TERM: M1-RAIA

SEMESTER: 2

AY: 2022-2023

Abdelbacet Mhamdi

Dr.-Ing. in Electrical Engineering

Senior Lecturer at ISET Bizerte

abdelbacet.mhamdi@bizerte.r-iset.tn

ARTIFICIAL INTELLIGENCE - PART 2

LAB MANUAL



Higher Institute of Technological Studies of Bizerte

Available @ https://github.com/a-mhamdi/jlai/

Honor code

THE UNIVERSITY OF NORTH CAROLINA AT CHAPEL HILL

Department of Physics and Astronomy

http://physics.unc.edu/undergraduate-program/labs/general-info/

"During this course, you will be working with one or more partners with whom you may discuss any points concerning laboratory work. However, you must write your lab report, in your own words.

Lab reports that contain identical language are not acceptable, so do not copy your lab partner's writing.

If there is a problem with your data, include an explanation in your report. Recognition of a mistake and a well-reasoned explanation is more important than having high-quality data, and will be rewarded accordingly by your instructor. A lab report containing data that is inconsistent with the original data sheet will be considered a violation of the Honor Code.

Falsification of data or plagiarism of a report will result in prosecution of the offender(s) under the University Honor Code.

On your first lab report you must write out the entire honor pledge:

The work presented in this report is my own, and the data was obtained by my lab partner and me during the lab period.

On future reports, you may simply write <u>"Laboratory Honor Pledge"</u> and sign your name."

Contents

1	Linear Regression	1
2	Classification	5
3	K-Means for Clustering	8
4	Project Assessment	12

In order to activate the virtual environment and launch **Jupyter Notebook**, we recommend you to proceed as follow

- ① Press simultaneously the keys 🎜 & 📳 on the keyboard. This will open the dialog box Run;
- ② Then enter cmd in the command line and confirm with [key on the keyboard;
- ③ Type the instruction <code>jlai.bat</code> in the console prompt line;



Finally press the key.

LEAVE THE SYSTEM CONSOLE ACTIVE.

1 Linear Regression

Student's name				
Score /20				
Detailed Credits				
Anticipation (4 points)				
Management (2 points)				
Testing (7 points)				
Data Logging (3 points)				



Interpretation (4 points)

In order to conduct the labs effectively, it is highly recommended to check the codes available at $https://github.com/a-mhamdi/jlai/ \rightarrow Codes \rightarrow Julia \rightarrow Part-2 \rightarrow .*regression.*jl$

Linear regression is a type of **Machine Learning** (ML) algorithm that is used to predict a continuous outcome variable based on one or more predictor variables. It is a type of regression analysis that models the relationship between the dependent variable y, aka target, and the independent variable x, aka feature, by fitting a straight line to the data. This line can then be used to make predictions about the value y based on the values of x. Linear regression is a simple and popular method for modeling relationships in data and is often used as a starting point for more complex ML algorithms.

Hereafter is an example of how we might implement linear regression in Julia:



```
# Define the input data
X = [0 2; 1 1; -1 0.5; 1 5] # matrix of input data
y = [2; 3; 4; 5] # vector of output values
```

1. Linear Regression 2

```
#= NORMAL EQUATION =#
5
   # Compute the coefficients using the normal equation
   coefficients = (X' * X) \setminus X' * y
   # Print the coefficients
   println("Coefficients are $coefficients")
10
11
   # Define some test input
   x_{test} = [1 6]
13
   # Compute the predicted output
14
   y_pred = x_test * coefficients
15
   # Print the predicted output
16
   println("Predicted output is $y_pred")
17
              #= LOADING `LinearRegressor` FROM `MLJLinearModels` =#
19
20
   # Import the required library
21
   using MLJ
22
   LR = @load LinearRegressor pkg=MLJLinearModels
   lr_ = LR(fit_intercept=false)
25
   \# Bind an instance of `lr_` to training data
26
   lr = machine(lr_, table(X), y) |> fit!
27
   # Display the fitted parameters
28
   println("Fitted parameters are $(fitted_params(lr))")
   # Recall the same previously defined test input
31
   x_{test} = [1 6]
32
   # Compute the predicted output
33
  y_hat = predict(lr, x_test)
   # Print the predicted output
   println("Predicted output is $y_hat")
```

