INTRO TO

# MACHINE LEARNING

@mihahribar

TOSHL FINANCE

coursera

**Taught by:** Andrew Ng, Co-founder, Coursera; Adjunct Professor, Stanford University; formerly head of Baidu AI Group/Google Brain

## Coursework

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https://www.coursera.org/learn/machine-learning

# Maths!

## Gradient descent

Repeat $\{$

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_0^{(i)}$$

$$\theta_j := \theta_j - \alpha \left[ \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)} + \frac{\lambda}{m} \theta_j \right]$$

$(j = \cancel{0}, 1, 2, 3, \ldots, n)$

$\}$

$$\theta_j := \theta_j (1 - \alpha \frac{\lambda}{m}) - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

$1 - \alpha \frac{\lambda}{m} < 1$

0.99

$\theta_j \times 0.99$

## Collaborative filtering optimization objective

- Given $x^{(1)}, \ldots, x^{(n_m)}$, estimate $\theta^{(1)}, \ldots, \theta^{(n_u)}$:

$$\min_{\theta^{(1)},\ldots,\theta^{(n_u)}} \frac{1}{2} \sum_{j=1}^{n_u} \sum_{i:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^{n} (\theta_k^{(j)})^2$$

- Given $\theta^{(1)}, \ldots, \theta^{(n_u)}$, estimate $x^{(1)}, \ldots, x^{(n_m)}$:

$$\min_{x^{(1)},\ldots,x^{(n_m)}} \frac{1}{2} \sum_{i=1}^{n_m} \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^{n} (x_k^{(i)})^2$$

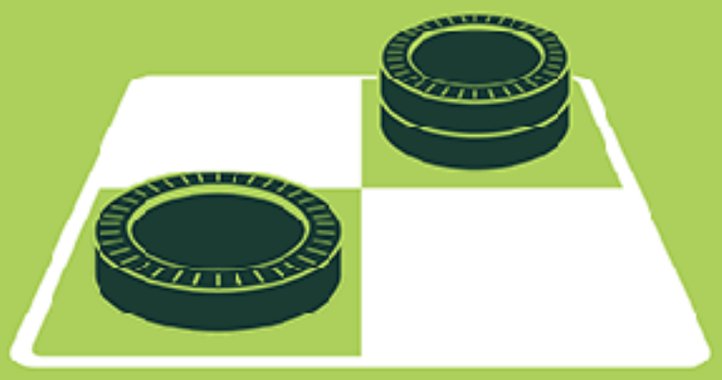
- Minimizing $x^{(1)}, \ldots, x^{(n_m)}$ and $\theta^{(1)}, \ldots, \theta^{(n_u)}$ simultaneously:

$$J(x^{(1)}, \ldots, x^{(n_m)}, \theta^{(1)}, \ldots, \theta^{(n_u)}) = \frac{1}{2} \sum_{(i,j):r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^{n} (x_k^{(i)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^{n} (\theta_k^{(j)})^2$$

$$\min_{\substack{x^{(1)},\ldots,x^{(n_m)} \\ \theta^{(1)},\ldots,\theta^{(n_u)}}} J(x^{(1)}, \ldots, x^{(n_m)}, \theta^{(1)}, \ldots, \theta^{(n_u)})$$

## ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



## MACHINE LEARNING

Machine learning begins to flourish.

## DEEP LEARNING

Deep learning breakthroughs drive AI boom.

1950's 1960's 1970's 1980's 1990's 2000's 2010's

Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

***“Field of study that gives computers the ability to learn without being explicitly programmed.”***

*– Arthur Samuel (1959)*

***“A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.”***

*– Tom Mitchell (1998)*

*“A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.”*

Example: spam email classification based on user input

**T**: Classifying emails as spam/not spam

**E**: Users marking emails as spam/not spam

**P**: Number of emails correctly marked as spam

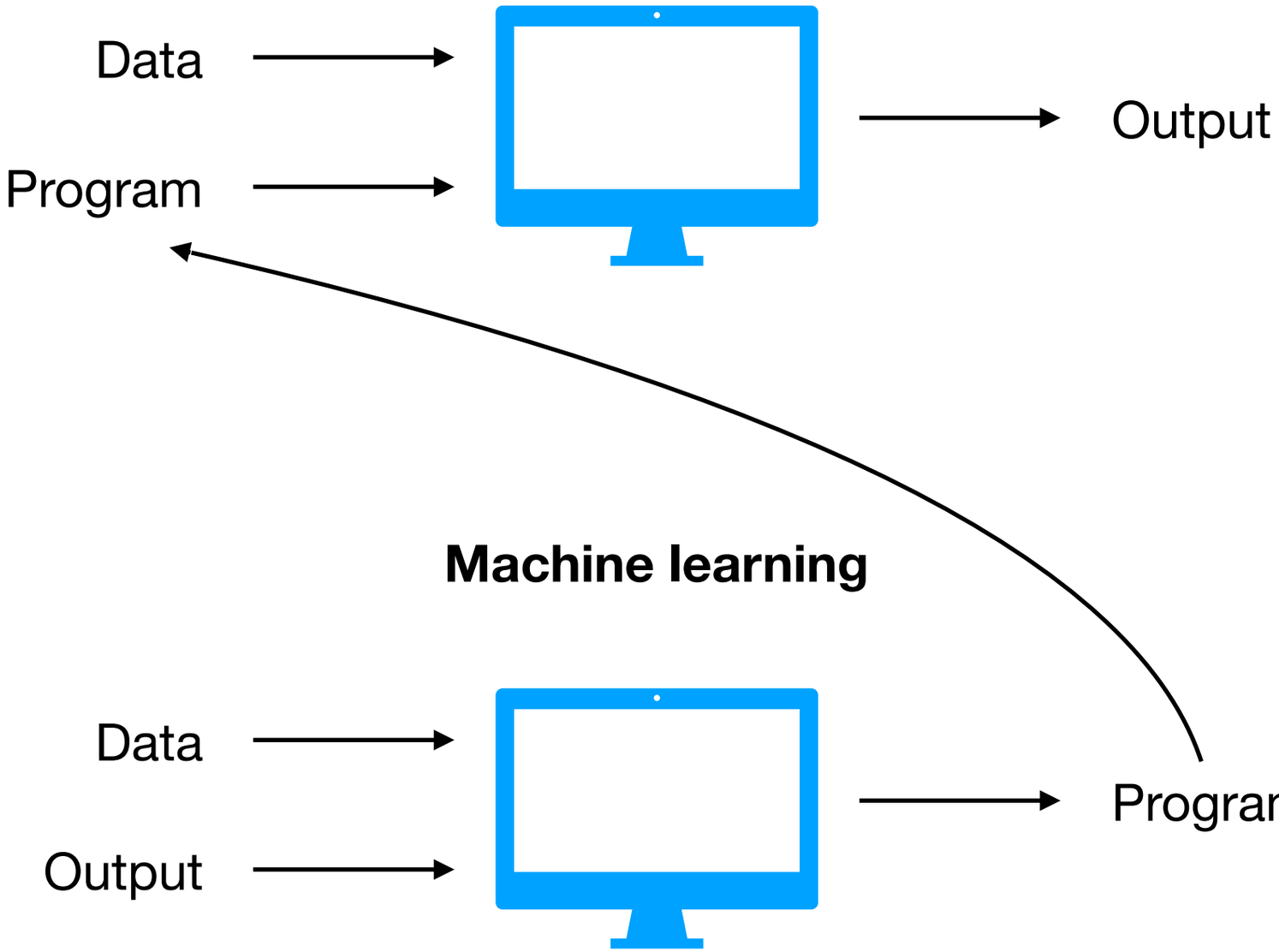
BASED ON YOUR INTERNET HISTORY, YOU MIGHT BE DUMB ENOUGH TO ENJOY EXTREME SPORTS.

CLICK HERE TO BUY A TICKET TO BASE JUMP FROM THE INTERNATIONAL SPACE STATION.

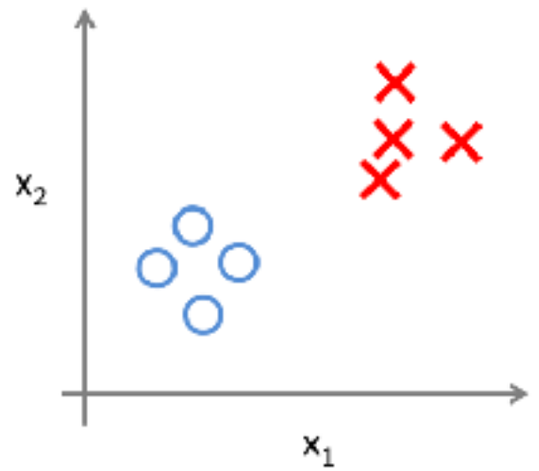
I THINK THE INTERNET IS TRYING TO KILL ME.

WE CALL IT "MACHINE LEARNING."

