. Deeplearning.ai Course 2. Forward Propagation - https://www.youtube.com/watch?v=a8i2eJin0lY&index=38&list=PLkDaE6sCZn6Ec-XTbcX1uRg2_u4xOEky0 3. Back Prop - https://www.youtube.com/watch?v=yXcQ4B-YSjQ&index=34&list=PLkDaE6sCZn6Ec-XTbcX1uRg2_u4xOEky0 4. Dropout - https://www.youtube.com/watch?v=D8PJAL-MZv8&index=6&list=PLkDaE6sCZn6Hn0vK8co82zjQtt3T2Nkqc
5. Appliedaicourse