▼ Remark 1

If you want to avoid the warning that pops up at the REPL, it is more convenient to coerce to continuous the scitypes of data being fed to model in machine when using **MLJ** package. You can further check the documentation by typing:

julia> @doc MLJLinearModels.LinearRegression

1. Linear Regression 3

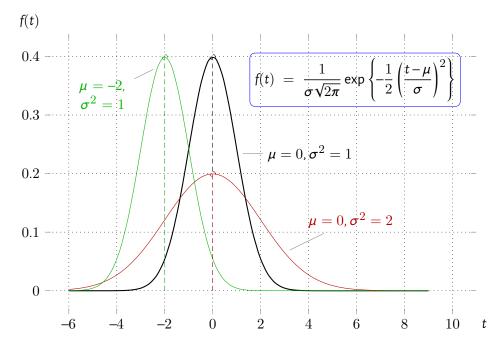
Exercise Nº 1:

 x_1 and x_2 both are vectors of 10000 random values. x_1 is an array of float values sampled from a normal distribution with mean equal to $\mu=-3$ and a standard deviation fixed to $\sigma=2.7$. The step change could be set at 0.01. The elements of x_2 are however integer values depicted from a uniform distribution ranging from -8 to 4.

- a) Write Julia code to generate and plot histograms of x_1 and x_2
- **b)** Standardize x_1 using the package **Distributions** at first, and then **MLJ**.
- c) Normalize x_2
- **d)** Say that we have a target $y = -x_1 + 3.5x_2$
 - Generate the vector *y*;
 - By applying normal equation, do you get $\hat{ heta} = \begin{bmatrix} -1 & 3.5 \end{bmatrix}^{\mathsf{T}}$
 - Using **MLJ** package, load a linear regression model, bind an instance of it to the data in $X = \text{hcat}(x_1, x_2)$. Compute $\hat{\theta}$ again.

▼ Remark 2

The graphs of some continuous univariate normal distributions are shown below:



1. Linear Regression 4



Model refers to the mathematical formula or equation that is used to make predictions based on the data.

Coefficient represent the strength and direction of the relationship between a particular predictor variable and the predicted variable.

Residual is the difference between the actual and predicted outputs. It is used to measure the goodness of fit of the model.

2 Classification

Student's name				
Score /20				
Detailed Credits				
Anticipation (4 points)				
Management (2 points)				
Testing (7 points)				
Data Logging (3 points)				
Interpretation (4 points)				

In order to conduct the labs effectively, it is highly recommended to check the codes available at https://github.com/a-mhamdi/jlai/ \rightarrow Codes \rightarrow Julia \rightarrow Part-2 \rightarrow {logistic-regression.jl, knn.jl & svc.jl}

Logistic regression is a popular type of statistical model that is used to predict the likelihood of an event occurring. It is a type of regression analysis that is generally used when the dependent variable is binary, meaning it can only take on one of two values, such as 0 or 1.

The output of a k-nearest neighbors (k-**NN**) model is a class membership (e.g. "cat" or "dog"). To make a prediction for a new data point, the algorithm finds the closest data points in the training set (i.e. the "nearest neighbors") and assigns, through the majority vote of their outputs mechanism, as the prediction for the new data point. The number of nearest neighbors (k) is a hyperparameter that must be specified in advance.

*k***-NN** is a simple and effective algorithm, but it can be computationally expensive and is not suitable for large datasets. It is also sensitive to the scale and distribution of the data.

Support vector machines (**SVM**s) are a powerful and flexible tool for solving a wide range of machine learning problems, and have been widely used in many different fields, including text classification,

2. Classification 6

image classification, and bioinformatics.

Hereafter is an example of how we might implement these types of classifiers in Julia:



```
using MLJ
1
   # Load the data
   X, y = make_blobs(100, 2; centers=2, cluster_std=[2., -1.])
   # Transform data into dataframe
  using DataFrames
   df = DataFrame(X)
   df.y = y
9
   first(df, 5)
10
11
   # Draw the scatter plot of features.
12
   using Plots
13
   scatter(df.x1, df.x2; group=df.y)
14
15
   # Load the classifiers `LR`, `KNN`, and `SVC`
16
   LR = @load LogisticClassifier pkg=MLJLinearModels
17
   KNN = @load KNNClassifier pkg=NearestNeighborModels
   SVC = @load SVC pkg=LIBSVM
19
20
   # Construct the pipelines
21
   lr_pipe_ = Standardizer() |> LR()
22
   knn_pipe_ = Standardizer() |> KNN()
   svc_pipe_ = Standardizer() |> SVC()
24
25
   # Feed and fit training data to pipelines
26
   lr_pipe = machine(lr_pipe_, X, y) |> fit!
27
   knn_pipe = machine(knn_pipe_, X, y) |> fit!
   svc_pipe = machine(svc_pipe_, X, y) |> fit!
30
   # Make evaluations
31
   evaluate!(lr_pipe, operation=predict_mode, measures=f1score)
32
   evaluate!(knn_pipe, operation=predict_mode, measures=f1score)
33
   evaluate!(svc_pipe, operation=predict, measures=f1score)
```

In this example, X is a table of 100 observations. It is formed by two predictors (aka features) and y is a vector of target labels (aka class labels).

