1. Diagnóstico de cáncer de mamas

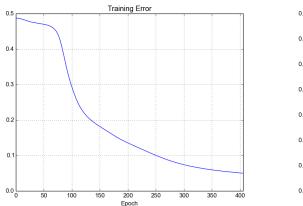
1.1. Ejemplos

La red elegida está compuesta por la capa de entrada con 10 neuronas (una por cada feature), una capa oculta con 12 neuronas y la capa de salida con una sola neurona.

1.1.1. Pruebas con distintos learning rates

Parámetros elegidos fijos:

- \bullet beta = 5
- \bullet mini_batch_size = 1
- \bullet epochs = 1000
- epsilon = 0.05
- $reg_param = 0.0$



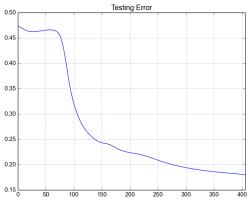
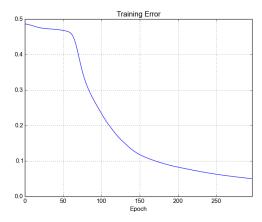


Figura 1: learning rate: 0.0075



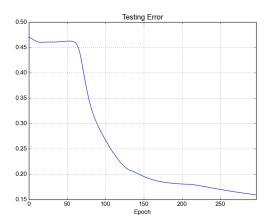


Figura 2: learning rate: 0.01

En estos gráficos se puede ver que el error fue menor a epsilon = 0,05. En el primero de ellos el coeficiente de aprendizaje utilizado es 0.0075 y en el segundo 0.01. Se observa que coeficiente de aprendizaje más pequeño el error sube. Por otro lado, se puede ver que cuanto más chico paso más épocas fueron necesarias para minimizar el error. Por lo que elegimos 0.01 como mejor learning rate.

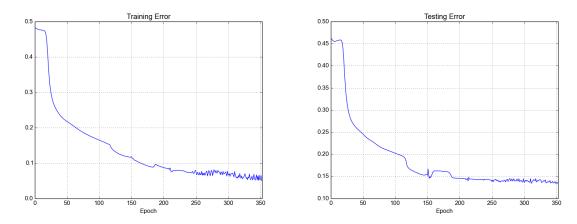


Figura 3: learning rate: 0.025

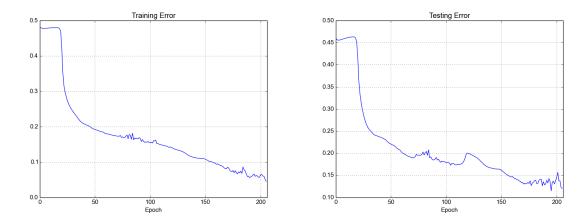


Figura 4: learning rate: 0.05

Estos dos gráficos muestran que al ser el coeficiente de aprendizaje es muy grande y se han encontrado mínimos locales por lo que el error empezó a oscilar. En estos casos, el error también fue menor a epsilon =0.05 pero fueron necesarias mayor cantidad de épocas para hacerlo. Estos learning rate no son óptimos para este modelo por lo que no son los elegidos.

1.2. Modo de Uso

Para entrenar la red:

Ejemplo:

python trainnet1.py -m TP1/models/ej1.lmodel -o ./salida.params -t 900 -e 0.05 -l 0.005 -b 1 -x TP1/ds/tp1_ej1_training.csv

Explicación:

- -m Ruta al archivo de modelo (lmodel)
- -o Ruta del archivo de salida con los pesos
- -t Epochs
- -e Epsilon
- -l Learning rate
- -b Size minibatch (default 1)
- -x Archivo de samples
- -m M Ruta al archivo de modelo (lmodel)
- -p O Ruta del archivo de entrada con los pesos
- -x X Archivo de features

Para predecir:

Ejemplo:

python predict1.py -m TP1/models/ej1.lmodel -p TP1/salida.params -x TP1/ds/tp1_ej1_training.csv

Explicación:

- -m Ruta al archivo de modelo (lmodel)
- -p Ruta del archivo de entrada con los pesos
- -x Archivo de features

