Lab03: Logistic Regression.

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How to do your homework

You will work directly on this notebook; the word `TODO` indicate the parts you need to do.

You can discuss ideas with classmates as well as finding information from the internet, book, etc...; but *this homework must be your*.

How to submit your homework

- Before submitting, save this file as `<ID>.jl`. For example, if your ID is 123456, then your file will be `123456.jl`. And export to PDF with name `123456.pdf` then submit zipped source code and pdf into `123456.zip` onto Moodle.

> Danger
>
> **Note that you will get 0 point for the wrong submit**.

Contents:

- Logistic Regression.

1. Feature Extraction

Import Library

```
begin
    using Distributions, Plots, Images, LinearAlgebra, Random
end
```

```
MersenneTwister(2024)
```

```
Random.seed!(2024)
```

Load data

```
# I DON'T KNOW WHAT YOUR OS, SO I ATTACHED DATA FOR YOU
# YOU DON'T NEED TO DOWNLOAD AND EXTRACT BY YOURSELF

# IF YOU WANT TO USE JULIA TO DOWNLOAD DATA, LET'S USE THESE CODE
# FOR EXTRACTING MNIST .gz FILE, PLEASE USE gzip

# function download_dataset(save_path::String="data")
#   # setup directory
#   mkpath(joinpath(dirname(@__FILE__), save_path))
#   data_dir = joinpath(dirname(@__FILE__), save_path)
#   mkpath(joinpath(data_dir, "train"))
#   train_dir =  joinpath(data_dir, "train")
#   mkpath(joinpath(data_dir, "test"))
#   test_dir = joinpath(data_dir, "test")

#   # download dataset
#   mkpath(joinpath(train_dir, "images"))
#   download("http://yann.lecun.com/exdb/mnist/train-images-idx3-
ubyte.gz",joinpath(train_dir, "images/train-images-idx3-ubyte.gz"))
#   train_images_file = joinpath(train_dir, "images/train-images-idx3-ubyte.gz")

#   mkpath(joinpath(train_dir, "labels"))
#   download("http://yann.lecun.com/exdb/mnist/train-labels-idx1-
ubyte.gz",joinpath(train_dir, "labels/train-labels-idx1-ubyte.gz"))
#   train_labels_file = joinpath(train_dir, "labels/train-labels-idx1-ubyte.gz")

#   mkpath(joinpath(test_dir, "images"))
#   download("http://yann.lecun.com/exdb/mnist/t10k-images-idx3-
ubyte.gz",joinpath(test_dir, "images/t10k-images-idx3-ubyte.gz"))
#   test_images_file = joinpath(test_dir, "images/t10k-images-idx3-ubyte.gz")

#   mkpath(joinpath(test_dir, "labels"))
#   download("http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-
ubyte.gz",joinpath(test_dir, "labels/t10k-labels-idx1-ubyte.gz"))
#   test_labels_file = joinpath(test_dir, "labels/t10k-labels-idx1-ubyte.gz")
# end
```

```
# If you have downloaded the dataset yet, please uncomment this line below and run
this cell. Otherwise, keep it in uncomment state.
# download_dataset()
```

```
10000
```

```
begin
    data_dir = joinpath(dirname(@__FILE__), "data")
    train_x_dir = joinpath(data_dir, "train/images/train-images.idx3-ubyte")
    train_y_dir = joinpath(data_dir, "train/labels/train-labels.idx1-ubyte")

    test_x_dir = joinpath(data_dir, "test/images/t10k-images.idx3-ubyte")
    test_y_dir = joinpath(data_dir, "test/labels/t10k-labels.idx1-ubyte")

    NUMBER_TRAIN_SAMPLES = 60000
    NUMBER_TEST_SAMPLES = 10000
end
```

```
60000×784 adjoint(::Matrix{Float64}) with eltype Float64:
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 ⋮                        ⋮              ⋱                       ⋮
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
```

```
begin
    # Init arrays
    train_x = Array{Float64}(undef, 28^2, NUMBER_TRAIN_SAMPLES)
    train_y = Array{Int64}(undef, NUMBER_TRAIN_SAMPLES)

    # Init io streams
    io_images = open(train_x_dir)
    io_labels = open(train_y_dir)

    # Iterating through sample length
    for i ∈ 1:NUMBER_TRAIN_SAMPLES
        seek(io_images, (i-1)*28^2 + 16) # offset 16 to skip header
        seek(io_labels, (i-1)*1 + 8) # offset 8 to skip header
        train_x[:,i] = convert(Array{Float64}, read(io_images, 28^2))
        train_y[i] = convert(Int, read(io_labels, UInt8))
    end

    # Close io streams
    close(io_images)
    close(io_labels)

    # Transpose features
    train_x = train_x'
end
```

```
10000×784 adjoint(::Matrix{Float64}) with eltype Float64:
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 ⋮                        ⋮              ⋱                       ⋮
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0     0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
```

```
begin
    # Init arrays
    test_x = Array{Float64}(undef, 28^2, NUMBER_TEST_SAMPLES)
    test_y = Array{Int64}(undef, NUMBER_TEST_SAMPLES)

    # Init io streams
    io_images_test = open(test_x_dir)
    io_labels_test = open(test_y_dir)

    # Iterating through sample length
    for i ∈ 1:NUMBER_TEST_SAMPLES
        seek(io_images_test, (i-1)*28^2 + 16) # offset 16 to skip header
        seek(io_labels_test, (i-1)*1 + 8) # offset 8 to skip header
        test_x[:,i] = convert(Array{Float64}, read(io_images_test, 28^2))
        test_y[i] = convert(Int, read(io_labels_test, UInt8))
    end

    # Close io streams
    close(io_images)
    close(io_labels)

    # Transpose features
    test_x = test_x'
end
```

```
((60000, 784), (60000), (10000, 784), (10000))
```

```
size(train_x), size(train_y), size(test_x), size(test_y)
```

