Fundamentals of Artificial Intelligence (57205HT16): Assignment 2 - Happy, Sad, Mischievous or Mad?

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1 Introduction

This report contains the documentation for a perceptron based classification system that guesses the emotional state of faces presented as input. The inputs are 20 x 20 pixel maps with 32 grey levels from white to black.

1.1 Running the program

The implementation is written in python 2.7 which means that a python 2.7 shell is required to run the implementation. Required program arguments are a search path to a training.txt, search path to an answer file training-facit.txt and a test file test-file.txt. The format of the training file should be the id of the image followed by the image on a new line. The answer file should be formatted as the image id follow by the correct answer (1,2,3 or 4).

Should the user fail to provide the required arguments, the program will immediately terminate with a massage explaining that not enough input arguments were provided.

Example usage of the program might look like:

```
python faces.py ../data/FaceTest/training-file.txt
../data/FaceTest/training-facit.txt test-file.txt
```

2 Problem description

The program works as such that it starts of by reading the *images*. An image consists of it's pixels (value from 0 - white to 31 - black) and it's ID (sad, mischievous, happy, mad). The program then filters the noise and then sends the images in the *Tutor* class. The tutor uses Perceptrons to learn what images look like (algorithm explained below). A perceptron is an algorithm for learning a binary classifier. Afterwards the Examiner class makes a guess and predicts which image belongs to which on a new set of image. The program will then output the percentage of the guesses that were correct.

2.1 Perceptron Learning Algorithm

The program implements an algorithm for supervised learning called *Perceptron Learning*. Supervised Learning is a technique for machine learning where the Artificial neural network is exposed to input and produces a guess based on the knowledge aquired from previous guesses. Since the desired output from the ANN, in supervised learning, is known for every input, the ANN is slightly modified with each iteration to eventually produce good outputs for every set of inputs.

The ANN in the produced program is composed by four different Perceptrons where each one represents one of the different facial expressions that are to be identified in the assignment.

Each perceptron is implemented in *Python* as a class composed by a list of 401 weights that mapps to the 400 pixel values that makes up an image. The additional weight is provided as a bias for the perceptron. A bias is used in order to shift the result of the activation function (more on that later) towards either the left or the right. I.e. to make the output more extreme so that it will produce a more distinct answer.

Training in the network occurs in the *Tutor* class where the provided set of training images is repetedly shown for each perceptron. The output from a perceptron, also known as *activation*, is computed using the formula:

$$a_i = act(\sum_j x_j * w_{j,i})$$

where x is the input, w is the weight and act is the activation function, which is the sigmoid function:

$$sigmoid(x) = 1/(1 + e^{-x})$$

The difference between the expected output and the actual output is the error e. The error e is then multiplied with the learning rate α and the pixel matrix to produce the gradient ∇w . This gradient is then added to every weight in the

internal weight matrix for each perceptron. This course of events can be described using the bellow formulas:

$$e_i = y_i - a_i$$

$$\nabla w_{j,i} = \alpha e_i x_j$$

$$w_{j,i} \leftarrow w_{j,i} + \nabla w_{j,i}$$

This process is repeated for the entire set of training images, however, only performing this process once would not produce very good results and therefore, when the network has used all the training data, the images are shuffled and the entire process described above is repeated.

The main problem encountered while training an ANN is finding the fine line right before the network gets overfitted. When the ANN gets overfitted, it becomes too specialized on the training data which will render it useless when exposed to previously unseen data. It is, however, still crucial to train the ANN as close to this limit as possible in order in order for it to be able to make generalizations to the data and produce decent output.

One way of determine when the network has reached the desired level of training is, for each iteration of the training data set, use a formula to compute the sum of the output errors for the network and end training when the value from this function gets below a predefined level. The function used in the current implementation is:

$$E = \frac{1}{2} \sum_{i=1}^{p} ||y^{(i)} - d^{(i)}||^2$$

Where p is the number of input/output vector pairs in the training set.

When the threshold for the error is reached, the perceptrons is deemed ready to passed on to the *Examiner* class where the network is exposed to the set of test images. Each image is shown to every perceptron in the network and the activation for each perceptron is recorded. The largest activation is chosen as the answer for

the network and is recorded into our list of answers. When every image in the test set has been classified the answers are printed to *stdout*.

