CS4013/5013 Assignment 2

Fall 2025

Due Date: Oct 3, 2025.

Note: Written tasks will be posted on Canvas. Below is the description of programming tasks.

In this assignment, we will implement and apply search techniques to estimate some correlation in data. In the following, we will first describe the data, then formalize the estimation problem, and finally approach it from a search perspective. Assignment tasks are detailed at the end.

1. A Credit Card Application Data Set

We have a data set 'CreditCard.csv' which contains the profile of 340 credit card applicants and their application results. Figure 1 is a screenshot of the data set, where each row contains the information of one applicant and the columns are attributes with the following interpretations.

– CreditApprove: '1' means application approved, '0' means denied. (Figure 1 only shows '1'.)

– Gender: 'M' means male, 'F' means female. You should encode 'M' to 1 and 'F' to 0.

– CarOwner: 'Y' means yes, 'N' means no. You should encode 'Y' to 1 and 'N' to 0.

– PropertyOwner: 'Y' mean yes, 'N' means no. You should encode 'Y' to 1 and 'N' to 0.

– #Children: number of children.

– WorkPhone: '1' means the applicant has a work phone, '0' means otherwise.

– Email: '1' means the applicant has an email ID, '0' means otherwise.

Note our data set is a subset of the public Credit Card data set[1].

2. The Correlation Estimation Problem

Let x denote an applicant and y be his/her application result. Suppose there is a linear relation between x's attributes and y, and we aim to approximate it using the following function

$$f(x) = w_1 \cdot x^{(1)} + w_2 \cdot x^{(2)} + w_3 \cdot x^{(3)} + w_4 \cdot x^{(4)} + w_5 \cdot x^{(5)} + w_6 \cdot x^{(6)}, \tag{1}$$

where $x^{(j)}$ is the j_{th} attribute of x in the above table i.e., $x^{(1)}$ is gender, ..., $x^{(6)}$ is email. To facilitate later discussion, let us write $w := [w^{(1)}, w^{(2)}, w^{(3)}, w^{(4)}, w^{(5)}, w^{(6)}]$.

The w_j's are unknown parameters of the function taking values in $\{-1, +1\}$. Our goal is to find w_j's that give the best approximation i.e., minimize the following approximation error

$$er(w) := \frac{1}{n} \sum_{i=1}^{n} (f(x_i) - y_i)^2, \tag{2}$$

where x_i is the i_{th} applicant, y_i is his/her application result and n is the number of applicants in the data set. In our problem, $n = 340$.

[1] https://www.kaggle.com/datasets/rohitudageri/credit-card-details

Applicant_ID	CreditApprove	Gender	CarOwner?	PropertyOwner?	#Children	WorkPhone?	Email?
5008827	1	M	Y	Y	0	0	0
5009744	1	F	Y	N	0	1	0
5009746	1	F	Y	N	0	1	0
5009749	1	F	Y	N	0	1	0
5009752	1	F	Y	N	0	1	0
5009754	1	F	Y	N	0	1	0
5009894	1	F	N	N	0	0	0
5010864	1	M	Y	Y	1	0	1
5010868	1	M	Y	Y	1	0	1
5010869	1	M	Y	Y	1	0	1
5018498	1	F	Y	Y	0	1	0
5018501	1	F	Y	Y	0	1	0
5018503	1	F	Y	Y	0	1	0
5021303	1	M	N	N	1	0	1
5021310	1	M	N	Y	0	0	0
5021314	1	M	N	Y	0	0	0
5021430	1	F	N	Y	0	0	0
5021431	1	F	N	Y	0	0	0
5021998	1	M	N	Y	0	0	1
5022053	1	M	N	N	0	0	0

Figure 1:

Problem $\min_w er(w)$ would be easier to solve if w_j's are continuous (e.g., by taking derivative of $er(w)$). But we have assumed $w_j \in \{-1, +1\}$ for better interpretability of the estimated relation (which simply tells us which attributes are useful but not the degree of their usefulness). This makes $\min_w er(w)$ an integer programming problem that is harder to solve.

3. Approach Estimation from a Search Perspective

We can approach $\min_w er(w)$ from a 'search' perspective. First, understand that there are many possible w's which may or may not minimize $er(w)$. Below are three examples

– $w = [1, 1, -1, -1, 1, -1]$

– $w = [-1, -1, -1, -1, 1, 1]$

– $w = [1, 1, 1, 1, 1, 1]$

Now, we can apply search techniques to find an optimal w, and optimality is measured by $er(w)$. Below is an example search process.