Extract Features

So we basically have 70000 samples with each sample having 784 features - pixels in this case and a label - the digit the image represent.

Let's play around and see if we can extract any features from the pixels that can be more informative. First I'd like to know more about average intensity - that is the average value of a pixel in an image for the different digits

```
compute_average_intensity (generic function with 1 method)
```

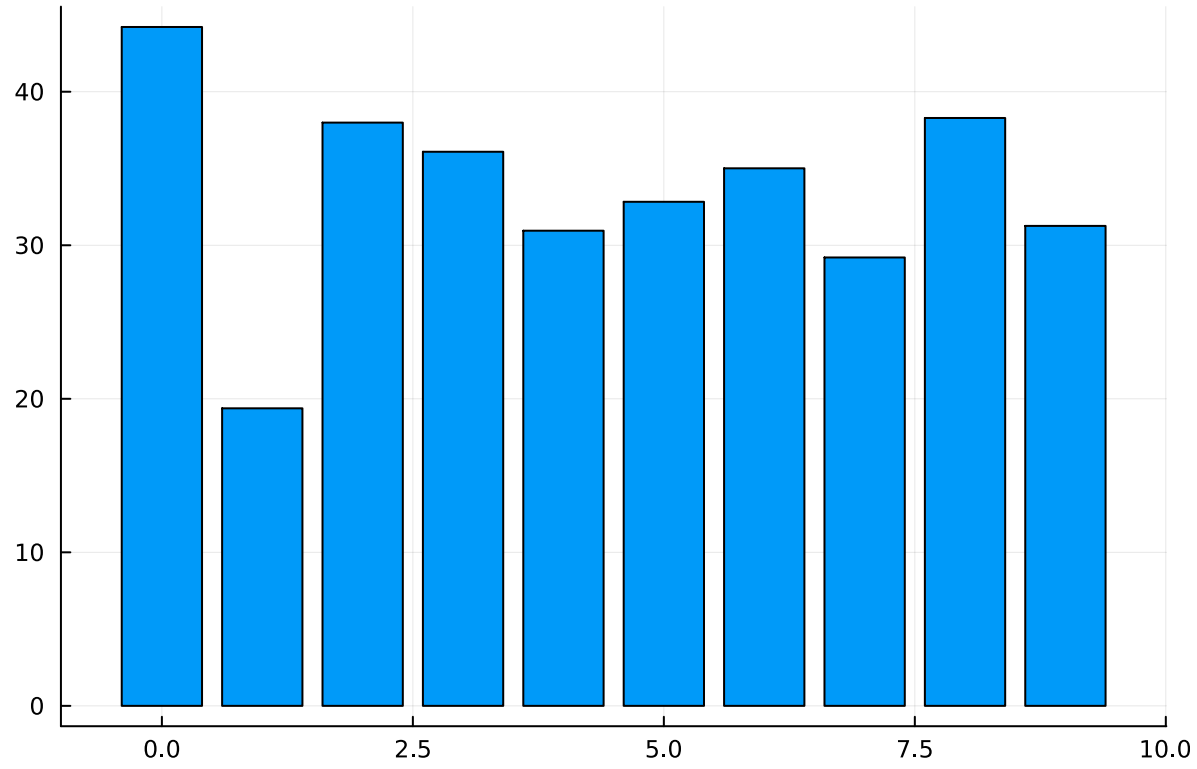
```
#TODO compute average intensity for each label
function compute_average_intensity(x, y)
    mean_ = zeros(10) # 10 is number of labels
    #TODO compute average intensity for each label
    for label in 0:9
        label_indices = findall(y .== label)
        if !isempty(label_indices)
            mean_[label + 1] = mean(mean(x[label_indices, :]))
        end
    end

    return mean_
end
```

```
l_mean =
 [44.2168, 19.3797, 37.9887, 36.0902, 30.9482, 32.8311, 35.012, 29.2046, 38.2898, 31.2604]
```

```
l_mean = compute_average_intensity(train_x, train_y)
```