2. Classification 7

Exercise Nº 2:

Consider the Fisher's classic <u>iris</u> dataset. The measurements are from 3 different species of <u>iris</u>: setosa, versicolor and virginica. There are 50 examples of each species. There are 4 measurements for each example: sepal length, sepal width, petal length and petal width. The measurements are in centimeters.

- a) Write a code that prepares a pipeline, a composite model which allows, at first, to standardize the features and then load the logistic classifier.
 - Evaluate the performances of your pipeline using a cross-validation set. Provide the measures you know as input argument to the 'evaluate!' function.
 - Write a code that draws the confusion matrix as shown by the builtin function 'confusion_matrix'.
 - Given the results you got, write a code to compute the accuracy, precision, recall and f1-score.
- **b)** Repeat the same steps for *k***-NN** classifier
- c) Apply the same process as before to a **SVM** classifier.

▼ Remark 3

If you want to load the iris dataset using **MLJ**, you can simply type:

julia> using MLJ
julia> X, y = @load_iris



Model refers to the mathematical formula or equation that is used to make the most plausible predictions based on the input data.

Class designates a group or a category to which a data point belongs. For example, in a classification task to predict whether an email is spam or not, the classes would be "spam" and "not spam".

Probability of a data point belonging to a particular class is often used to make predictions. For example, if a model predicts that a given email has a 90% probability of being spam, it is likely to be classified as spam.

3 K-Means for Clustering

Student's name				
Score /20				
Detailed Credits				
Anticipation (4 points)				
Management (2 points)				
Testing (7 points)				
Data Logging (3 points)				
Interpretation (4 points)				



The notebook is available at https://github.com/a-mhamdi/jlai/ \rightarrow Codes \rightarrow Julia \rightarrow Part-2 \rightarrow kmeans.il

K-Means clustering is a method of unsupervised learning in machine learning. It is used to divide a dataset into a specified number (k) of clusters, with each cluster containing data points that are similar to each other. The goal of the algorithm is to minimize the within-cluster sum of squares, which measures the similarity of the data points within each cluster.

To perform K-Means clustering, the algorithm first randomly selects k data points from the dataset and assigns them to be the centroids of the k clusters. It then computes the distance between each data point and each centroid, and assigns each data point to the cluster whose centroid is closest to it. The algorithm then updates the centroids of each cluster by taking the mean of all of the data points in the cluster. This process is repeated until the centroids of the clusters no longer change, or until a maximum number of iterations is reached.

K-Means clustering is often used for exploratory data analysis, to identify underlying patterns and structures in a dataset. It is also commonly used in data compression, where it is used to group similar data points together

K-Means is a clustering algorithm that is used to partition a dataset into a specified number of clusters. Here are two examples of K-means implemented in Julia:



```
using Clustering
1
2
    function kmeans(X::Array{T, 2}, k::Int) where {T <: Real}
3
       # Initialize cluster centers randomly
       centers = zeros(k, size(X, 2))
       for i in 1:k
6
          centers[i, :] = X[rand(1:size(X, 1)), :]
       end
          # Repeat until convergence
          converged = false
11
          while !converged
12
          # Calculate distances between each point and each cluster center
13
          dists = pairwise(Euclidean(), X, centers)
14
15
          # Assign each point to the closest cluster center
          clusters = argmin(dists, dims=1)
17
18
          # Calculate the new cluster centers as the mean of all points in
19
     ⊶the cluster
          new_centers = zeros(k, size(X, 2))
20
          for i in 1:k
21
             if sum(clusters .== i) > 0
22
                new_centers[i, :] = mean(X[clusters .== i, :], dims=1)
             else
24
                # If a cluster is empty, randomly initialize a new center
25
                new_centers[i, :] = X[rand(1:size(X, 1)), :]
26
             end
27
          end
28
          # Check for convergence
30
          converged = isapprox(centers, new_centers, rtol=1e-6)
31
32
          # Update the cluster centers
33
          centers = new_centers
       end
35
36
```

```
return centers, clusters
end
```

```
## Import Librairies
1
    using CSV, DataFrames
2
3
    ## Load The Dataset From CSV File
4
    df = CSV.read("./datasets/Mall_Customers.csv", DataFrame);
6
    ## Take A Look @ Data
7
    first(df, 5)
8
    income = df[!, 4];
    ss = df[!, 5];
10
11
    ## Plots PKG
12
    using Plots
13
    scatter(income, ss, legend=false)
14
15
    ## Clustering PKG
16
    using Clustering
17
18
    ## Features Construction
19
    X = hcat(ss, income);
20
    typeof(X)
21
    hat_clusters = kmeans(X', 5; display=:iter)
22
23
    ## Scatter Plot
24
    scatter(ss, income, marker_z=hat_clusters.assignments,
25
        color=:winter,
26
        legend=false)
27
28
    scatter!(hat_clusters.centers[1,:]', hat_clusters.centers[2,:]',
29
        color=:black,
30
        labels=["#1" "#2" "#3" "#4" "#5"],
31
        legend=true)
32
```