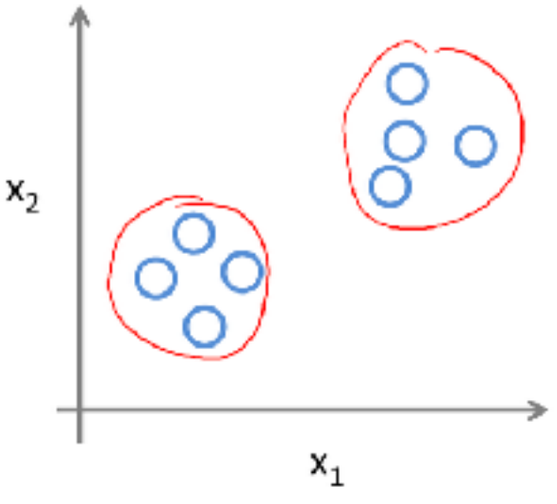
## Traditional programming



- **Supervised learning**
  Computer is presented with example inputs and their desired outputs and the goal is to learn a general rule that maps inputs to outputs




- **Unsupervised learning**
  No labels are given to the learning algorithm, leaving it on its own to find structure in its input.

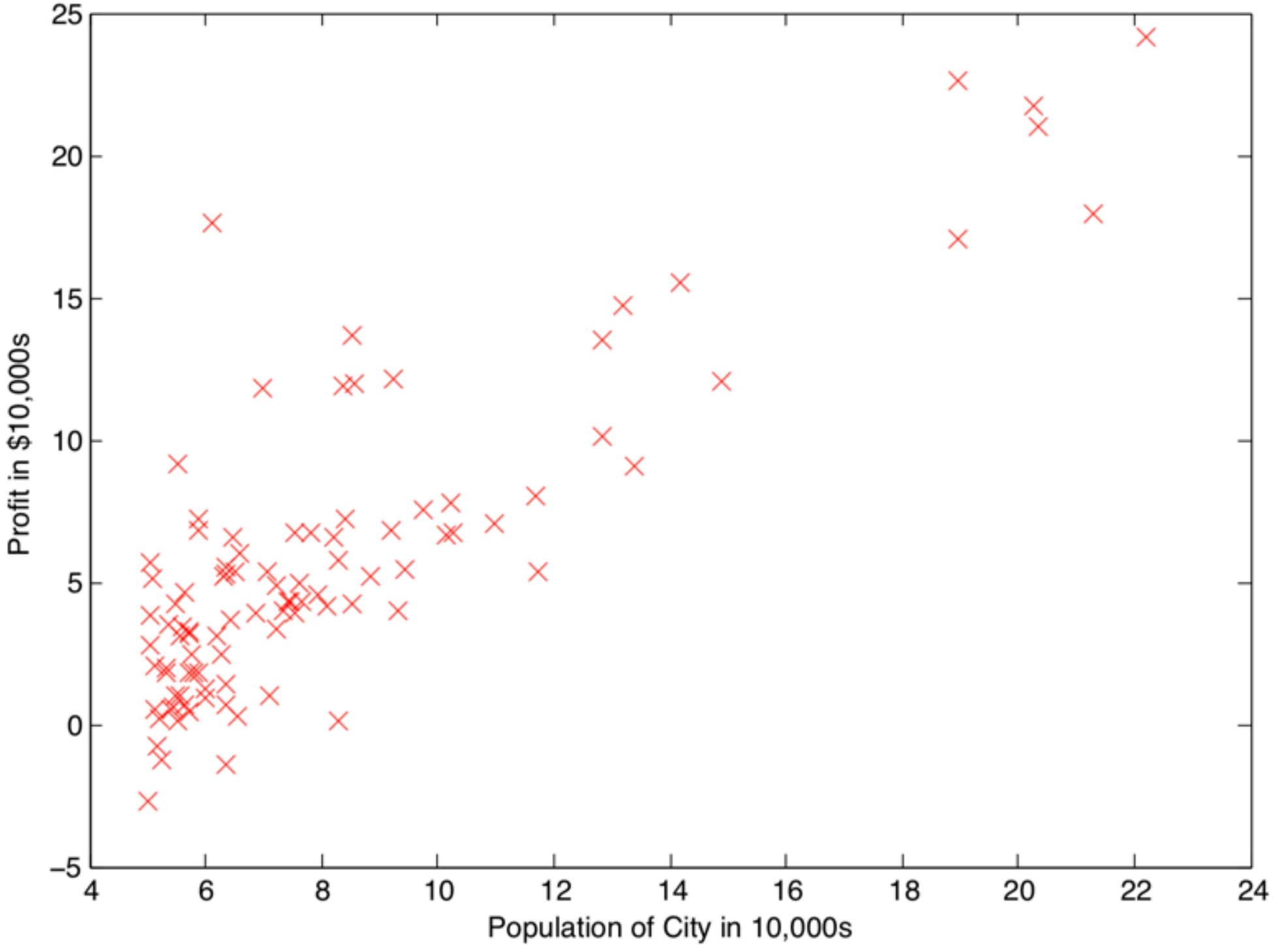


## Supervised learning

- Linear regression
- Logistic regression
- Support Vector Machines
- Neural networks

## Unsupervised learning

- K-means
- Anomaly detection
- Neural networks
- Recommender systems


25
20
15
10
5
0
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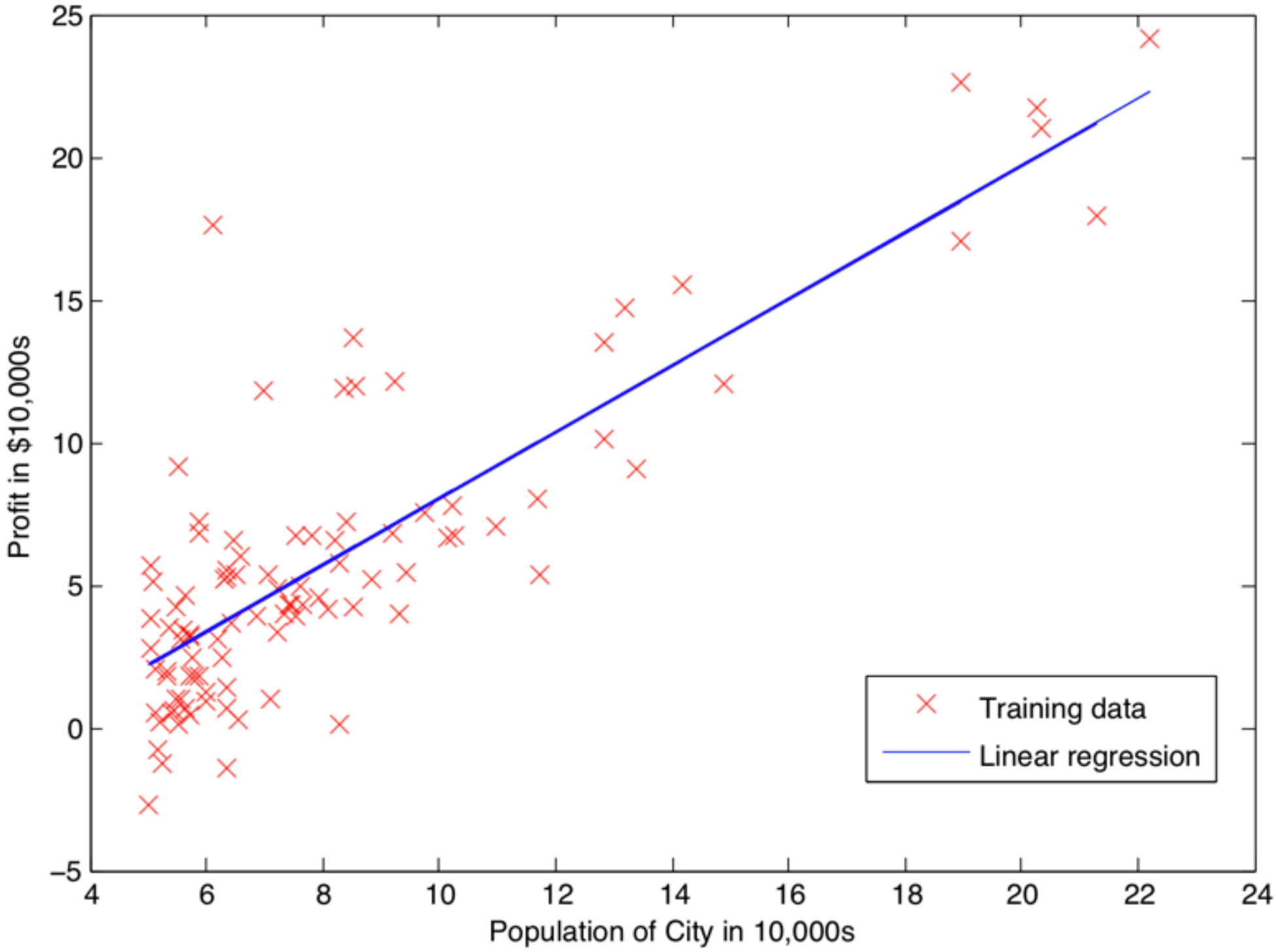
Profit in $10,000s
4
6
8
10
12
14
16
18
20
22
24
Population of City in 10,000s


25
20
15
10
5
0
−5
4
6
8
10
12
14
16
18
20
22
24
Profit in $10,000s
Population of City in 10,000s
Training data
Linear regression