3 Concluding discussion

The biggest difficulty was choosing which programming language to use. It was difficult choosing between Haskell and Python. Ultimately we chose Python as our knowledge in Haskell was not sufficient to write this program. It would be interesting to implement more AI and more specifically in machine learning programs in a functional programming language as it's easier to deal with concurrency. If you wanted to scale this program and have a larger neural network it might be necessary to add concurrency.

```
import sys
 import re
 from Enum import Enum
 from Perceptron import Perceptron
 from Tutor import Tutor
 from Utils import flatten
 from Examiner import Examiner
 from Image import Image
 # Program arguments: training-set, answer-set, examination-set (
     from spec)
11 \mid EXPECTED\_ARGS = 3
 Types = Enum(["HAPPY", "SAD", "MISCHIEVOUS", "MAD"])
 # Optimal values (derived from experiments):
_{15} # learning_rate = 0.01
 # threshold = 1
_{17} LEARNING RATE = 0.1
 THRESHOLD = 1
19
 def parse_ans(ans_file):
      Opens the provided answer file and extracts the answers
     which are
      returned as a list of integers. NON PURE FUNCTION!
      :param ans_file: path to answer file
      :return: list of integers
      12 = filter(lambda 1: len(1) > 0, map(get_answer, open(
     ans_file, 'r')))
      return flatten (12)
  def parse_img_file(image_file):
33
      Opens the provided image file and extracts its content into
      list of image objects that gets returned. NON PURE FUNCTION!
35
      :return: list of image objects
```

```
.....
37
      f = open(image_file, 'r')
      return reduce_img_file(f.readlines(), [])
39
41
  def reduce_img_file(lines, images):
43
      Consumes the lines of the image file in order to extract all
      the images and their ids. In the end it will return a list
45
      of image objects.
      :return: list om image objects
47
      if not lines: return images
49
      if re.search('Image', lines[0]) is not None:
          img = Image(extract_img_data(20, lines[1:]))
51
          return reduce_img_file(lines[20:], images + [img.set_id(
     lines [0])])
53
      return reduce_img_file(lines[1:], images)
55
 def extract_img_data(acc, lines):
57
      Sub consumes all the lines that contains an image row and
      returns a 2D array containing list of lists of integers
      :param acc: int representing how many more lines to read
61
      :param lines: the lines of the file
      :return: 2D array of integers
63
      if acc == 1: return [format_img_row(lines[0])[0]]
65
      return [format_img_row(lines[acc-1])[0]] + extract_img_data(
     acc - 1, lines)
67
 def format_img_row(row):
69
      format_img_row receives a row from the image file
     representing a pixel
      row in an image and returns it as a list of floats in [0,1)
      :param row: image pixel row
      :return: list of integers
75
      return map(lambda 1: map(lambda i: (float(i)/31), 1), map(
     lambda i: i.rstrip().split(' '), [row]))
77
```

```
def get_answer(line):
      get_answer retrieves the value for the answer from a line in
81
      answer file
      :param line: line from answer file
83
      :return: Integer representing the answer for the line
      return map(lambda s: int(s), re.findall(r' b d+b', line))
87
  def validate_arguments():
      makes sure that the user provided the right amount of
91
      arguments to the
      program, else: fail gracefully. NON PURE FUNCTION!
      :return:
93
      # Since program name is provided as additional first
95
      argument
      if len(sys.argv) < EXPECTED_ARGS + 1:</pre>
           print "This program expects exactly %d args. %d was
      provided "% \
                 (EXPECTED\_ARGS, len(sys.argv) - 1)
           sys.exit(0)
99
101
  def print_results(res_arr):
103
      Expects a list with formatted answer strings that gets
      printed to stdout
105
      if not res_arr: return
      print res_arr[0]
107
       print_results(res_arr[1:])
109
  def main():
      validate_arguments()
      perceptrons = (Perceptron (Types.HAPPY), Perceptron (Types.SAD
113
                      Perceptron (Types.MISCHIEVOUS), Perceptron (
      Types .MAD))
115
```

```
# Get content of the data files
img_list = parse_img_file(sys.argv[1])
ans_list = parse_ans(sys.argv[2])
test_set = parse_img_file(sys.argv[3])

# Link image and answer
images = map(lambda ans: img_list.pop(0).set_ans(ans),
ans_list)

trained_p = Tutor(perceptrons, images, LEARNING_RATE,
THRESHOLD).train()
print_results(Examiner(trained_p, test_set).examine())

if __name__ == "__main__":
    main()
```

../src/faces.py

```
class Enum(set):

""" Enum is a python 2.7 implementation of a Enum
provided by http://stackoverflow.com/a/2182437/4689625

def __getattr__(self, name):
    if name in self:
        return name
    raise AttributeError
```