1.3. Código fuente

Carga de datos

```
Ejercicio 1:
import numpy as np
from cStringIO import StringIO
from preprocessor import OutlierFilter, FeatureNormalizer
class Ej1DataLoader:
    def LoadData(self, fname):
        str_data=open (fname, "r").read()
        #Reemplazo M y B por enteros
        str_data = str_data.replace("B", "0")
        str_data = str_data.replace("M", "1")
        raw_data = np.genfromtxt(StringIO(str_data), delimiter=",")
        #np.random.shuffle(raw_data)
        #Primero filtramos labels con features, luego separamos
        transformed_data=OutlierFilter().process(raw_data)
        features = transformed_data[:, 1:]
        labels = transformed_data[:, 0]
        labels = labels.reshape((labels.shape[0],1))
        #Normalizamos features
        transformed_features = FeatureNormalizer().process(features)
        return [transformed_features, labels]
  Ejercicio 2:
import numpy as np
from preprocessor import OutlierFilter, FeatureNormalizer
class Ej2DataLoader:
   def LoadData(self):
        raw_data = np.genfromtxt('./ds/tp1_ej2_training.csv', delimiter=",")
        np.random.shuffle(raw_data)
        #Primero filtramos labels con features, luego separamos
        transformed_data=OutlierFilter().process(raw_data)
        \#transformed_data=FeatureNormalizer().process(transformed_data)
        features = transformed_data[:, 0:8]
        transformed_features = FeatureNormalizer().process(features)
        labels = transformed_data[:, 8:]
        transformed_labels = FeatureNormalizer().process(labels)
        transformed_labels = transformed_labels.reshape((transformed_labels.shape
        return [transformed_features, transformed_labels]
```