# Linear regression

## hypotheses

$$h(x) = \sum_{i=0}^{n} \theta_i x_i = \theta^T x,$$

$$h_\theta(x) = \theta^T x = \theta_0 + \theta_1 x_1$$

## cost function

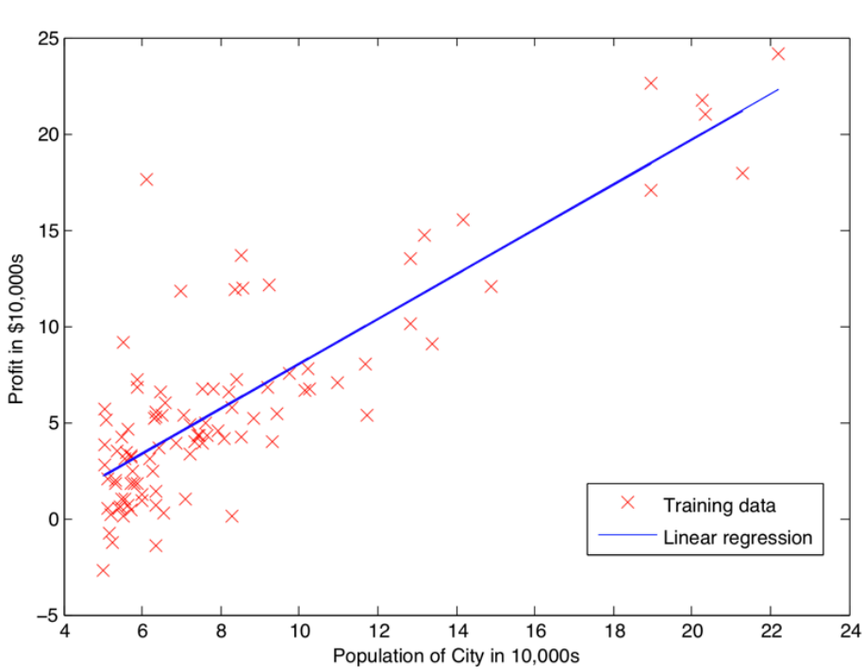
$$J(\theta) = \frac{1}{2} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2.$$

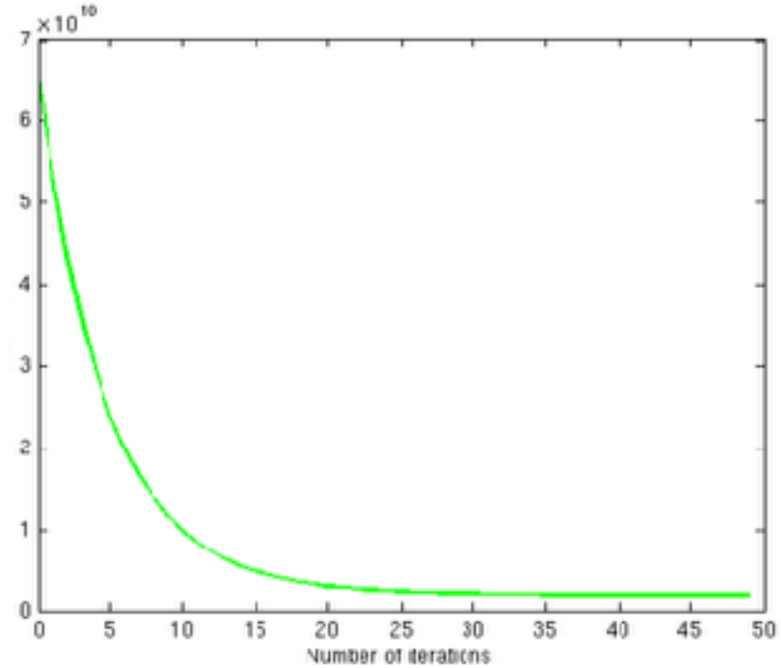
## gradient descent

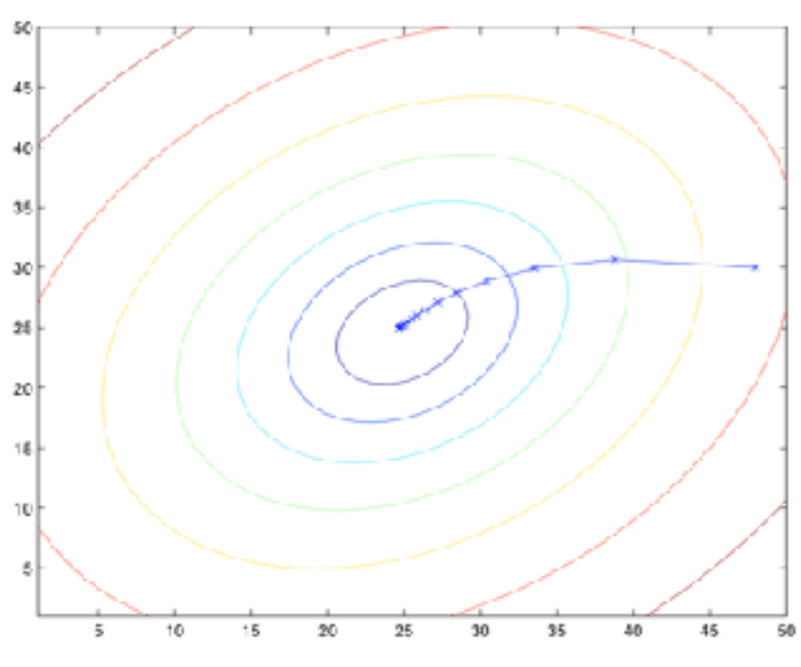
Repeat until convergence {

$$\theta_j := \theta_j + \alpha \sum_{i=1}^{m} \left( y^{(i)} - h_\theta(x^{(i)}) \right) x_j^{(i)}$$