Plot the average intensity using matplotlib




```
bar(0:9, l_mean, legend=false)
```

```
(60000)
```

```
begin
    #TODO compute average intensity for each data sample
    intensity = [mean(train_x[i,:]) for i in 1:size(train_x,1)]
    size(intensity)
end
```

Some digits are symmetric (1, 3, 8, 0) some are not (2, 4, 5, 6, 9). Creating a new feature capturing this could be useful. Specifically, we calculate $s = -\frac{s_1+s_2}{2}$ for each image:

- s_1 : flip the image along y-axis and compute the mean value of result
- s_2 : flip the image along x-axis and compute the mean value of result

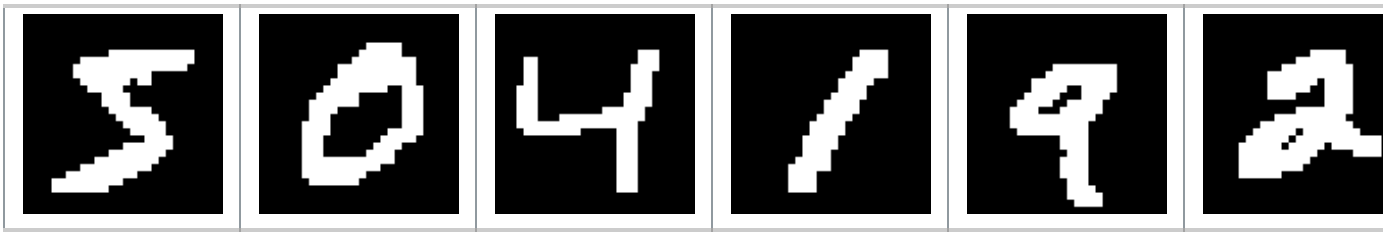
```
compute_symmetry (generic function with 1 method)
```

```
function compute_symmetry(train_x)
    symmetry = []
    for i in 1:size(train_x)[1]
        img = reshape(train_x[i,:], (28,28))
        s1 = mean(abs.(img - reverse(img, dims=1)))
        s2 = mean(abs.(img - reverse(img, dims=2)))
        s = -0.5 .* (s1 + s2)
        append!(symmetry, s)
    end
    return symmetry
end
```

```
(60000)
```

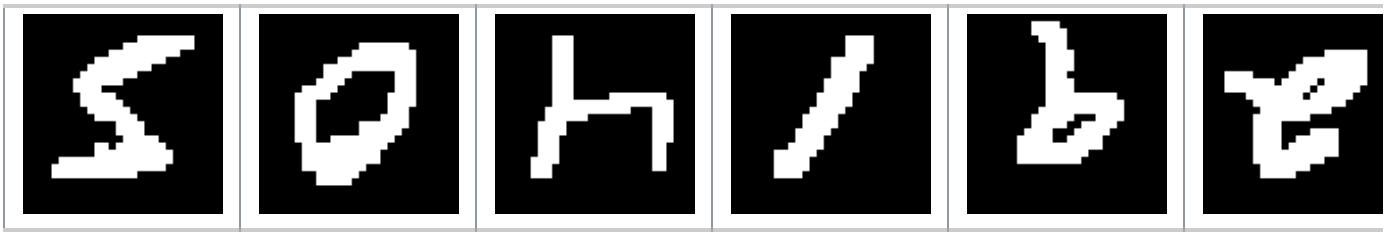
```
begin
    symmetry = compute_symmetry(train_x)
    size(symmetry)
end
```