Preprocesamiento de datos

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

```
class FeatureNormalizer:
    def process(self, features):
____:param_features:_datos_a_normalizar
____:return:_devuelve_datos_normalizados_por_columna
        feature_means = np.mean(features, axis=0)
        features_std = np.std(features, axis=0)
        features_normalized = (features - feature_means) / features_std
        return features_normalized
class OutlierFilter:
    def process(self, features):
   ___:param_features:_datos
____:return:_datos_sin_outliers
        features_std = np.std(features, axis=0)
        feature_means = np.mean(features, axis=0)
        features_wo_outliers = np.array(filter(self.isOutlier(feature_means,
            features_std), features))
        # print(len(features), len(features_wo_outliers))
        # for i in range(len(features[0])):
        ##boxplot
        # fig = plt.figure(1, figsize=(9, 6))
        \# ax = fig.add\_subplot(111)
        \# bp = ax.boxplot([features[:,i],features_wo_outliers[:,i]])
        # plt.show()
        ##histograma de la 3era feature con cortes de outliers
        # plt.hist(features[:,i],bins=np.max(features[:,i])-np.min(features[:,i]))
        # plt.axvline(feature_means[i]-2*features_std[i], color='b',
                linestyle='dashed', linewidth=2)
        # plt.axvline(feature_means[i]+2*features_std[i], color='b',
                linestyle = 'dashed', linewidth = 2)
        # plt.show()
        # print("features_wo_outliers:", features_wo_outliers.shape)
        return features_wo_outliers
    def isOutlier(self, means, std):
        return lambda item: (np.abs(means - item) < 2 * std).all()
Modelo
import numpy as np
class LayerModel:
    # numInputUnits: Cantidad de unidades de entrada
    # hiddenLayers: Array con la cantidad de hidden layers de la red
    # numOutputLayers: Cantidad de unidades de salida
def __init__(self , layers):
        self._layers = layers
        self._layer_sizes = [l.get_num_layers() for l in layers]
        self._activations_fns = [l.activation for l in layers]
        self._derivative_fns = [i.derivative for l in layers]
        self._biases = [np.random.randn(y, 1) / 1000 for y in self._layer_sizes[1:]]
        self._weights = [np.random.randn(y, x) / 1000
                         for \ x, \ y \ in \ zip(self.\_layer\_sizes[:-1], \ self.\_layer\_sizes[1:])
        self._num_layers = len(self._layer_sizes)
    def getInitializedWeightMats(self):
        return self._weights
    def getInitializedBiasVectors(self):
```

```
return self._biases
    def getZeroDeltaW(self):
        return [np.zeros(w.shape) for w in self._weights]
    def getZeroDeltaB(self):
        return [np.zeros(b.shape) for b in self._biases]
    def activation(self, layer, z):
        return self._layers[layer].activation(z)
    def derivative(self, layer, z):
        return self._layers[layer].derivative(z)
    def getNumLayers(self):
        return self._num_layers
    def getLayerSizes(self):
        return self._layer_sizes
    def getActivationFns(self):
        return self._activations_fns
    def getDerivativeFns(self):
        return self._derivative_fns
import functools
import sigmoid
class Layer:
    def get_num_layers(self):
        return self._num_layers
    def activation(self, z):
        raise NotImplementedError('subclass_responsibility')
    def derivative(self, z):
        raise NotImplementedError('subclass_responsibility')
class SigmoidLayer (Layer):
    def __init__(self, num_layers, beta):
        self._num_layers = num_layers
        self._activation = functools.partial( sigmoid.sigmoid_array, beta)
        self._derivative = functools.partial( sigmoid.sigmoid_gradient_array, beta)
    def activation (self, z):
        return self._activation(z)
    def derivative(self, z):
        return self._derivative(z)
class InputLayer(Layer):
    def = -init_{--}(self, num\_layers):
        self._num_layers = num_layers
    def activation(self, z):
        raise NotImplementedError('input_layers_do_not_activate')
    def derivative(self, z):
        raise NotImplementedError('input_layers_do_not_define_derivative')
Funciones sigmoideas
import numpy as np
def sigmoid_array(b, x):
    return 1.0 / (1.0 + np.exp(-b * x))
def sigmoid_gradient_array(b, x):
```

```
return b * sigmoid_array(b, x) * (1.0 - sigmoid_array(b, x))
def sigmoid_tanh_array(b, x):
    return np.tanh(b * x)
def sigmoid_tanh_gradient_array(b, x):
    return b * (1 - (np.power(sigmoid_tanh_array(b, x), 2)))
Algoritmos
import numpy as np
from layer_model import LayerModel
import sigmoid
class NetworkSolver:
    def __init__(self, layer_model, weights, biases):
         self.\_weights = weights
         self._biases = biases
         self._layer_model = layer_model
    def do_activation(self, sample):
         aa = [np.reshape(sample, (len(sample), 1))]
         zz = []
         # Bias
         l = 0
         for b, w in zip(self._biases, self._weights):