}



# 1 iteration

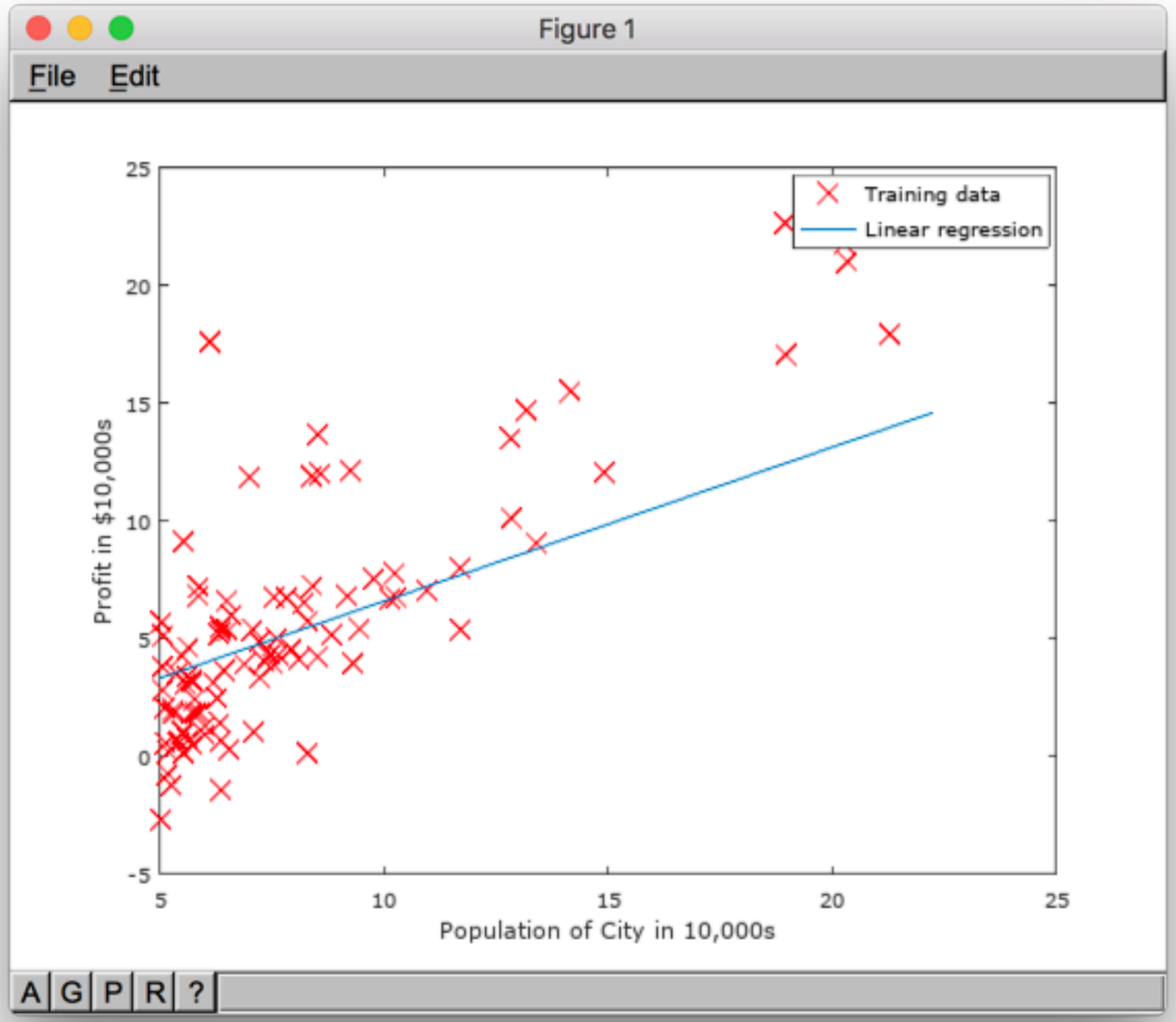
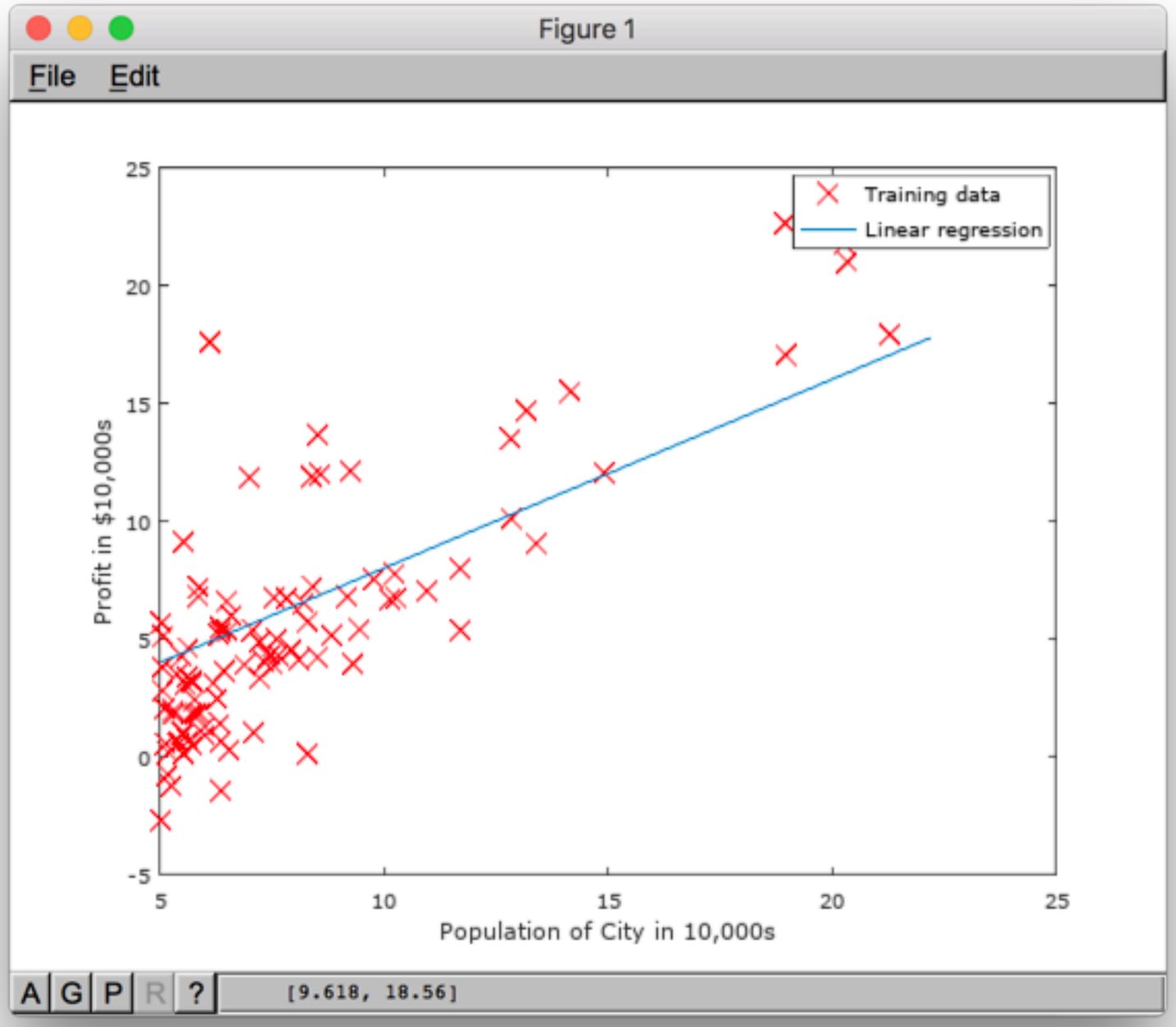
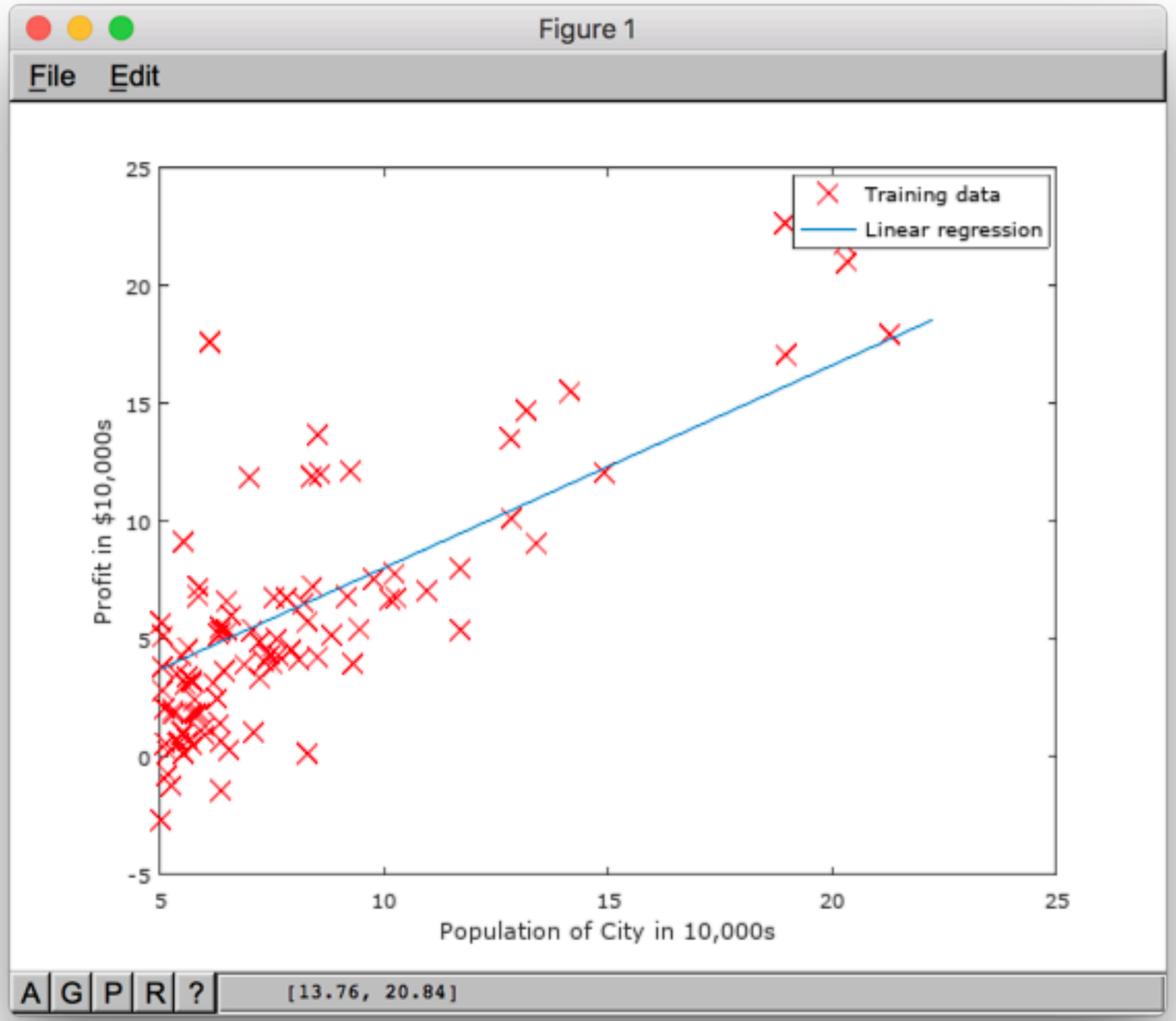


Figure 1
File Edit
Training data
Linear regression
Profit in $10,000s
Population of City in 10,000s
25
20
15
10
5
0
-5
5
10
15
20
25
A G P R ?

