

CS 5600/6600: F20: Intelligent Systems

Assignment 1

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Learning Objectives

1. Perceptrons
2. Perceptron Networks

Introduction

Like most of the upcoming assignments for this course, this assignment has two components: technical reading/writing and coding. The technical reading/writing problem is the first in a series of reading/writing assignments that ask you to read a paper and write its technical analysis. All these papers are written by AI masters. While their writing may be occasionally dense, their ideas are profound. Most of those ideas continue to shape AI today.

These papers will give you additional information and background on the issues discussed in class and, possibly and more importantly, some ideas for your final projects or long-term research directions. I am not expecting from you an in-depth understanding and mastery of every issue discussed in the paper. My objective is more modest – to get you to think about various AI-related problems.

Don't think that if a paper is written a long time ago and uses some unfamiliar terminology, it's somehow less relevant than a paper full of recent buzzwords (e.g., deep learning, data science, cloud computing, etc.) written this year or within the past 5 years. The key concepts of calculus, classical mechanics, and number theory that are driving the developments in such branches of science as fluid dynamics, aviation, and cryptography are centuries old. In AI, if a paper discusses a problem that you haven't heard about, more often than not it means that AI, as a field, has failed to solve it and moved on to other lower hanging fruit, as frequently happens in many branches of science due to the cut-throat publish-or-perish attitude.

Some students, when writing their analyses, start to recite the paper to fill up space. This problem is not specific to students. I regularly write peer reviews for different journals and observe this problem in many submissions that come across my desk. And, I've done it on occasion, too, to meet the strict page requirements for some conferences or journals. But, do your best to avoid reciting the paper just for the sake of filling up space. You'll have only one page to write. If you need to cite some sentence/paragraph/section, by all means do so, but do it to support the point you're trying to make. You can always use phrases like "I agree with the authors' point in paragraph X on page Y, because ..." or "I disagree with the point the authors make in Section Z, because ..." etc. I am (and as my fellow scientists/researchers you should also be) interested in your analyses of the authors' arguments. If you agree/disagree with a point, briefly explain why. If you find something inspiring, say so and outline the things that you feel inspired to do after reading the paper.

The coding problems ask you to code up simple perceptrons in Python (use Python 3), which will drive home the material discussed in Lectures 1 and 2 and make sure that your Python installation is up and ready for the remainder of the semester. I've given some installation links and pointers in the syllabus pdf (see the Announcements Section for this class in Canvas).

Problem 1 (2 points)

Read the included paper "A Logical Calculus of the Ideas Immanent in Nervous Activity" by McCulloch and Pitts ([McCullochPittsPaper.pdf](#)) and write a one page analysis of this paper. Your font size should be no larger than 11 and your analysis should include four components: 1) a brief statement of the problems addressed in the paper in your own words; 2) what you agree with/like in the paper and why; 3) what you disagree with/dislike in the paper and why; 4) any

inspirations you found in the paper. Each of these points should be addressed in a separate paragraph. Save your summary in `mcculloch_and_pitts.pdf` for Canvas submission.

Problem 2 (1 point)

Implement the binary `and`, `or`, and `not` perceptrons as Python classes. In each class the `__init__()` function initializes the `weights` and `bias` attributes to appropriate values. As we discussed in class, there are multiple ways of building these perceptrons by using different weights and biases. The `output()` takes a 2-element binary numpy array as input and outputs 0 or 1 as computed by the perceptron. The starter code is in `cs5600_6600_f20_hw01.py`. The unit tests are in `cs5600_6600_f20_hw01_uts.py`.