Visualize 10 samples in order to illustrate symmetry



(a vector displayed as a row to save space)

```
begin
    num_img = 10
    img_flat = train_x[1:num_img,:]
    img = [reshape(img_flat[i,:], (28,28))' for i in 1:num_img]
    [colorview(Gray, Float32.(img[i])) for i in 1:num_img]
end
```



(a vector displayed as a row to save space)

```
begin
    img_reverse_flat = reverse(img_flat, dims=2)
    img_reverse = [reshape(img_reverse_flat[i,:], (28,28))' for i in 1:num_img]
    [colorview(Gray, Float32.(img_reverse[i])) for i in 1:num_img]
end
```

Our new data will have 70000 samples and 2 features: intensity, symmetry.

```
(60000, 2)
```

```
begin
    #TODO create X_new by horizontal stack intensity and symmetry
    begin
        train_x_new = hcat(intensity, symmetry)
        size(train_x_new)
    end
end
```

2. Training

Usually logistic regression is a good first choice for classification. In this homework we use logistic regression for classifying digit 1 images and not digit 1's images.

Normalize data

First normalize data using Z-score normalization

- **TODO: Study about Z-score normalization**

Z-score normalization is a process of normalizing every value in a dataset such that the mean of all of the values is 0 and the standard deviation is 1. The formula to perform a z-score normalization on every value in a dataset is:

$$New\_value = \frac{(x-\mu)}{\sigma}$$

where:

- Original value: x
- Mean of data: μ
- Standard deviation of data: σ

The normalized values represent the number of standard deviations that the original value is from the mean.

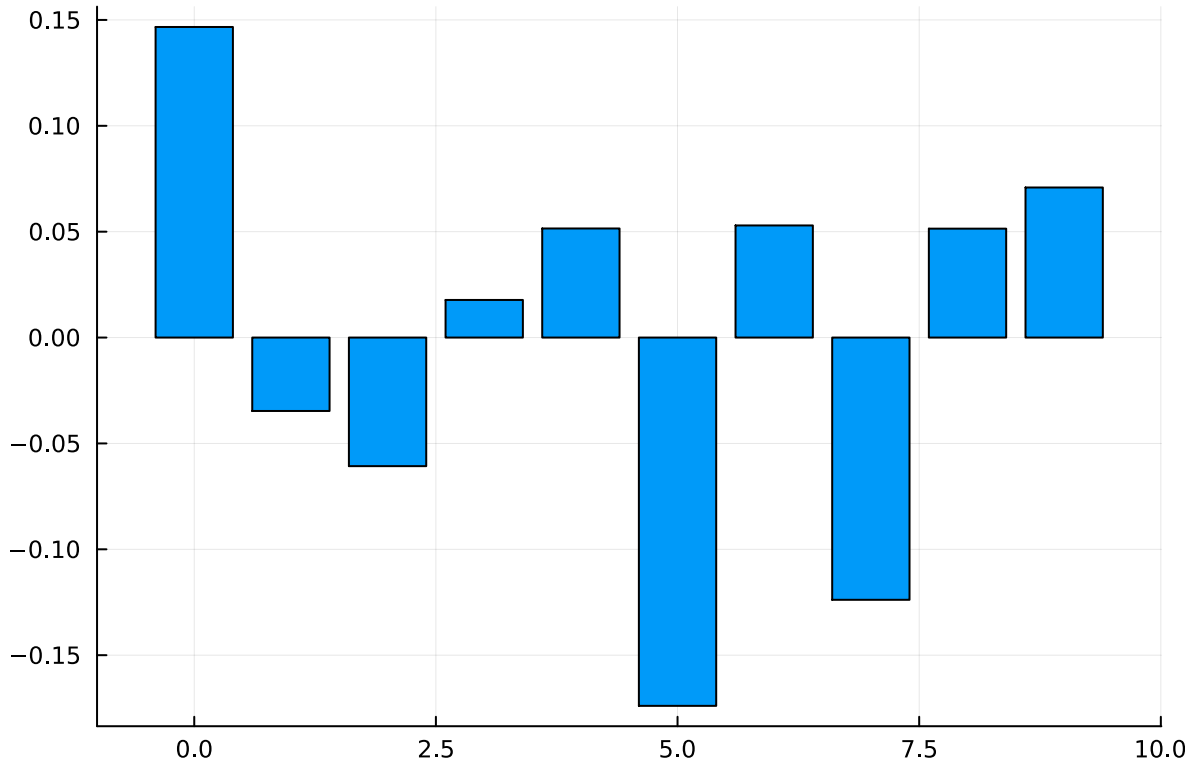
- **TODO: Why should we normalize data?**