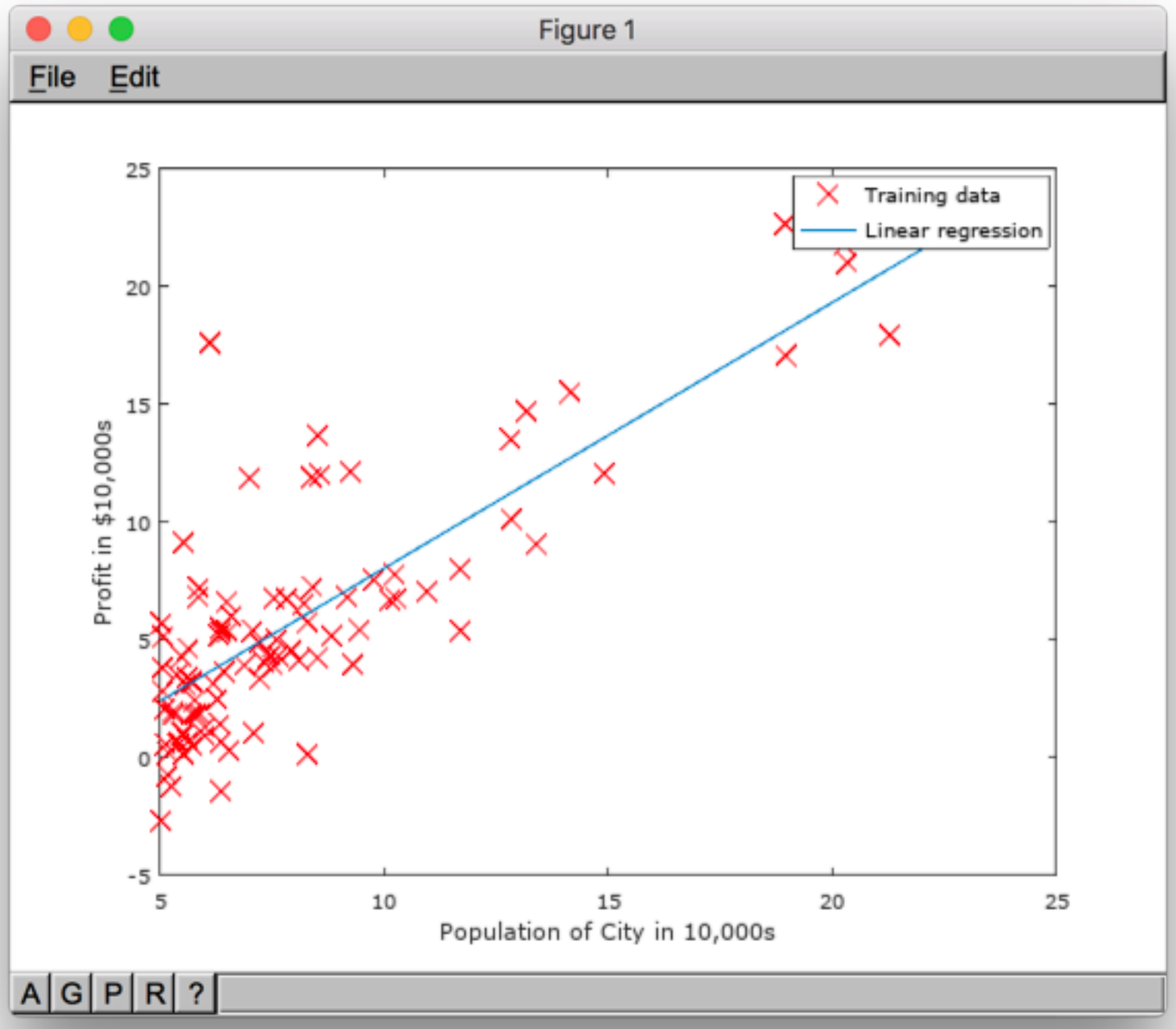
# 10 iterations



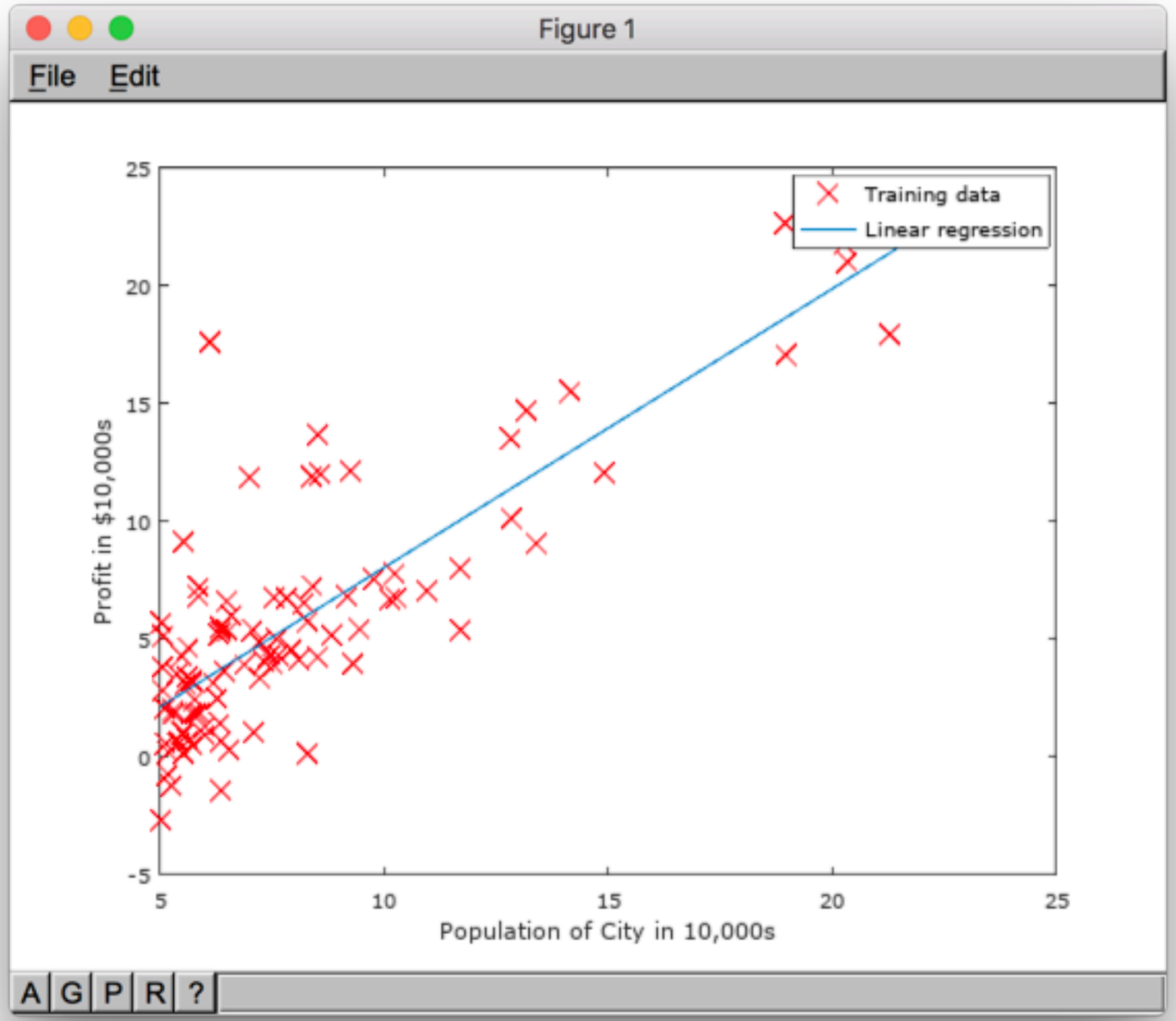
# 100 iterations



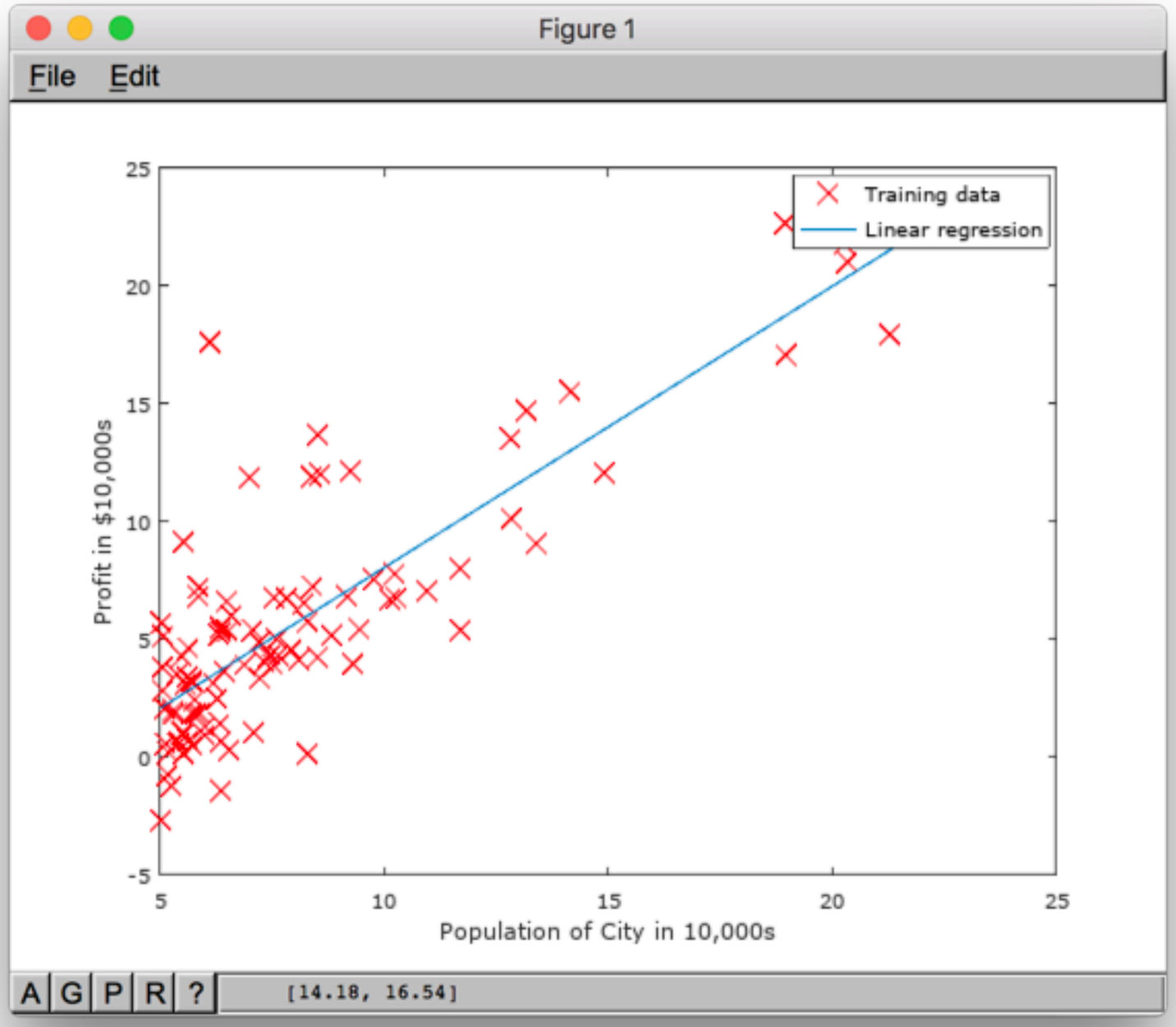
# 1000 iterations



# 2000 iterations

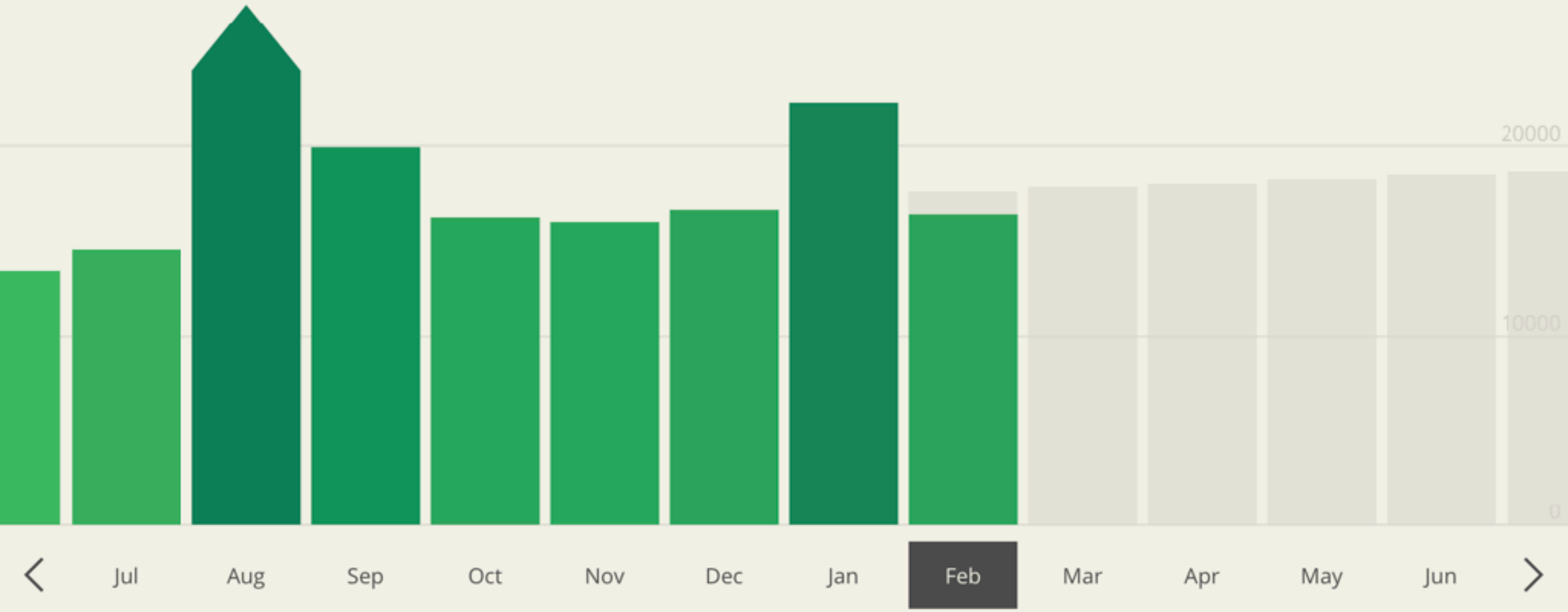