This implementation uses the *Clustering* package to calculate distances. It takes as input the dataset X and the number of clusters k, and returns the cluster centers and the cluster assignments of each point.



Cluster It refers to a group of data points that are similar to one another.

Centroid In clustering algorithms such as *K*-Means, the centroid of a cluster is the mean of all the data points in that cluster.

Distance It measures are used to determine how similar or dissimilar two data points are. The distance between two points is often used to determine which points belong in the same cluster.

4 Project Assessment

The final project will offer you the possibility to cover in depth a topic discussed in class which interests you, and you like to know more about it. The overall goal is to provide you with a challenging but achievable assessment that allows you to demonstrate your knowledge and skills in fuzzy logic or neural networks.

Here are some potential machine learning projects that you could consider:

Predicting stock prices: You could try building a model to predict future stock prices using historical data and financial news articles.

Sentiment analysis: You could build a model to classify text data (such as movie reviews or social media posts) as positive, negative, or neutral.

Fraud detection: You could build a model to identify fraudulent transactions in a dataset of credit card or bank transactions.

Image classification: You could build a model to classify images into different categories (such as animals, objects, or scenes).

Spam filtering: You could build a model to classify emails as spam or not spam.

Customer segmentation: You could build a model to cluster customers into different groups based on their characteristics and behavior.

Speech recognition: You could build a model to transcribe spoken words into text.

Recommendation systems: You could build a model to recommend products, movies, or other items to users based on their past behavior and preferences.

You have to provide all necessary resources, such as sample code, relevant datasets, as well as creating a set of slides to present your work. You are expected to demonstrate your understanding of the material covered throughout this course, as well as familiarizing yourselves with relevant programming languages and libraries. The final project is comprised of:

- 1. proposal;
- 2. report documenting your work, results and conclusions;
- 3. presentation;

4. source code (You should share your project on **GITHUB**.)



It is about two pages long. It includes:

- · Title
- · Datasets (If needed!)
- · Idea
- Software (Not limited to what you have seen in class)
- Related papers (Include at least one relevant paper)
- Teammate (Teams of three to four students. You should highlight each partner's contribution)



It is about ten pages long. It revolves around the following key takeaways:

- Context (Input(s) and output(s))
- · Motivation (Why?)
- · Previous work (Literature review)
- · Flowchart of code, results and analysis
- · Contribution parts (Who did what?)

Typesetting using Let is a bonus. You can use LyX (https://www.lyx.org/) editor. A template is available at https://github.com/a-mhamdi/jlai/tree/main/Codes/Report. Here what your report might contain:

- 1. Provide a summary which gives a brief overview of the main points and conclusions of the report.
- 2. Use headings and subheadings to organize the main points and the relationships between the different sections.
- 3. Provide an outline or a list of topics that the report will cover. Including a table of contents can help to quickly and easily find specific sections of your report.
- 4. Use visuals: Including visual elements such as graphs, charts, and tables can help to communicate the content of a report more effectively. Visuals can help to convey complex information in a more accessible and intuitive way.

If you used Julia, you can generate the documentation using the package **Documenter.jl**. It is a great way to create professional-looking material. It allows to easily write and organize documentation using a variety of markup languages, including **Markdown** and **MTEX**, and provides a number of features to help create a polished and user-friendly documentation website.

I will assess your work based on the quality of your code and slides, as well as your ability to effectively explain and demonstrate your understanding of the topic. I will also consider the creativity and originality of your projects, and your ability to apply what you have learned to real-world situations. I also make myself available to answer any questions or provide feedback as you work on your projects.

The overall scope of this manual is to introduce **Artificial Intelligence (AI)**, through either some numerical simulations or hands-on training, to the students enrolled in the master's program **RAIA**.

The topics discussed in this manuscript are as follow:

① Data Preprocessing

cleaning; transformation; normalization

2 Regression

model; coefficient; residual

3 Classification

model; class; probability

4 Clustering

cluster; centroid; distance

Julia; REPL; Pluto; Fuzzy; MLJ; DATAFRAMES; artificial intelligence; regression; classification; clustering.