

# 204789: Machine Learning and Neural Network

2/59

The logo for the Julia programming language. It features the word "julia" in a dark grey, lowercase, sans-serif font. The letter 'j' has a blue circle above it. The letter 'i' has a red circle above it. The letter 'l' has a green circle above it. The letter 'i' has a purple circle above it. The letter 'a' has a green circle above it.

julia

# Defining a function

- สามารถนิยามโดย

```
function name(arg1, arg2, ... )
```

```
    # function body
```

```
    return ret1, ret2, ...           # สามารถ return ได้มากกว่า 1 ค่า
```

```
end
```

- Function call

```
[a, b, c ... ] = name(arg1, arg2, ...)
```

# Exercise 1

- ให้ลองสร้างฟังก์ชัน `logisticRegression()`
- ฟังก์ชันนี้จะรับ input คือ
  - $X$  = input data
  - $Y$  = input label
  - $W$  = weight vector
- ฟังก์ชันนี้จะคืนค่า optimised  $W$  กลับมา
- ทดลอง `classify boston.mat` dataset เพื่อตรวจสอบความถูกต้อง

## Exercise 2

- ใช้ Logistic Regression ที่สร้างไปข้างต้นผนวกเข้ากับ GaussianKernel
- สิ่งที่ได้ก็คือ kernel logistic regression ที่สามารถ classify non-linear data ได้
- ทดลอง classify banana.mat data ว่า kernel LR ที่สร้างขึ้นมาได้ผลหรือไม่

# Using the kernel

```
srand(123)  
x = rand(5,2)
```

5x2 Array{Float64,2}:

0.768448	0.662555
0.940515	0.586022
0.673959	0.0521332
0.395453	0.26864
0.313244	0.108871

$X_1$

```
k1 = kernelmatrix(K,x)
```

5x5 Array{Float64,2}:

1.0	0.931528	0.466226	0.55511	0.357882
0.931528	1.0	0.490574	0.451289	0.288724
0.466226	0.490574	1.0	0.779673	0.765927
0.55511	0.451289	0.779673	1.0	0.937472
0.357882	0.288724	0.765927	0.937472	1.0

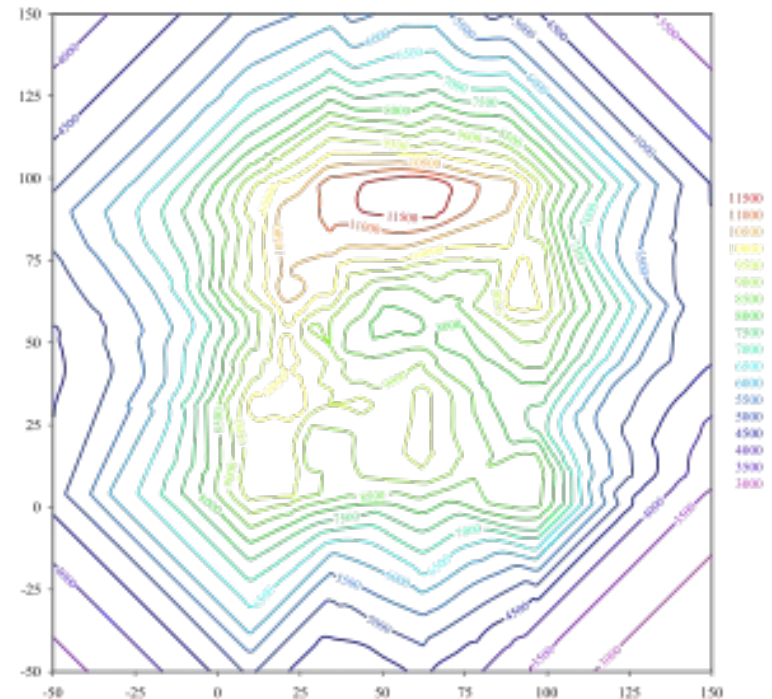
# Contour package

- Contour is a curve along which function has a constant value (aka isoline)
- มีประโยชน์ในการ plot decision boundary
  - E.g., function value along the boundary is zero.

