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solution

This branch is 8 commits ahead, 10 commits behind master.

bpurdy-ds fixed 3 typos ... 2 weeks ago 9

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README.md

Introduction to Neural Networks - Lab

Introduction

In this lab, you'll practice everything you have learned during the lecture. We know there is quite a bit of math involved, but don't worry! Using Python and trying things out yourself will actually make a lot of things much more clear! Before we start, let's load some necessary libraries so we can import our data.

Objectives

In this lab you will:

- Import images using Keras
- Build a "shallow" neural network from scratch

As usual, we'll start by importing the necessary packages that we'll use in this lab.

```python
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import array_to_img, img_to_array, load_img
import numpy as np
import os
```

In this lab, you'll import a bunch of images to correctly classify them as "Santa", meaning that Santa is present on the image or "not Santa" meaning that something else is in the images.

If you have a look at this GitHub repository, you'll notice that the images are simply stored in `.jpeg` files and stored under the folder `'/data'`. Luckily, `keras` has great modules that make importing images stored in this type of format easy. We'll do this for you in the cell below.

The images in the `'/data'` folder have various resolutions. We will reshape them so they are all 64 x 64 pixels.

Run the code as you see it below.

```python
# Directory path
train_data_dir = 'data/train'
test_data_dir = 'data/validation'

# Get all the data in the directory data/validation (132 images), and reshape them
test_generator = ImageDataGenerator().flow_from_directory(
        test_data_dir,
        target_size=(64, 64), batch_size=132)

# Get all the data in the directory data/train (790 images), and reshape them
train_generator = ImageDataGenerator().flow_from_directory(
        train_data_dir,
        target_size=(64, 64), batch_size=790)

# Create the datasets
train_images, train_labels = next(train_generator)
test_images, test_labels = next(test_generator)
```

```
Found 132 images belonging to 2 classes.
Found 790 images belonging to 2 classes.
```

Inspect and prepare data

Look at some images

Note that we have four numpy arrays now: `train_images` , `train_labels` , `test_images` , and `test_labels` . We'll need to make some changes to the data in order to work with them, but before we do anything else, let's have a look at some of the images we loaded in `train_images` . You can use `array_to_img()` from `keras.processing.image` on any image (select any `train_image` using `train_image[index]` to look at it).

```
array_to_img(train_images[10])
```


```
array_to_img(train_images[130])
```

The shape of data

Now, let's use `np.shape()` to look at what these numpy arrays look like.

```
print(np.shape(train_images))
print(np.shape(train_labels))
print(np.shape(test_images))
print(np.shape(test_labels))
```

```
(790, 64, 64, 3)
(790, 2)
(132, 64, 64, 3)
(132, 2)
```

`train_images` and `test_images`

Let's start with `train_images`. From the lesson, you might remember that the expected input shape is n x l. How does this relate to what we see here?

l denotes the number of observations, or the number of images. The number of images in `train_images` is 790. n is the number of elements in the feature vector for each image, or put differently, n is the number of rows when unrowing the 3 (RGB) 64 x 64 matrices.

So, translated to this example, we need to transform our `(790, 64, 64, 3)` matrix to a `(64*64*3, 790)` matrix!

> Hint: You should use both the `.reshape()` method and then transpose the result using `.T`.

```
# Reshape the train images
train_img_unrow = train_images.reshape(790, -1).T
```

Verify that the shape of the the newly created `train_img_unrow` is correct.

```
# Preview the shape of train_img_unrow
np.shape(train_img_unrow)
```

```
(12288, 790)
```

Next, let's transform `test_images` in a similar way. Note that the dimensions are different here! Where we needed to have a matrix shape of n x l for `train_images`; for `test_images`, we need to get to a shape of n x m. What is m here?

```
# Define appropriate m
m = 132
test_img_unrow = test_images.reshape(m, -1).T
```

```
# Preview the shape of test_img_unrow
np.shape(test_img_unrow)
```

```
(12288, 132)
```

`train_labels` and `test_labels`

Earlier, you noticed that `train_labels` and `test_labels` have shapes of $(790, 2)$ and $(132, 2)$ respectively. In the lesson, we expected 1 x l and 1 x m.