# 10000 iterations



February

Balance | Expenses | Incomes | Net Worth




Jul Aug Sep Oct Nov Dec Jan Feb Mar Apr May Jun

# Normal equation

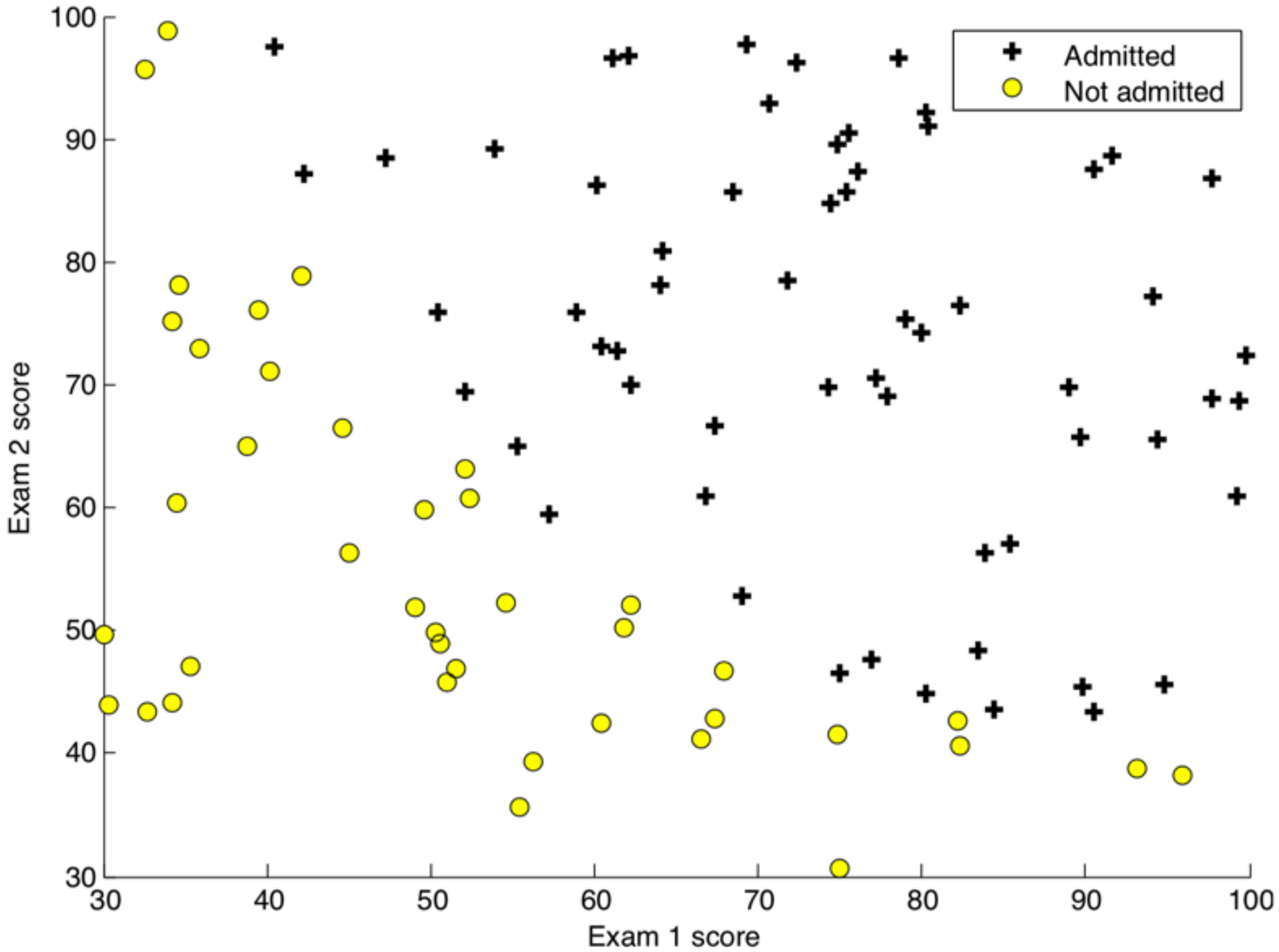
$$\theta = \left(X^T X\right)^{-1} X^T \vec{y}.$$