             l = l + 1
             z = np.dot(w, aa[-1]) + b
              a = self.\_layer\_model.getActivationFns()[1](z)
             zz.append(z)
             aa.append(a)
         return (aa,zz)
    def do_backprop_and_return_grad(self, x, y):
         grad_w = self._layer_model.getZeroDeltaW()
         grad_b = self._layer_model.getZeroDeltaB()
         # feedforward
         activations, zs = self.do_activation(x)
         delta = (activations[-1] - np.reshape(y, (len(y), 1))) * self.\_layer\_model.
              \mathtt{getDerivativeFns}\,(\,)\,[\,-1\,](\,\mathtt{zs}\,[\,-1\,])
         \operatorname{grad}_{-b}[-1] = \operatorname{delta}
         \operatorname{grad_{-w}}[-1] = \operatorname{np.dot}(\operatorname{delta}, \operatorname{activations}[-2].\operatorname{transpose}())
         for l in xrange(2, self._layer_model.getNumLayers()):
             z = zs[-l]
              sp = self.\_layer\_model.getDerivativeFns()[-1](z)
              delta = np.dot(self._weights[-l+1].transpose(), delta) * sp
              grad_b[-1] = delta
              \operatorname{grad}_{-w}[-1] = \operatorname{np.dot}(\operatorname{delta}, \operatorname{activations}[-1-1], \operatorname{transpose}())
         return (grad_b, grad_w)
    def correction_mini_batch(self, mini_batch, lr, n, lmbda=0.0):
 .____: param_mini_batch: _set_de_entrenamiento
____:param_lr:_learning_rate
____:param_n:_cantidad_de_samples
____:param_lmbda:_regularization_parameter
         grad_b = [np.zeros(b.shape) for b in self._biases]
         grad_w = [np.zeros(w.shape) for w in self._weights]
         for x, y in mini_batch:
              delta\_grad\_b, delta\_grad\_w = self.do\_backprop\_and\_return\_grad(x, y)
              grad\_b \, = \, \left[ \, gb + deltagb \quad for \quad gb \, , \quad deltagb \quad in \quad zip \left( \, grad\_b \, , \quad delta\_grad\_b \, \right) \, \right]
              grad_w = [gw+deltagw for gw, deltagw in zip(grad_w, delta_grad_w)]
```

```
self._weights = [(1.0 - lr*(lmbda/n))*w - (lr/len(mini_batch)) * gw
                                                 for w, gw in zip(self._weights, grad_w)]
                #clasico sin regularizacion
                          self._weights = [w - (lr / len(mini_batch)) * gw
                                                   for w, gw in zip(self._weights, grad_w)]
                self._biases = [b - (lr / len(mini_batch)) * gb
for b, gb in zip(self._biases, grad_b)]
        def learn_minibatch(self, mini_batches, mini_batches_testing, lr, epochs, epsilon,
                 lmbda=0.0):
____:param_mini_batches: _set_de_entrenamiento
____:param_mini_batches_testing:_set_de_testing
____:param_lr:_learning_rate
____:param_epochs:_cantidad_de_epocas
____:param_epsilon:_cota_de_error
LULLULL: param_lmbda: _parametro_de_regularizacion , _si_no_se_especifica , _no_se_
       regulariza
\verb"lucus" imprime \verb"lerrores" a delentrenamiento \verb"ly" testing \verb"lpor" a cada \verb"lepoca" in the contraction of the contraction 
T = epochs
                t = 0
                e = 999
                n = sum([len(mbatch) for mbatch in mini_batches])
                while e > epsilon and t < T:
                         for b in mini_batches:
                               self.correction_mini_batch(b, lr, n, lmbda)
                         t = t + 1
                        e = self.get_prediction_error(mini_batches, False)
                         et = self.get_prediction_error(mini_batches_testing, False)
                         print ("Training_Error:_", e, "Val_error:", et)
                #e = self.get_prediction_error(mini_batches, True)
        def get_prediction_error(self, mini_batches, bprint):
                e = 0
                cant = 0
                for b in mini_batches:
                         for x, y in b:
                                 cant = cant + 1
                                 aa, zz = self.do_activation(x)
                                 e = e + np.linalg.norm(aa[-1] - y)
                                 if bprint:
                                         print e / cant, np.linalg.norm(aa[-1] - y), aa[-1][0][0], y[0]
                return e / cant
        def predict(self, batch):
                e = 0
                 for x, y in batch:
                        aa, zz = self.do_activation(x)
                        e = e + np. linalg.norm(aa[-1] - y)
                        print "Original: ", y[0], "Predicted: ",aa[-1][0]
                return e / len(batch)
        def get_hits(self, test_data):
             __:param_test_data:_set_de_datos_de_testing
____: return: _Devuelve_el_numero_de_aciertos_de_inputs_de_test_para_los_que
____los_outputs_que_devuelve_la_red_son_correctos.
                test_results = [(self.get_result(self.do_activation(x)[0][-1]), y)
                for (x, y) in test_data] return sum(int(x == y) for (x, y) in test_results)
        def get_result(self, act):
```

```