Let's have a closer look.

```
train_labels
```

```
array([[1., 0.],
       [0., 1.],
       [1., 0.],
       ...,
       [0., 1.],
       [0., 1.],
       [0., 1.]], dtype=float32)
```

Looking at this, it's clear that for each observation (or image), `train_labels` doesn't simply have an output of 1 or 0, but a pair - either `[0, 1]` or `[1, 0]` .

Having this information, we still don't know which pair corresponds with `santa` versus `not_santa` . Luckily, this was stored using `keras.preprocessing_image` , and you can get more info using the command `train_generator.class_indices` .

```
train_generator.class_indices
```

```
{'not_santa': 0, 'santa': 1}
```

Index 0 (the first column) represents `not_santa` , index 1 represents `santa` . Select one of the two columns and transpose the result such that you get 1 x l and 1 x m vectors respectively, and value `1` represents `santa` .

```
train_labels_final = train_labels.T[[1]]
```

```
np.shape(train_labels_final)
```

```
(1, 790)
```

```
test_labels_final = test_labels.T[[1]]
```

```
np.shape(test_labels_final)
```

```
(1, 132)
```

As a final sanity check, look at an image and the corresponding label, so we're sure that santa is indeed stored as 1.

- First, use `array_to_image()` again on the original `train_images` with index 240 to look at this particular image
- Use `train_labels_final` to get the 240th label

```
array_to_img(train_images[240])
```

```
train_labels_final[:,240]
```

```
array([1.], dtype=float32)
```

This seems to be correct! Feel free to try out other indices as well.

Standardize the data

Remember that each RGB pixel in an image takes a value between 0 and 255. In Deep Learning, it is very common to standardize and/or center your dataset. For images, a common thing that is done is to make sure each pixel value is between 0 and 1. This can be done by dividing the entire matrix by 255. Do this here for the `train_img_unrow` and `test_img_unrow`.

```
train_img_final = train_img_unrow/255
test_img_final = test_img_unrow/255
```

```
type(test_img_unrow)
```

```
numpy.ndarray
```

Build a logistic regression-based neural network

Math recap

Now we can go ahead and build our own basic logistic regression-based neural network to distinguish images with Santa from images without Santa. You saw in the lesson that logistic regression can actually be represented as a very simple neural network.

Remember that we defined that, for each $x^{(i)}$:

$$\mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = -\big(y^{(i)}\log(\hat{y}^{(i)}) + (1-y^{(i)})\log(1-\hat{y}^{(i)})\big)$$

$$\hat{y}^{(i)} = \sigma(z^{(i)}) = \frac{1}{1+e^{-(z^{(i)})}}$$

$$z^{(i)} = w^T x^{(i)} + b$$

The cost function is then given by:

$$J(w,b) = \frac{1}{l}\sum_{i=1}^{l}\mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

In the remainder of this lab, you'll do the following:

- Initialize the parameters of the model
- Perform forward propagation, and calculate the current loss
- Perform backward propagation (which is basically calculating the current gradient)
- Update the parameters (gradient descent)

Parameter initialization

w and b are the unknown parameters to start with:

- remember that b is a scalar
- w however, is a vector of shape n x 1, with n being `horizontal_pixel x vertical_pixel x 3`

Initialize b

Initialize b as a scalar with value 0.

```
b = 0
```

Initialize w

Define a function `init_w()` , with a parameter `n` . The function should return an array with zeros that has a shape n x 1.

```
def init_w(n):
    w = np.zeros((n, 1))
    return w
```

```
w = init_w(64*64*3)
```

Forward propagation

In forward propagation, you:

- get `x`
- compute `y_hat` :

$$(\hat{y}^{(1)}, \hat{y}^{(2)}, \ldots, \hat{y}^{(l)}) = \sigma(w^T x + b) = \left(\frac{1}{1 + exp(w^T x^{(1)} + b)}, \ldots, \frac{1}{1 + exp(w^T x^{(l)} + b)}\right)$$

- You calculate the `cost` function: $J(w, b) = -\frac{1}{l} \sum_{i=1}^{l} y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})$

Here are the two formulas you will be using to compute the gradients. Don't be scared by the mathematics. The long formulas are just to show that this corresponds with what we derived in the lesson!

$$\frac{dJ(w,b)}{dw} = \frac{1}{l} \sum_{i=1}^{l} \frac{d\mathcal{L}(\hat{y}^{(i)}, y^{(i)})}{dw} = \frac{1}{l} \sum_{i=1}^{l} x^{(i)} dz^{(i)} = \frac{1}{l} \sum_{i=1}^{l} x^{(i)} (\hat{y}^{(i)} - y^{(i)}) = \frac{1}{l} x(\hat{y} - y)^T$$

$$\frac{dJ(w,b)}{db} = \frac{1}{l} \sum_{i=1}^{l} \frac{d\mathcal{L}(\hat{y}^{(i)}, y^{(i)})}{db} = \frac{1}{l} \sum_{i=1}^{l} dz^{(i)} = \frac{1}{l} \sum_{i=1}^{l} (\hat{y}^{(i)} - y^{(i)})$$

```
def propagation(w, b, x, y):
    l = x.shape[1]
    y_hat = 1/(1 + np.exp(- (np.dot(w.T, x) + b)))
    cost = -(1/l) * np.sum(y * np.log(y_hat) + (1-y)* np.log(1 - y_hat))
    dw = (1/l) * np.dot(x,(y_hat - y).T)
    db = (1/l) * np.sum(y_hat - y)
    return dw, db, cost
```

```
dw, db, cost = propagation(w, b, train_img_final, train_labels_final)
```

```
print(dw)

print(db)

print(cost)
```

```
[[-0.05784065]
 [-0.05436336]
 [-0.06367089]
 ...
 [-0.07482998]
 [-0.06692231]
 [-0.07262596]]
-0.01139240506329114
0.6931471805599452
```

Optimization

Next, in the optimization step, we have to update w and b as follows:

$$w := w - \alpha * dw$$

Note that this `optimization()` function uses the `propagation()` function. It loops over the `propagation()` function in each iteration, and updates both w and b right after that!

```
def optimization(w, b, x, y, num_iterations, learning_rate, print_cost = False):

    costs = []

    for i in range(num_iterations):
```

```
        dw, db, cost = propagation(w, b, x, y)
        w = w - learning_rate*dw
        b = b - learning_rate*db

        # Record the costs and print them every 50 iterations
        if i % 50 == 0:
            costs.append(cost)
        if print_cost and i % 50 == 0:
            print ("Cost after iteration %i: %f" %(i, cost))

    return w, b, costs
```

```
w, b, costs = optimization(w, b, train_img_final, train_labels_final,
                           num_iterations= 151, learning_rate = 0.0001, print_cost =
```

```
Cost after iteration 0: 0.693147
Cost after iteration 50: 0.675005
Cost after iteration 100: 0.668414
Cost after iteration 150: 0.662114
```

Make label predictions: Santa or not?