Below's unit test 1 that tests the `and`-perceptron. Unit tests 2 and 3 test the `or`- and `not`-perceptrons.

```
def test_assgn_01_ut_01(self):
    print('\n***** Assign 01: UT 01 *****')
    x00 = np.array([0, 0])
    x01 = np.array([0, 1])
    x10 = np.array([1, 0])
    x11 = np.array([1, 1])
    andp = and_percep()
    assert andp.output(x00) == 0
    assert andp.output(x01) == 0
    assert andp.output(x10) == 0
    assert andp.output(x11) == 1
    print('Assign 01: UT 01: passed...')
```

Use your implementations of the above perceptrons to implement the binary `xor` perceptron that consists of 2 `and`-perceptrons, 1 `or`-perceptron, and 1 `not`-perceptron, as discussed in class. The `__init__()` function constructs the four perceptrons as attributes and the `output()` function takes a 2-element binary numpy array and uses the `output` attributes of the four attribute perceptrons to produce the required output (i.e., 0 or 1). The starter code is in `cs5600_6600_f20_hw01.py`. Unit test 4 (see below) in `cs5600_6600_f20_hw01_uts.py` will test your implementation of the `xor`-perceptron.

```
def test_assgn_01_ut_04(self):
    print('\n***** Assign 01: UT 04 *****')
    x00 = np.array([0, 0])
    x01 = np.array([0, 1])
    x10 = np.array([1, 0])
    x11 = np.array([1, 1])
    xorp = xor_percep()
    assert xorp.output(x00) == 0
    assert xorp.output(x01) == 1
    assert xorp.output(x10) == 1
    assert xorp.output(x11) == 0
    print('Assign 01: Unit Test 04: passed...')
```

Problem 3 (1 point)

Now implement another `xor` perceptron class, call it `xor_perceptron2`, that implements the `xor` logic directly, i.e., in terms of cells, connections, and biases, and not in terms of other perceptrons. This perceptron takes as input a 2-element binary numpy array and outputs a 1-element binary numpy array. The starter code is in `cs5600_6600_f20_hw01.py`. Unit test 5 (see below) in `cs5600_6600_f20_hw01_uts.py` will test your implementation of the `xor`-perceptron.

```
def test_assgn_01_ut_05(self):
    print('\n***** Assign 01: UT 05 *****')
    x00 = np.array([0, 0])
    x01 = np.array([0, 1])
    x10 = np.array([1, 0])
    x11 = np.array([1, 1])
    xorp2 = xor_percep2()
```

```

assert xorp2.output(x00)[0] == 0
assert xorp2.output(x01)[0] == 1
assert xorp2.output(x10)[0] == 1
assert xorp2.output(x11)[0] == 0
print('Assign 01: UT 05: passed...')

```

Problem 4 (1 point)

This problem will drive home the point that networks of perceptrons can be built to simulate arbitrary logical gates. Implement the class `percep_net` that runs a small network of perceptrons to simulate the logical expression $((x_0 \vee x_1) \wedge \neg x_2) \vee x_3$, where \vee stands for logical or, \wedge for logical and, and \neg for logical not. The starter code is in `cs5600_6600_f20_hw01.py`. Unit test 6 (see below) in `cs5600_6600_f20_hw01_uts.py` will test your implementation of your perceptron network.

```

def test_hw01_ut06(self):
    print('\n***** Assign 01: UT 06 *****')
    pn = percep_net()
    x0000 = np.array([0, 0, 0, 0])
    x0100 = np.array([0, 1, 0, 0])
    x1100 = np.array([1, 1, 0, 0])
    x1101 = np.array([1, 1, 0, 1])
    x1110 = np.array([1, 1, 1, 0])
    assert pn.output(x0000) == 0
    assert pn.output(x0100) == 1
    assert pn.output(x1100) == 1
    assert pn.output(x1101) == 1
    assert pn.output(x1110) == 0
    print('Assign 01: UT 06 passed...')

```

What To Submit

Save your 1-page analysis for Problem 1 in `mcculloch_and_pitts.pdf`. Save and code your solutions to problems 2, 3, 4 in `cs5600_6600_f20_hw01.py`. Zip these two files as `hw01.zip` and submit the zip in Canvas.

Happy Reading, Writing, and Hacking!