____:param_act:_resultado_de_nuestra_red
LLLLLL: return: Lellresultado Les Lellmas L cercano Lallresultado
____que_devolvio_la_red_entre_0_y_1
\begin{array}{ll} \textbf{return} & \text{np.argmin} \; ( \left[ \; \textbf{abs} \left( \; \text{act} \; -0 \right) \;, \; \; \textbf{abs} \left( \; \text{act} \; -1 \right) \; \right] \; ) \end{array}
Test
   Ejercicio 1:
import argparse
import ej1_data_loader
from model_io import ModelIO
from params_io import ParamsIO
from layer_model import LayerModel
from feed_forward_solver import NetworkSolver
import functools
parser = argparse.ArgumentParser(description='Parametros_de_la_red')
parser.add_argument('-m', type=str,
                      help='Ruta_al_archivo_de_modelo_(lmodel)', required=True)
parser.add_argument('-p', type=str,
                      help='Ruta_del_archivo_de_entrada_con_los_pesos', required=True)
parser.add_argument('-x', type=str, default=1,
                      help='Archivo_de_features', required=True)
args = parser.parse_args()
loader = ej1_data_loader.Ej1DataLoader()
data = loader.LoadData(args.x)
features = data[0] #shape=(333,10)
labels = data[1]
test_data = zip (features, labels)
mini_batches_testing = [test_data]
mloader = ModelIO()
model = mloader.load_model(args.m)
ploader = ParamsIO()
weights, biases = ploader.load_params(args.p)
solver = NetworkSolver (model, weights=weights, biases=biases)
E = solver.predict(mini_batches_testing[0])
print "Error_cuadratico_promedio:_", E
import argparse
import ej1_data_loader
from model_io import ModelIO
from params_io import ParamsIO
from layer_model import LayerModel
from feed_forward_solver import NetworkSolver
import functools
parser = argparse.ArgumentParser(description='Parametros_de_la_red')
parser.add_argument('-m', metavar='M', type=str,
                      help='Ruta_al_archivo_de_modelo_(lmodel)', required=True)
parser.add_argument('-o', metavar='O', type=str,
```

```
help='Ruta_del_archivo_de_salida_con_los_pesos', required=True)
parser.add_argument('-t', metavar='T', type=int,
                    help='Epochs', required=True)
parser.add_argument('-e', metavar='E', type=float,
                    help='Epsilon', required=True)
parser.add_argument('-1', metavar='L', type=float,
                    help='Learning_rate', required=True)
parser.add_argument('-b', metavar='B', type=int, default=1,
                    help='Size_minibatch_(default_1)', required=True)
parser.add_argument('-x', metavar='X', type=str, default=1,
                    help='Archivo_de_samples', required=True)
args = parser.parse_args()
loader = ej1_data_loader.Ej1DataLoader()
data = loader.LoadData(args.x)
features = data[0] \#shape=(333,10)
labels = data[1]
all_data = zip(features, labels)
num_training_samples = int(len(all_data) * 0.75)
num_test_samples = len(all_data) - num_training_samples
training_data = all_data [0:num_training_samples - 1]
test_data = all_data [num_training_samples:len(all_data) -1]
mini_batch_size = args.b
n = len(training_data)
mini_batches_training = [
                training_data[k:k+mini_batch_size]
                for k in xrange(0, num_training_samples - 1, mini_batch_size)]
mini_batches_testing = [
                test_data[k:k+mini_batch_size]
                for k in xrange(0, num_test_samples - 1, mini_batch_size)]
mloader = ModelIO()
model = mloader.load_model(args.m)
solver = NetworkSolver(model, weights=model.getInitializedWeightMats(), biases=model.
   getInitializedBiasVectors())
lr = args.l
epochs = args.t
epsilon = args.e
reg_param = 0.0
solver.learn_minibatch(mini_batches_training, mini_batches_testing, lr,epochs, epsilon,
   reg_param)
pio=ParamsIO()
pio.save_params( args.o , solver._weights, solver._biases)
print "Pesos_guardados_en_", args.o
  Ejercicio 2:
import sigmoid
import ej2_data_loader
from layer_model import LayerModel
from feed_forward_solver import NetworkSolver
import functools
loader = ej2_data_loader.Ej2DataLoader()
data = loader.LoadData()
features = data[0] #shape=(333,10)
labels = data[1]
all_data = zip (features, labels)
```

```
num_training_samples = int(len(all_data) * 0.75)
num_test_samples = len(all_data) - num_training_samples
training_data = all_data [0:num_training_samples - 1]
test_data = all_data [num_training_samples:len(all_data) -1]
mini_batch_size = 1
n = len(training_data)
beta = 0.01
mini_batches_training = [
                training_data[k:k+mini_batch_size]
                for k in xrange(0, num_training_samples - 1, mini_batch_size)]
mini_batches_testing = [
                test_data[k:k+mini_batch_size]
                for k in xrange(0, num_test_samples - 1, mini_batch_size)]
model = LayerModel([8,10,2], functools.partial(sigmoid.sigmoid.array,beta),functools
   .partial(sigmoid.sigmoid_gradient_array, beta))
solver = NetworkSolver(layer_model=model)
lr = 2.5
epochs = 1000
epsilon = 0.05
reg_param = 0.0
solver.learn_minibatch(mini_batches_training,mini_batches_testing,lr,epochs,epsilon,
   reg_param)
```