../src/Enum.py

```
class Examiner:

Examiner is a class that, provided a set of trained neurons and test images, examines the training results of the network Attributes:

perceptrons: tuple of trained perceptrons
```

```
test_set: set of test images
      0.00
10
      def __init__(self, perceptrons, test_set):
          self.perceptrons = perceptrons
          self.test_set = test_set
14
      def examine(self):
16
          Tests the provided perceptrons on the provided set of
18
          : return: A list of formatted answer strings
20
          return map(self._make_guess, self.test_set)
      def _make_guess(self, image):
24
          Exposes the provided image to the network and returns a
     string
          that is compliant with the specification of what a guess
26
      should
          look like
          :return:
          guess = self._expose_perceptrons(image, {"type": 0, "
30
     activation": 0}, self.perceptrons)
          return self._format_answer(image, guess["type"])
32
      def _expose_perceptrons(self, image, current_guess,
     perceptrons):
34
          Shows an image to all of the perceptrons and returns the
      largest
          activation from the network
36
          :param image: image to show
          :param current_guess: The previous largest activation in
38
      the network
          :param perceptrons: consumed list of perceptrons
          : return:
40
42
          if not perceptrons: return current_guess
          activation = perceptrons[0].process(image)
          if activation > current_guess["activation"]:
44
              current_guess = self._update_guess(activation,
```

```
perceptrons [0])
46
          return self._expose_perceptrons(image, current_guess,
     perceptrons [1:])
48
      def _update_guess(self , activation , perceptron):
50
          Returns a new dictionary containing the activation for
     the
          perceptron type
          return {"type": perceptron.get_type_id(), "activation":
54
     activation }
      def _format_answer(self, img, guess):
56
          Returns properly formatted string based on the networks
58
     guess of
          the provided image
60
          return "" + img.get_id() + " " + str(guess)
```

../src/Examiner.py

```
import Utils
 FILTER_VAL = float(3)/float(32) # Derived from experiments
 class Image:
      Image represents an image that holds a list of pixels, id,
     and what
      facial expression the image represents.
      Attributes:
          img: list of pixel values
          id: the id of the image on format ImageXX
11
          ans: integer 1-4 representing what facial expression the
      img represents
      .....
13
      def __init__(self, img):
          self.img = self._preprocess_img(img)
```

```
self.id = None
          self.ans = None
17
      def _preprocess_img(self, img):
19
          Performs preprocessing operations in order to sanitize
21
          the input data so that it contains what we expects.
23
          i1 = Utils.flatten(img)
          i1.append(1)
          return map(self._filter_noise, i1)
27
      def _filter_noise(self, pix):
29
          Since the images contains a lot of noise, we're
     filtering
          away those pixels that wont't impact the result other
31
     than
          to make it unambiguous.
33
          return pix if pix > FILTER_VAL else float(0)
35
      def get_img(self):
37
          Returns the pixel data for the image as a list of
     integers
          return self.img
41
      def set_ans(self, ans):
43
          Updates the answer for the image. Should be a single
     integer
          between 1-4
45
          self.ans = ans
47
          return self
49
      def get_ans(self):
51
          Returns the answer as an integer between 1-4
53
          return self.ans
55
      def set_id(self, id):
```

```
Updates the id of the image

self.id = str(id).rstrip()

return self

def get_id(self):

Returns the id of the image

"""

return self.id
```

../src/Image.py

```
import random
  import math
 from Utils import *
  class Perceptron:
      Perceptron represents a perceptron in the network. A
     perceptron
     represent one of the four feelings specified in the TYPE
     It reacts to an input image with a response based on it's
     training.
      Attributes:
11
          TYPES: mapping of the perceptron type and type id
          weights: a list of weights that maps to image pixels
          type_id: the type id of the perceptron
15
      def __init__(self , percept_type):
17
          self.TYPES = {"HAPPY": 1, "SAD": 2, "MISCHIEVOUS": 3, "
     MAD": 4}
          self.weights = self._generate_weights(401)
19
          self.type_id = self.TYPES[percept_type]
      def process(self, img):
23
```

```
Uses the formula sum(w[i], x[i]) from lecture notes to
     process an image
          :return: summed weight of inputs
25
          11 = apply(float.__mul__, img.get_img(), self.weights)
27
          return self._act(sum(11))
29
      def _act(self, val):
          Computes the activation for the perceptron based on the
     sum of the
          weighted input
33
          :param val: summed weight in input
          :return: activation of the perceptron
35
          return 1 / (1 + math.exp(-val))
37
      def update_weight(self, dw):
39
          adds the provided delta error for the last iteration to
41
     each
          value in the internal weight matrix according to lecture
      notes
          : return: None
43
          self.weights = apply(float.__add__, flatten(dw), self.
45
     weights)
      def get_type_id(self):
47
          Returns the type id for this perceptron. Consult the
49
     type
          type attribute for explanation of the meaning of the
     returned
51
          :return: type id as an integer [1, 4]
53
          return self.type_id
55
      def _generate_weights(self, acc):
57
          Returns a list of the specified length containing pseudo
          random values in interval [0.0, 1.0)
59
          :param acc: length of the list to generate
          :return: list of pseudo random floats
61
```

```
return [random.random()] if acc == 1 else self.
_generate_weights(acc-1) + [random.random()]
```