Next, let's create a function that makes label predictions. We'll later use this when we will look at our Santa pictures. What we want is a label that is equal to 1 when the predicted y is bigger than 0.5, and 0 otherwise.

```
def prediction(w, b, x):
    l = x.shape[1]
    y_prediction = np.zeros((1, l))
    w = w.reshape(x.shape[0], 1)
    y_hat = 1/(1 + np.exp(- (np.dot(w.T, x) + b)))
    p = y_hat

    for i in range(y_hat.shape[1]):
        if (y_hat[0,i] > 0.5):
            y_prediction[0, i] = 1
        else:
            y_prediction[0, i] = 0
    return y_prediction
```

Let's try this out on a small example. Make sure you have 4 predictions in your output here!

```
w = np.array([[0.035], [0.123], [0.217]])
b = 0.2
x = np.array([[0.2, 0.4, -1.2, -2],
              [1, -2., 0.1, -1],
              [0.2, 0.4, -1.2, -2]])

prediction(w, b, x)
```

```
array([[1., 1., 0., 0.]])
```

The overall model

Now, let's build the overall model!

```
def model(x_train, y_train, x_test, y_test, num_iterations = 2000, learning_rate = 0

    b = 0
    w = init_w(np.shape(x_train)[0])

    # Gradient descent (≈ 1 line of code)
    w, b, costs = optimization(w, b, x_train, y_train, num_iterations, learning_rate

    y_pred_test = prediction(w, b, x_test)
    y_pred_train = prediction(w, b, x_train)

    # Print train/test errors
    print('train accuracy: {} %'.format(100 - np.mean(np.abs(y_pred_train - y_train)
    print('test accuracy: {} %'.format(100 - np.mean(np.abs(y_pred_test - y_test)) *

    output = {'costs': costs,
              'y_pred_test': y_pred_test,
              'y_pred_train' : y_pred_train,
              'w' : w,
              'b' : b,
              'learning_rate' : learning_rate,
              'num_iterations': num_iterations}

    return output
```

```
# ⏰ Expect your code to take several minutes to run
output = model(train_img_final, train_labels_final, test_img_final, test_labels_fina
               num_iterations=2000, learning_rate=0.005, print_cost=True)
```

```
Cost after iteration 0: 0.693147
Cost after iteration 50: 0.880402
Cost after iteration 100: 0.763331
Cost after iteration 150: 0.628797
Cost after iteration 200: 0.518186
Cost after iteration 250: 0.442320
Cost after iteration 300: 0.391254
Cost after iteration 350: 0.354488
Cost after iteration 400: 0.326262
Cost after iteration 450: 0.304070
Cost after iteration 500: 0.287473
Cost after iteration 550: 0.276690
Cost after iteration 600: 0.269139
Cost after iteration 650: 0.262364
Cost after iteration 700: 0.255995
Cost after iteration 750: 0.249976
Cost after iteration 800: 0.244271
Cost after iteration 850: 0.238848
Cost after iteration 900: 0.233684
Cost after iteration 950: 0.228756
Cost after iteration 1000: 0.224046
Cost after iteration 1050: 0.219537
Cost after iteration 1100: 0.215215
Cost after iteration 1150: 0.211066
Cost after iteration 1200: 0.207080
Cost after iteration 1250: 0.203246
Cost after iteration 1300: 0.199553
Cost after iteration 1350: 0.195995
Cost after iteration 1400: 0.192562
Cost after iteration 1450: 0.189248
Cost after iteration 1500: 0.186047
Cost after iteration 1550: 0.182951
Cost after iteration 1600: 0.179957
Cost after iteration 1650: 0.177057
Cost after iteration 1700: 0.174249
Cost after iteration 1750: 0.171527
Cost after iteration 1800: 0.168887
Cost after iteration 1850: 0.166326
Cost after iteration 1900: 0.163839
Cost after iteration 1950: 0.161424
```

```
train accuracy: 96.9620253164557 %
test accuracy: 75.0 %
```

Summary

Well done! In this lab you built your first neural network in order to identify images of Santa! In the upcoming labs you'll see how to extend your neural networks to include a larger number of layers and how to then successively prune these complex schemas to improve test and train accuracies.

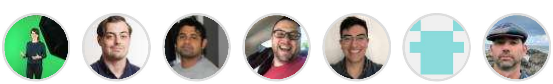
Releases

No releases published

Packages

No packages published

Contributors 7



Languages

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