1. It corrects duplicate data and anomalies. When you apply normalization methods to the database, you can identify and correct duplicate information quickly so it doesn't affect the rest of the database.
2. It removes unwanted data connections. Data normalization methods help remove data connections that don't relate to the main data.
3. It prevents data deletion. Using well-established data normalization methods can help prevent you from deleting data that relates to the main key data.
4. It optimizes data storage space. Data normalization can help remove unnecessary data from databases.
5. It ensures your feature distributions have mean = 0 and standard deviation = 1. It's useful when there are a few outliers, but not so extreme that you need clipping.
6. It allows the data to be queried and analyzed more easily which can lead to better business decisions.

```
normalize (generic function with 3 methods)
```

```
function normalize(x, mean_=nothing, std_=nothing)
    if mean_ == nothing && std_ == nothing
        #TODO normalize x_train
        mean_ = mean(x, dims=1)
        std_ = std(x, dims=1)
        normalized_train_x = (x .- mean_) ./ std_
        return normalized_train_x, mean_, std_
        #return `normalized_train_x`, `mean_`, `std_`
        #mean_ and std_ will be re-used to pre-process test set
    end
    return (x .- mean_) ./ std_ #return `normalized_train_x` calculated by using mean_ and std_ (both of them are passed and not null)
end


```




```
begin
    normalized_train_x, mean_, std_ = normalize(train_x_new)

    s_mean = compute_average_intensity(normalized_train_x, train_y)
    bar(0:9, s_mean, legend=false)
end
```

Construct data

```
(60000, 1)
```

```
begin
    train_y_new = reshape(deepcopy(train_y), (size(train_y)[1], 1))
    train_y_new[train_y_new .!= 1] .= 0
    size(train_y_new)
end
```

```
(60000, 3)
```

```
begin
    # contruct data by adding ones
    add_one_train_x = hcat(ones(size(normalized_train_x)[1],), normalized_train_x)
    size(add_one_train_x)
end
```

Sigmoid function and derivative of the sigmoid function

```
sigmoid_activation (generic function with 1 method)
```

```
function sigmoid_activation(x)
    #TODO
    """compute the sigmoid activation value for a given input"""
    #return?
    return 1.0 ./(1.0 .+ exp.(-x))
end
```

```
sigmoid_deriv (generic function with 1 method)
```

```
function sigmoid_deriv(x)
    #TODO
    """
    Compute the derivative of the sigmoid function ASSUMING
    that the input 'x' has already been passed through the sigmoid
    activation function
    """
    #return?
    return sigmoid_activation(x) .*(1.0 .- sigmoid_activation(x))
end
```

Compute output

```
compute_h (generic function with 1 method)
```

```
function compute_h(W, X)
    #TODO
    """
    Compute output: Take the inner product between our features 'X' and the weight
    matrix 'W'
    """
    return X*W
end
```

```
predict (generic function with 1 method)
```

```
function predict(W, X)
    #TODO
    """
    Take the inner product between our features and weight matrix,
    then pass this value through our sigmoid activation
    """
    preds = sigmoid_activation(compute_h(W,X))


    # apply a step function to threshold the outputs to binary
    # class labels
    preds[preds .<= 0.5] .= 0
    preds[preds .> 0] .= 1

    return preds
end
```