Step 1. Initialize $w = [-1, -1, -1, -1, -1, -1]$ is an initial solution (randomly picked)

Step 2. Pick the next solution e.g., $w' = [1, 1, 1, 1, 1, 1]$. If $er(w') < er(w)$, update $w = w'$.

Step 3. Repeat step 2 until convergence.

Note different search techniques pick the next w with different strategies e.g., local search picks w' that is adjacent to w (with a proper definition of adjacency) and evolutionary search generates w' with proper probability.

Also note the above example process only picks and examines one w' at a time, while some search techniques may pick and examine a bag of w''s at a time (and update w to the best).

Programming Tasks

Task 1. Implement hill climbing local search algorithm and apply it to find the w that (aims to) minimize $er(w)$. Recall that in each round of local search, we examine all solutions adjacent to the current solution and identify the best one. We define adjacency as follows:

Two solutions w and w' are adjacent if they differ by exactly one element e.g., $w = [1, 1, 1, 1, 1, 1]$ and $w' = [-1, 1, 1, 1, 1, 1]$ are adjacent, so are $w = [-1, -1, 1, 1, 1, 1]$ and $w' = [-1, -1, 1, 1, -1, 1]$.

After implementation, you need to present two results below.

– In Figure 2, plot a curve of $er(w)$ versus the round of search. The x-axis of this figure is the round of search and the y-axis of this figure is $er(w)$. Your figure should include enough rounds so we can see $er(w)$ converges.

Figure 2:

– Present the optimal w and $er(w)$ returned by your search algorithm below.

$$w = \tag{3}$$

$$er(w) = \tag{4}$$

Task 2. Implement the genetic algorithm and apply it to find w that (aims to) minimize $er(w)$. Treat each w as a chromosome (note it is a binary string) and treat $e^{-er(w)}$ as fitness function. You can configure the genetic algorithm by yourself. But here are some suggestions

– Do not set the population size too large. Keep in mind w contains only six binary variables, which means there are at most $2^6 = 64$ different w's.

– Set the number of parents that come together to form offspring to 2.

– When you select chromosomes to be the parents of the next generation, select them based on probabilities proportional to their fitness values. You can generate probabilities by normalization e.g., suppose there are three candidate chromosomes in with fitness values $0.1, 2, 0.8$, then their selection probabilities can be computed as

$$0.1 \rightarrow \frac{0.1}{0.1 + 2 + 0.8} = 0.034 \tag{5}$$

$$2 \rightarrow \frac{2}{0.1 + 2 + 0.8} = 0.689 \tag{6}$$

$$0.8 \rightarrow 1 - 0.034 - 0.689 = 0.277 \tag{7}$$

– Fix the crossover point to the middle of w i.e., the first three elements of one w gets to be recombined with the last elements of another w'.

– Set the mutation rate by yourself. Try small values first.

After implementation, you need to present two results (based on your chosen configuration) below.

– In Figure 3, plot a curve of $er(w)$ versus generation. The x-axis of this figure is the round of generation and the y-axis of this figure is $er(w)$. Your figure should include enough generations so we can see $er(w)$ converges.

Figure 3:

– Present the optimal w and $er(w)$ returned by your search algorithm below.

$$w = \tag{8}$$

$$er(w) = \tag{9}$$

Submissions Instructions

You should generate 6 results for the programming tasks, including

(1) a figure of $er(w)$ versus search round for local search, placed in Figure 2.

(2) optimal w and $er(w)$ returned by local search, placed in equations (3) and (4)

(3) a figure of $er(w)$ versus generation for genetic algorithm, place in Figure 3

(4) optimal w and $er(w)$ returned by genetic algorithm, placed in equations (8) and (9)

(5) a Python code named 'hw2_local.py' that generates the figure in (1)

(6) a Python code named 'hw2_genetic.py' that generates the figure in (2)

You should place results (1)(2)(3)(4) in a pdf file named 'hw2.pdf' and upload it to Canvas through the submission page for hw2. You also need to upload hw2_local.py and hw2_genetic.py.

A latex template 'hw2_Latex.txt' will be provided.