../src/Perceptron.py

```
import random
  from Utils import mmult, flatten
 class Tutor:
      Tutor represents a supervisor object that is responsible for
      training a
      set of perceptrons using a provided set of training images
     until a
      certain level of correctness is reached.
      Attributes:
          perceptrons: a tuple of perceptrons to train
          images: a list of image objects to train on
          learning_rate: value specifying how quickly the network
13
     should learn
          threshold: the value that indicates when to stop
     training
15
      def __init__(self, perceptrons, images, learning_rate,
17
     threshold):
          self.perceptrons = perceptrons
          self.images = images
          self.learning_rate = learning_rate
          self.threshold = threshold
      def train(self):
          Trains the perceptrons provided to this object with the
25
     provided
          using the provided training images until the desired
     threshold
          for the sum squared error of the network is reached. The
27
      trained
```

```
perceptrons are returned as a tuple.
29
          self._do_training([])
          return self.perceptrons
      def _do_training(self, errors):
          This function is what actually does what's described in
35
     the train
          method. This separation is done so that the user of this
      method is
          not bothered by the fact that the method is implemented
37
     recursively.
          if self._accurate(errors): return self
39
          random.shuffle(self.images)
          self._do_training(flatten(map(self._each_perceptron,
41
     self.images)))
      def _each_perceptron(self, image):
43
          Shows the provided image to all the perceptrons and
45
     returns a list
          containing the error for every perceptron.
47
          return map(lambda p: self._expose(image, p), self.
     perceptrons)
49
      def get_perceptrons(self):
51
          get_perceptrons returns a tuple of perceptrons. This
     method returns
          the perceptrons in their current state. The train()
53
     method should be
          called until desired MSE is achieved before a call to
     this method
          makes sense.
55
          :return: perceptrons as a tuple
          return self.perceptrons
59
      def _expose(self, image, perceptron):
61
          Shows the provided image to the specific perceptron and
     uses the
```

```
formula for perceptron learning from lecture notes to
63
     update the
          internal weights in the perceptron based on the delta
     error
          for the perceptron on the image.
65
          :return:
          0.00
67
          err = self._error(self._desired(image, perceptron),
     perceptron . process(image))
          dw = self._delta_weight(image, err)
69
          perceptron.update_weight(dw)
          return err
71
      def _delta_weight(self , inp , err):
73
          Uses the formula (error * learning rate * input) from
75
     lecture notes
          to produce the delta error for the activation of the
     perceptron
          which is returned.
77
          :param inp: the perceptron input (image)
          :param out: desired output, either 0 or 1
79
          :param act: the activation of the perceptron
          :return:
81
          return mmult(inp.get_img(), self.learning_rate * err)
83
      def _error(self, out, act):
85
          Computes the error between the desired output and the
87
     actual activation
          return out - act
89
      def _accurate(self, err_list):
91
          Determines the size of the error using the formula for
93
     computing
          the error of a network provided over at:
          http://lcn.epfl.ch/tutorial/english/perceptron/html/
95
     learning.html
          Uses the user provided threshold value to determine
     whether the
          network performs well enough.
97
```

```
if not err_list: return False
99
           mse = (sum(map(lambda x: x**2, err_list)))/2
           return mse < self.threshold</pre>
101
      def _desired(self, img, percept):
103
           Compares the provided image and perceptron to determine
105
      whether
           the neuron should be firing on the image. The decision
      i s
           represented as either 0 or 1.
107
           :return: 1 or 0 if the neuron should fire
109
           return int(img.get_ans() == percept.get_type_id())
```

../src/Tutor.py

```
def mmult(m, c):
      Receives a matrix and returns a new matrix
      where every element in the matrix is multiplied
      by the provided constant
      :param m: matrix
      :param c: constant
      :return: new matrix with the applied constant
10
      return map(lambda x: x * c, m)
14
  def msum(m):
16
      Returns the sum of every element in the matrix
18
      return sum(map(sum, m))
20
 def apply(op, 11, 12):
      Returns a list of the same length as 11 and 12 where each
24
```

```
index is the result of the provided operation on 11[i] & 12[
     NOTE: Shadows built in function apply but since it is
26
     deprecated
      since version 2.3 we don't care.
      Reference: https://docs.python.org/2/library/functions.html#
28
     apply
     return map(lambda tup: op(float(tup[0]), float(tup[1])), zip
30
     (11, 12)
32
 def flatten(1):
34
      Receives a nested list and returns all the values in a
          Example: [[1], [2, 3], 4] \rightarrow [1, 2, 3, 4]
      :return: flattened list
38
      if not 1: return 1
      return flatten(1[0]) + flatten(1[1:]) if isinstance(1[0],
40
     list) else 1[:1] + flatten(1[1:])
```

../src/Utils.py