Compute gradient

Loss Function: Average negative log likelihood

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} -\left(y^i \ln h_{\mathbf{w}}\left(\mathbf{x}^i\right) + \left(1-y^i\right) \ln\left(1-h_{\mathbf{w}}\left(x^i\right)\right)\right)$$

$$\text{Sigmoid Activation: } z = \sigma\left(h\right) = \frac{1}{1+e^{-h}}$$

$$\text{Cross-entropy: } J(w) = -\left(ylog(z) + (1-y)log(1-z)\right)$$

$$\text{Chain rule: } \frac{\partial J(w)}{\partial w} = \frac{\partial J(w)}{\partial z}\frac{\partial z}{\partial h}\frac{\partial h}{\partial w}$$

$$\frac{\partial J(w)}{\partial z} = -\left(\frac{y}{z} - \frac{1-y}{1-z}\right) = \frac{z-y}{z(1-z)}$$

$$\frac{\partial z}{\partial h} = z(1-z)$$

$$\frac{\partial h}{\partial w} = X$$

$$\frac{\partial J(w)}{\partial w} = X^T(z-y)$$

```
compute_gradient (generic function with 1 method)
```

```
function compute_gradient(error, train_x)
    #TODO
    """
    This is the gradient descent update of "average negative loglikelihood" loss function.
    In lab02 our loss function is "sum squared error".
    """
    return return (train_x' * error) / size(train_x, 1)
end
```

```
train (generic function with 1 method)
```

```
function train(W, train_x, train_y, learning_rate, num_epochs)
    losses = []
    for epoch in 1:num_epochs
        y_hat = sigmoid_activation(compute_h(W, train_x))
        error = y_hat - train_y
        append!(losses, mean(-1 .* train_y .* log.(y_hat) .- (1 .- train_y) .* log.(1 .- y_hat)))
        grad = compute_gradient(error, train_x)
        W -= learning_rate * grad

        if epoch == 1 || epoch % 50 == 0
            print("Epoch=$epoch; Loss=$(losses[end])\n")
        end
    end
    return W, losses
end
```

