

1.1

As mentioned in the class, a learning algorithm receives as input a training set S sampled from an unknown distribution \mathcal{D} and labeled by some target function f. Since the learner does not know what \mathcal{D} and f are, we use a training set of examples, which acts as a snapshot of the world that is available to the learner. In ERM we would like to find a solution that works well on that data.

An aligned circle classifier in the plane is a classifier that assigns the value 1 to a point if and only if it is inside a certain circle. Formally, given a point (c_1, c_2) and a radius r, define the classifier $h(c_1, c_2, r)$ by,

$$h(x; c_1, c_2, r) = \begin{cases} 1 & \text{if } \sqrt{(c_1 - x_1)^2 + (c_1 - x_2)^2} \le r \\ 0 & \text{otherwise} \end{cases}$$

Let A be the algorithm that returns the smallest circle enclosing all positive examples in the training set. Explain why A is **NOT** an ERM.

Note: We rely on the realizability assumption.

1.2

Let \mathcal{H} be the hypothesis space of binary classifiers over a domain \mathcal{X} . Let \mathcal{D} be an unknown distribution over \mathcal{X} , and let f be the target hypothesis in \mathcal{H} . Denote $h \in \mathcal{H}$. Let us define the *true error* of h as,

$$L_{\mathcal{D}}(h) = \mathbb{P}_{x \sim \mathcal{D}}[h(x) \neq f(x)]$$

Let us define the *empirical error* of h over the training set S as,

$$L_S(h) = \frac{1}{m} \sum_{i=1}^{m} \mathbb{1}_{[h(x) \neq f(x)]}$$

where m is the number of training examples.

Show that the expected value of $L_S(h)$ over the choice of S equals $L_D(h)$, namely,

$$\mathbb{E}_{S \sim \mathcal{D}} \big[L_s(h) \big] = L_{\mathcal{D}}(h)$$

2 Sound Compression

Guidelines

- 1. You are not allowed to use external packages other than numpy and scipy.
- In order to submit your solution please upload your files to Submit and check your inbox for the feedback mail.
- 3. Technical questions about this exercise should be asked at the course' piazza.
- 4. Private/Personal issues regarding the deadline should be directed to Yosi shrem.

In this part of the exercise we will use the k-means algorithm for sound compression, i.e. you should implement the k-means algorithm on the **amplitude values** and then replace each value by its centroid.

You should implement the k-means algorithm as described in class (slide no. 15 in recitation 2 presentation). You will train your algorithm and report results using the sample.wav as shown in Figure 1. For visualization, you can use Praat (http://www.fon.hum.uva.nl/praat/) (Nonmandatory for this exercise)

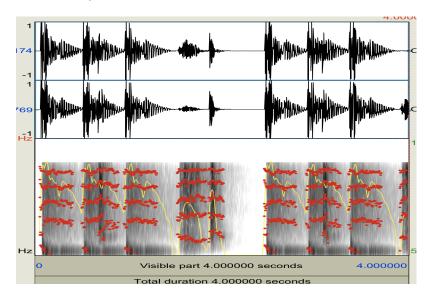


Figure 1: sample.wav

The centroids initialization will be provided to you in a text file which will be received as an argument to your program. The run command to your program should be:

\$ python ex_1.py <wav_file_path> <centroinds_init_path>
For example:

\$ python ex_1.py sample.wav cents1.txt

```
sample,centroids = sys.argv[1],sys.argv[2]
fs, y = scipy.io.wavfile.read(sample) #reading
x=np.array(y.copy())
centroids=np.loadtxt(centroids)

#your code goes here#
...
...
scipy.io.wavfile.write("compressed.wav", fs, np.array(new_values, dtype=np.int16))#saving
```

The following snippet contains commands for reading and writing sound files as well as reading the centroids initialization:

When displaying your compressed file you should get similar results to the following,

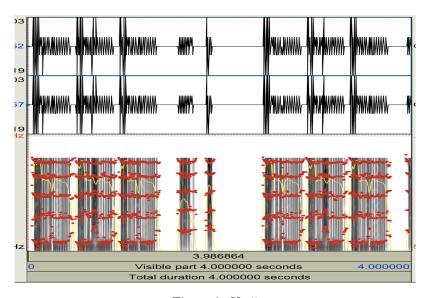


Figure 2: K=5

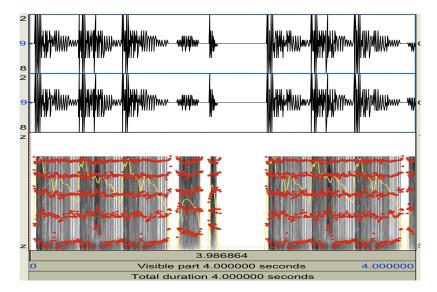


Figure 3: K=10

Reproducibility. Originally, the initial centroids in k-means are randomly generated. For reproducible purposes we provided you with the centroids initialization. Moreover, In case when 2 centroids are evenly close to a certain point, the one with the lower index "wins". To evaluate your program outputs, we provided you with 2 examples - cents1.txt and cents3.txt for centroid initialization, and with output1.txt and output3.txt the requested outputs. Please note that given these pre-defined values, your sequence of centroid updates should be deterministic and not random in any way.

Note: Your code should run for 30 iterations or until convergence. Your program should **create** a file named **output.txt**, consisting of your centroids after each centroid update step as follows:

For example, when using cents3.txt the requested out should be:

As you can see the algorithm converged and stopped (same centroids). For consistency, after each centroids update, use the built-in round() function on each dimension. We define convergence when the centroids don't update.

The sample.wav was taken from here: https://www.youtube.com/watch?v=7vQ831z0528

(Lucille Crew - Something).

Lastly, your code can not run on the u2 servers, to overcome formatting issues, we ask you to run your code using the cents2.txt as the centroids initialization, and then manually change the filename from output.txt to output2.txt. Once submitted you will get a feedback email describing whether the expected output matches the requested format- check it and correct if needed. Part of your grade will consist of automatic checks - follow the format guidelines.

3 What to submit?

You should submit the following files:

- A txt file, named details.txt with your name and ID.
- A PDF file named ex_1.pdf with your answers to 1.1 and 1.2.
- Python 3.6+ code for question 2. Your main function should reside in a file called ex_1.py. The main function writes the centroids to output.txt as explained above.
- A txt file named output2.txt Your program's output when using the cents2.txt for initialization.(i.e. run your code using the cents2.txt and then manually change the filename from output.txt to output2.txt)
- A PDF report including the following plots: The average loss/cost value as a function of the iterations (you can stop at 10) for k = 2, 4, 8, 16 (4 plots in total). Explain shortly about your centroids initialization process.

Overall: ex_1.py, ex_1.pdf, details.txt, output2.txt and report.pdf

Good Luck!