- computed in one step
- slow if n is large
- need to compute inv(X'X) - very slow
- problem if X'X not invertible
- prune outliers

```
import org.apache.commons.math3.linear.*;

private RealVector linearRegression(List<BigDecimal> list)
{
        double[] vector = new double[list.size()];
        double[][] matrix = new double[list.size()][2];
        // fill in vector and matrix
        RealMatrix X = MatrixUtils.createRealMatrix(matrix);
        RealVector y = MatrixUtils.createRealVector(vector);
        return MatrixUtils
                        .inverse(X.transpose().multiply(X))
                        .multiply(X.transpose())
                        .operate(y);
}
```

$$h_\theta(x) = \theta^T x = \theta_0 + \theta_1 x_1$$


Admitted
Not admitted
Exam 2 score
Exam 1 score
100
90
80
70
60
50
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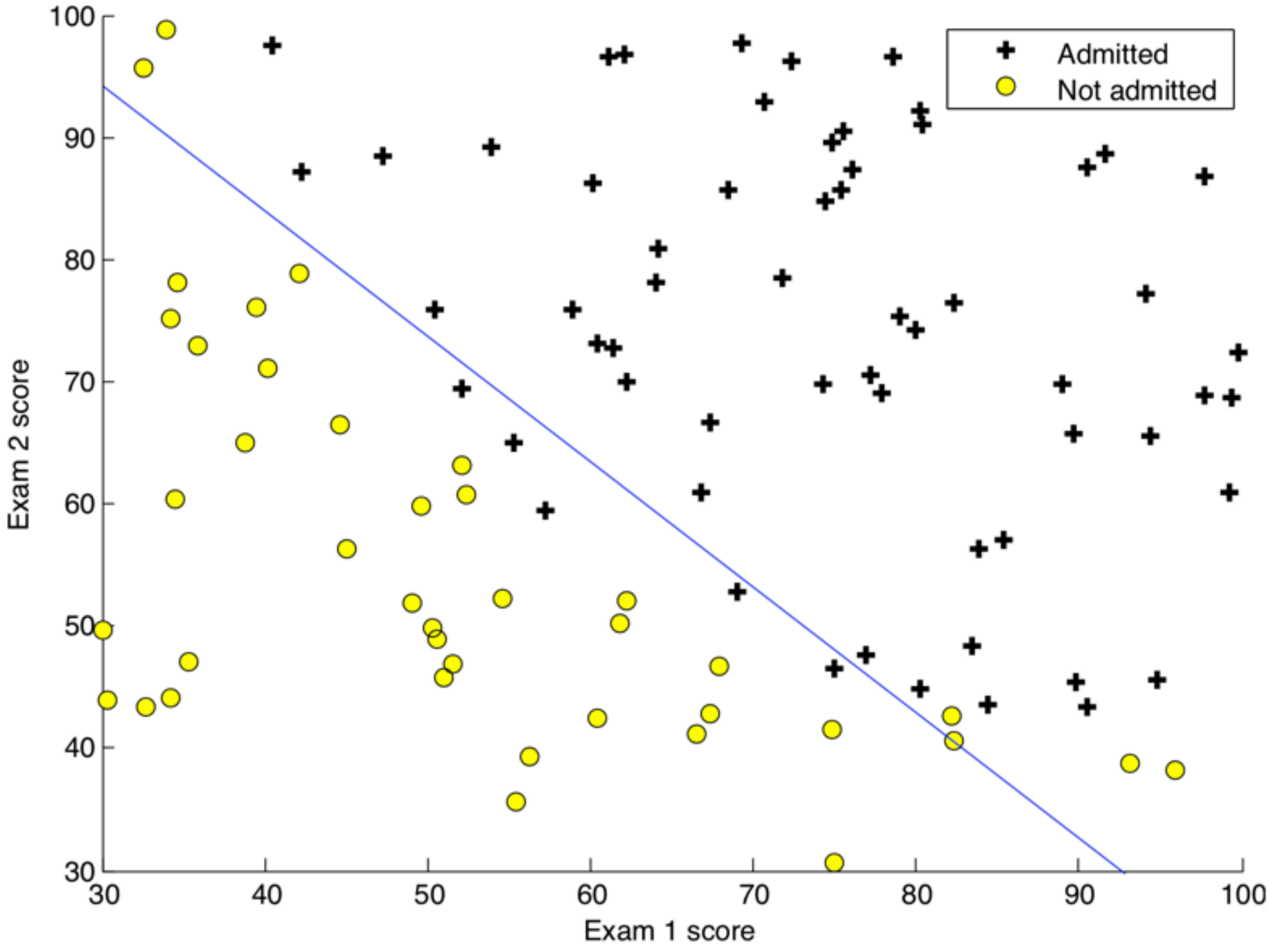
90
100


Admitted
Not admitted
Exam 2 score
Exam 1 score
100
90
80
70
60
50
40
30
30
40
50
60
70
80
90
100

# Logistic regression

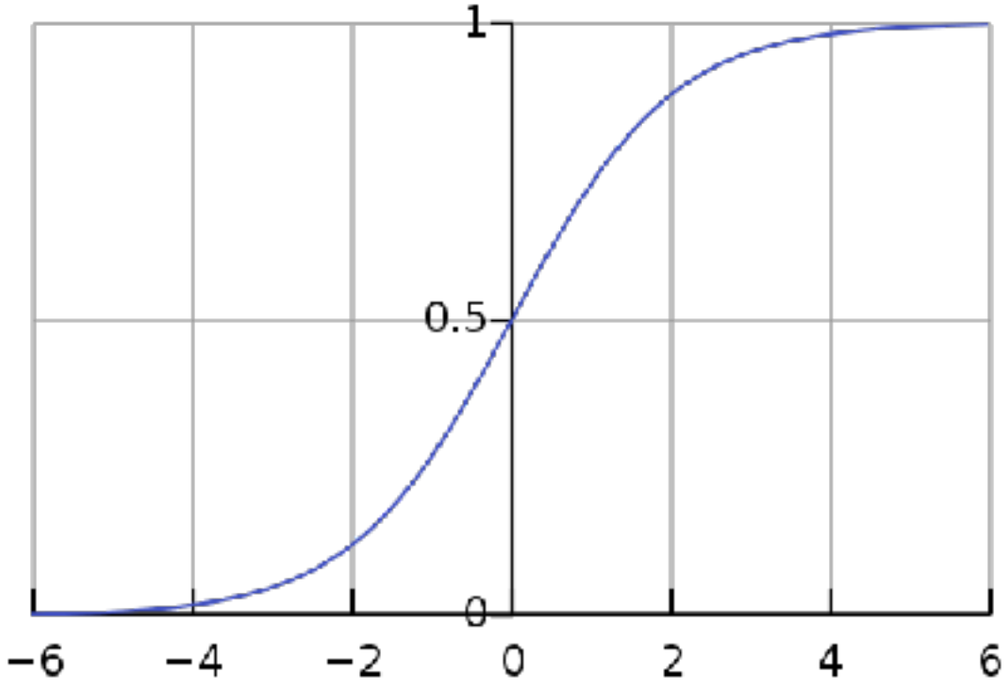
**hypotheses**

$$h_\theta(x) = g(\theta^T x),$$

$$g(z) = \frac{1}{1+e^{-z}}.$$

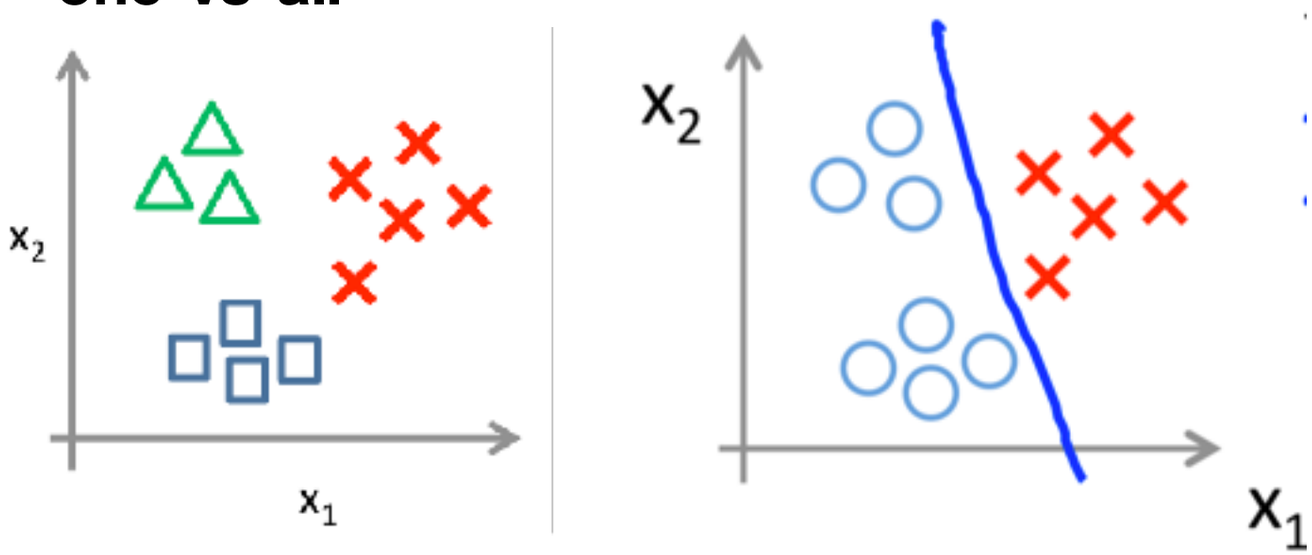
**cost function**

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m}\left[-y^{(i)}\log(h_\theta(x^{(i)})) - (1-y^{(i)})\log(1-h_\theta(x^{(i)}))\right]$$




$$g(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{if } z < 0 \end{cases}$$