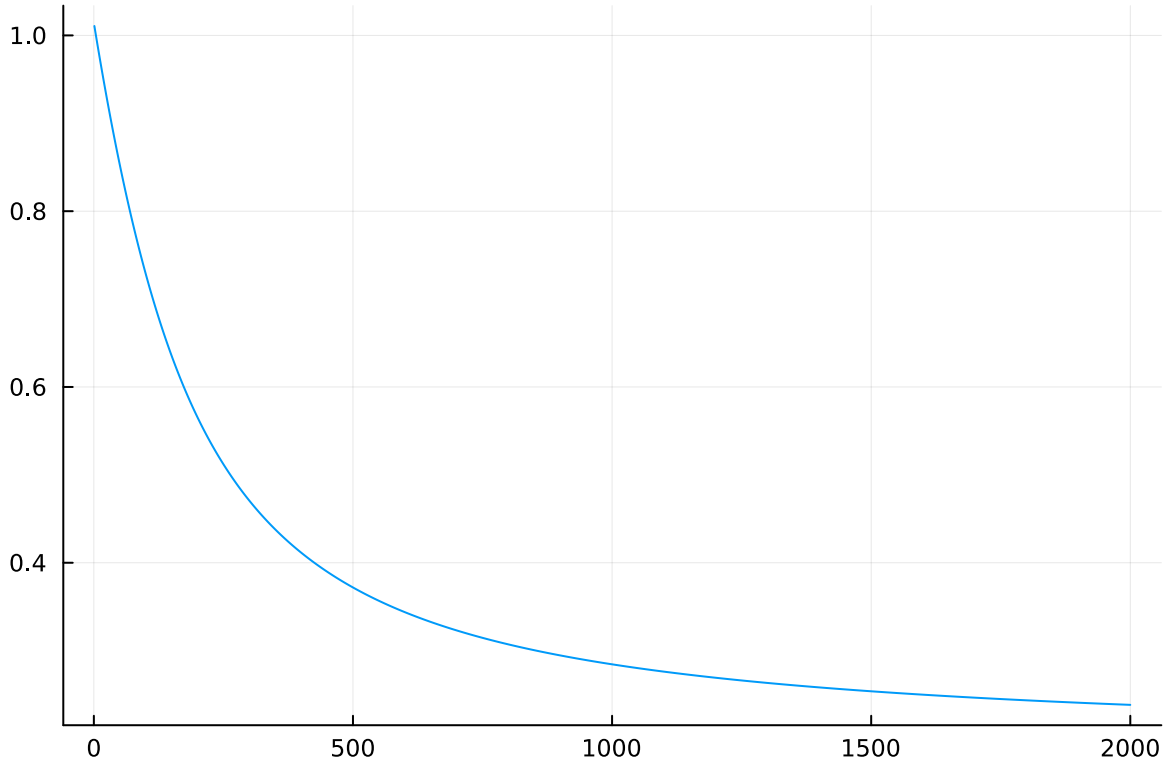
Train our model

```
(3×1 Matrix{Float64}:, [1.01072, 1.00711, 1.00352, 0.999944, 0.996386, 0.992845, 0.98932,
  -2.20626
  -1.01475
   0.380485
```

```
begin
    W = rand(Normal(), (size(add_one_train_x)[2], 1))

    num_epochs=2000
    learning_rate=0.01
    W, losses = train(W, add_one_train_x, train_y_new, learning_rate, num_epochs)
end
```

```
Epoch=1; Loss=1.0107165937378937
Epoch=50; Loss=0.8529187508405665
Epoch=100; Loss=0.7289056224861379
Epoch=150; Loss=0.6355990443551653
Epoch=200; Loss=0.5654684888661189
Epoch=250; Loss=0.5120871625773824
Epoch=300; Loss=0.4706846760006857
Epoch=350; Loss=0.43792818985241083
Epoch=400; Loss=0.4115246664907461
Epoch=450; Loss=0.389884534161352
Epoch=500; Loss=0.3718866342113632
Epoch=550; Loss=0.3567239856344007
Epoch=600; Loss=0.34380395321263585
Epoch=650; Loss=0.3326831259825387
Epoch=700; Loss=0.3230241165939837
Epoch=750; Loss=0.3145663231389152
Epoch=800; Loss=0.30710573352519993
Epoch=850; Loss=0.30048070238317465
Epoch=900; Loss=0.2945617531602912
Epoch=950; Loss=0.2892441462498928
Epoch=1000; Loss=0.28444238271154026
Epoch=1050; Loss=0.2800860852322049
Epoch=1100; Loss=0.276116874029645
Epoch=1150; Loss=0.27248597148641895
Epoch=1200; Loss=0.2691523472428833
Epoch=1250; Loss=0.2660812686974031
Epoch=1300; Loss=0.26324315877619725
Epoch=1350; Loss=0.2606126888121362
Epoch=1400; Loss=0.2581680528963465
Epoch=1450; Loss=0.25589038343866827
Epoch=1500; Loss=0.25376327743460514
Epoch=1550; Loss=0.25177241013606777
Epoch=1600; Loss=0.2499052181839656
Epoch=1650; Loss=0.24815063828741568
Epoch=1700; Loss=0.24649889058367572
Epoch=1750; Loss=0.24494129813965596
Epoch=1800; Loss=0.24347013584380375
Epoch=1850; Loss=0.24207850332019992
Epoch=1900; Loss=0.24076021757320298
Epoch=1950; Loss=0.23950972191380943
Epoch=2000; Loss=0.23832200838246376
```




```
plot(1:num_epochs, losses, legend=false)
```

3. Evaluate our model

In this section, you will evaluate your model on train set and test set and make some comment about the result.

Evaluate model on training set

```
tpfptnfn_cal (generic function with 2 methods)
```

```
function tpfptnfn_cal(y_test, y_pred, positive_class=1)
    true_positives = 0
    false_positives = 0
    true_negatives = 0
    false_negatives = 0

    # Calculate true positives, false positives, false negatives, and true negatives
    for (true_label, predicted_label) in zip(y_test, y_pred)
        if true_label == positive_class && predicted_label == positive_class
            true_positives += 1
        elseif true_label != positive_class && predicted_label == positive_class
            false_positives += 1
        elseif true_label == positive_class && predicted_label != positive_class
            false_negatives += 1
        elseif true_label != positive_class && predicted_label != positive_class
            true_negatives += 1
        end
    end

    return true_positives, false_positives, true_negatives, false_negatives
end
```

```
begin
    preds_train = predict(W, add_one_train_x)
    train_y_n = reshape(train_y_new, length(train_y_new), 1)

    acc = 0
    precision = 0
    recall = 0
    f1 = 0

    for i ∈ 1:10
        # Calculate true positives, false positives, false negatives, and true
        negatives
        true_positives, false_positives, true_negatives, false_negatives =
    tpfptnfn_cal(train_y_n, preds_train)

        # Calculate precision, recall, and F1-score
        acc += (true_positives + true_negatives) / (true_positives + false_positives
        + true_negatives + false_negatives)
        precision += true_positives / (true_positives + false_positives)
        recall += true_positives / (true_positives + false_negatives)
    end

    acc = acc / 10
    precision = precision / 10
    recall = recall / 10
    f1 = 2 * precision * recall / (precision + recall)
    print(" acc: $acc\n precision: $precision\n recall: $recall\n f1_score: $f1\n")
end
```

```
acc: 0.9175166666666665
precision: 0.8733860891295295
recall: 0.3110353010975971
f1_score: 0.4587115826315213
```