- Install the package

```
Pkg.add("Contour")
```

using Contour



# Contour Example

- Want to plot a contour of  $f(x,y) = x^2+y^2$

`x = -3:0.01:3`

`y = -4:0.02:5`

`z = [Float64((xi^2 + yi^2)) for xi in x, yi in y]`

- Now find the contours

`c = contours(x,y,z)`



# Contour Example

- We can extract levels from contour 'c' using

`lv = levels(c)`  $\leq$  this returns an iterator

- Extract z value in that level using

`zlv = level(lv)`  $\leq$  this return float

- We can extract line segments in each level using

`ln = lines(lv)`  $\leq$  this also return an iterator

- We can extract end points of each line using

`xs, ys = coordinates(ln)`

# Contour: the whole thing

```
using Winston, Contour

# define x,y,z as above

# define FramedPlot()

for lv in levels(contours(x,y,z))

    zlv = level(lv)

    for line in lines(lv)

        xs, ys = coordinates(line)
    add(p,Curve(xs,ys,color=Winston.default_color(Integer(floor(zlv))))))

    end

end

# call p to show the figure
```

# Exercise 3

Plot the decision boundary of

1. Logistic regression on banana.mat
2. Kernel logistic regression on the same dataset

# AdaBoost

- There is a package call 'DecisionTree' that implements adaboost using a stump (very very simple tree)
- But simply using the package is too easy.
- We will do it a hard way.

# What to boost ?

- Theoretically, you can boost anything.
- Yeh, anything but it needs some mod.
- For example,
  - SVM: by putting 'C' parameters on each of the slack variables and adjusting 'C' parameters according to  $D(i)$
  - Logistic regression: by multiplying the likelihood term by  $D(i)$

# Let's boost LR

- First, we need to rewrite the objective function by including the  $D(i)$  terms.
- Next, find the first order partial derivatives
  - And also the Hessian.
- You are now ready to boost LR.
- Remember that LR is pretty stable classifier, try to shake it a bit to get diverse set of LRs.

# AdaBoost Algorithm

**Data:**  $S = \{x_i, y_i\}_{i=1}^N$ ,  $x_i \in X$  and  $y_i \in \{-1, 1\}$

initialization: uniform weight for initial data  $D_1(i) = \frac{1}{N}$ ;

**for**  $t = 1 \dots T$  **do**

Learn a classifier  $h_t : X \rightarrow \{-1, 1\}$  that minimises training error,

$$\epsilon_j = \sum_{i=1}^N D_t(i) [y_i \neq h_j(x_i)] ;$$

**if**  $\epsilon_t > 0.5$  **then**

STOP;

**else**

Set  $\alpha_t = \frac{1}{2} \ln \frac{1-\epsilon_t}{\epsilon_t}$  ;

Reweighting by  $D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$  ;

( $Z_t$  is a normaliser making  $\sum_{i=1}^N D_{t+1}(i) = 1$ );

**end**

**end**

**Result:**  $f_{ada}(x) = \sum_{t=1}^T \alpha_t h_t(x)$

# Exercise 4

- Implement AdaBoost and try to boost logistic regression classifiers.



# Classifier comparison

- Usually done using 5 or 10 fold cross validation
  - Divide data into 10 parts
  - Hold out 1 part at a time for testing
  - Final accuracy is the average of 10 (partial) accuracies
- Report the average and the standard deviations, for example
  - LR: 97.35 +/- 3.00 , SVM: 98.27 +/- 4.22

# Is the difference significant ?

- Report the average and the standard deviations, for example
  - LR: 97.35 +/- 3.00 , SVM: 98.27 +/- 4.22
- Perform statistical test
  - People mostly use Wilcoxon ranksum test at 0.05 level of significant.
  - Consult the 1<sup>st</sup> Julia Slides for more example on statistical testing package.

Thank you !!

Work hard, play harder !