Evaluate model on test set

In order to predict the result on test set, you have to perform data pre-process first. The pre-process is done exactly what we have done on train set. That means, you have to:

- Change the label in `test_y` to `0` and `1` and store in a new variable named `test_y_new`
- Calculate `test_intensity` and `test_symmetry` to form `test_x_new` (the shape should be `(10000,2)`)
- Normalized `test_x_new` by z-score. Note the you will re-use variable `mean_` and `std_` to calculate `test_x_new` instead of compute new ones. You will store the result in `normalized_test_x`
- Add a column that's full of one to `test_x_new` and store in `add_one_test_x` (the shape should be `(10000,3)`)

```
(10000, 3)
```

```
begin
    #TODO
    # compute test_y_new
    test_y_new = reshape(deepcopy(test_y), (size(test_y)[1], 1))
    test_y_new[test_y_new .!= 1] .= 0


    # compute test_intensity and test_symmetry to form test_x_new
    test_intensity = [mean(test_x[i,:]) for i in 1:size(test_x,1)]
    test_symmetry = compute_symmetry(test_x)
    test_x_new = [test_intensity test_symmetry]

    # normalize test_x_new to form normalized_test_x
    normalized_test_x = (test_x_new .- mean_) ./ std_

    # add column `ones` to test_x_new
    add_one_test_x = [ones(size(test_x_new, 1)) normalized_test_x]
    size(add_one_test_x)
end
```

After doing all these stuffs, you now can predict and evaluate your model

```
begin
    preds_test = predict(W, add_one_test_x)

    test_y_n = reshape(test_y_new, length(test_y_new), 1)

    _acc = 0
    _p = 0
    _r = 0
    _f1 = 0

    for i ∈ 1:10
        # Calculate true positives, false positives, false negatives, and true
        negatives
        tp, fp, tn, fn = tpfptnfn_cal(test_y_n, preds_test)

        # Calculate precision, recall, and F1-score
        _acc += (tp + tn) / (tp + fp + tn + fn)
        _p += tp / (tp + fp)
        _r += tp / (tp + fn)
    end

    _acc = _acc / 10
    _p = _p / 10
    _r = _r / 10
    _f1 = 2 * _p * _r / (_p + _r)

    print(" acc: $_acc\n precision: $_p\n recall: $_r\n f1_score: $_f1\n")
end
```

```
acc: 0.9182
precision: 0.866050808314087
recall: 0.3303964757709252
f1_score: 0.4783163265306123
```

TODO: Comment on the result

- The model's accuracy is 91.82%, which means it correctly predicted the outcome in about 91.82% of the cases in the test dataset.
- However, the precision and recall values tell a slightly different story. The precision of 86.61% suggests that when the model predicts a positive outcome, it is correct about 86.61% of the time.
- On the other hand, the recall of 33.04% indicates that the model identified only 33.04% of the actual positive outcomes in the dataset. This could mean that the model is missing a significant number of positive outcomes, which might be a concern depending on the specific context and the cost associated with false negatives.
- The F1 score, which is the harmonic mean of precision and recall, is 47.83%. The F1 score gives us a single metric that considers both precision and recall. A low F1 score may suggest that the model's performance is not balanced and is skewed towards precision at the cost of recall.

In conclusion, while the model's accuracy is high, its ability to detect positive outcomes (as indicated by the recall and F1 score) may need to be improved. This could potentially be achieved by adjusting the model's threshold for predicting a positive outcome, or by using a different model or feature set. Further investigation and experimentation would be necessary to determine the best course of action.