**one-vs-all**




$$\max_i h_\theta^{(i)}(x)$$

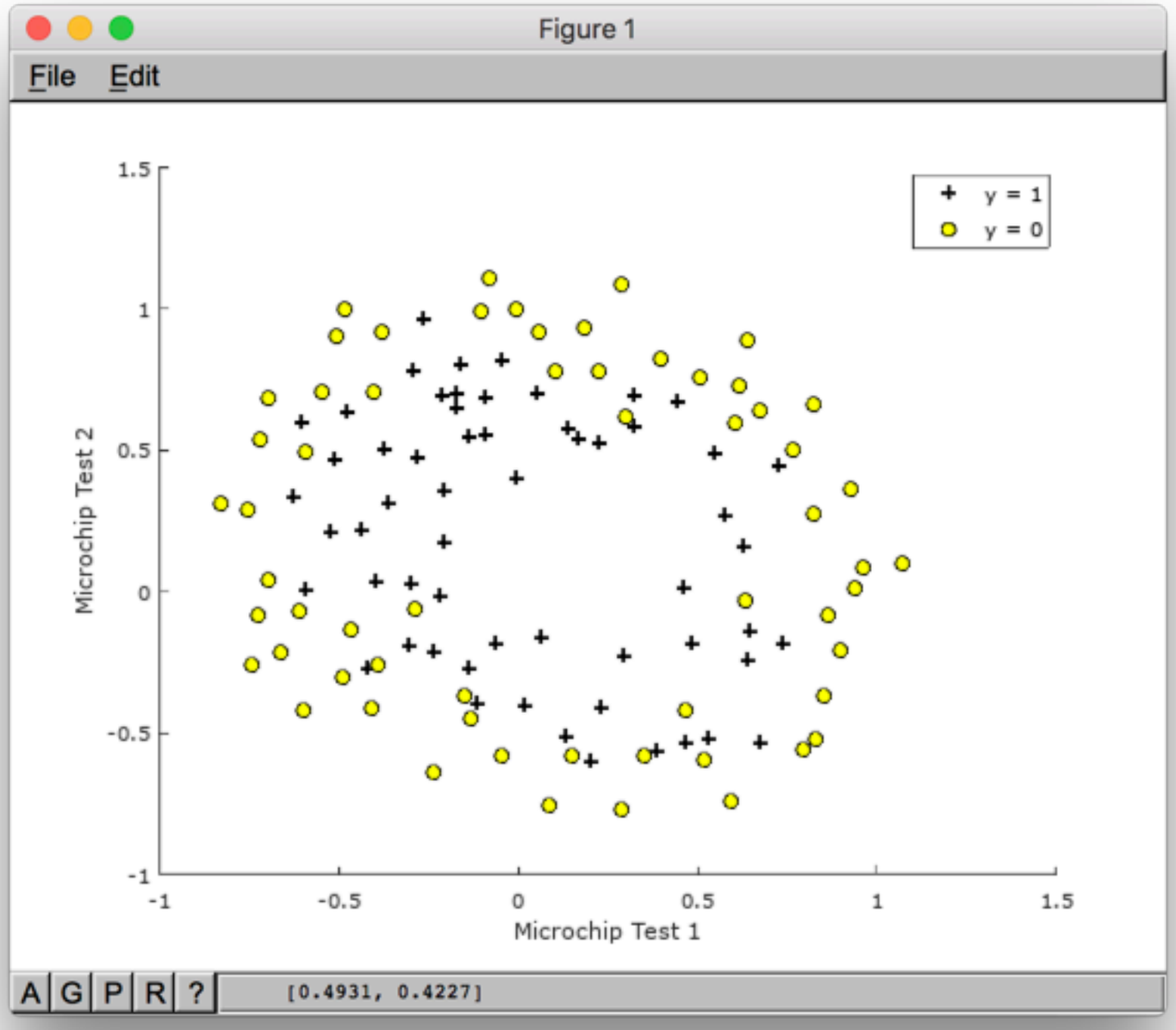


Figure 1
File Edit
y = 1
y = 0
1.5
1
0.5
0
-0.5
-1
-1
-0.5
0
0.5
1
1.5
Microchip Test 2
Microchip Test 1
A G P R ?
[0.4931, 0.4227]

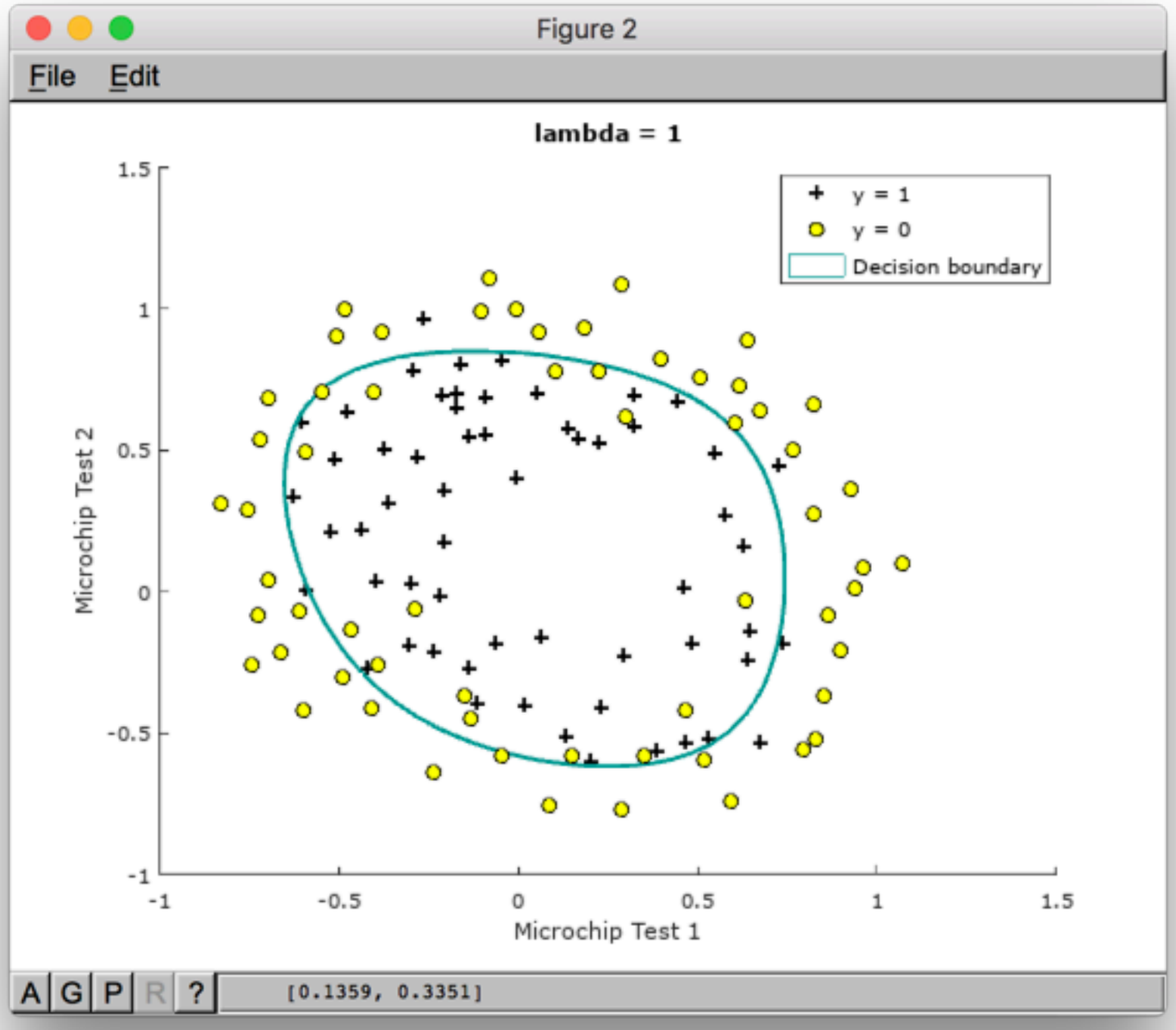


Figure 2
File Edit
lambda = 1
y = 1
y = 0
Decision boundary
Microchip Test 2
Microchip Test 1
1.5
1
0.5
0
-0.5
-1
-1
-0.5
0
0.5
1
1.5
A G P R ?
[0.1359, 0.3351]

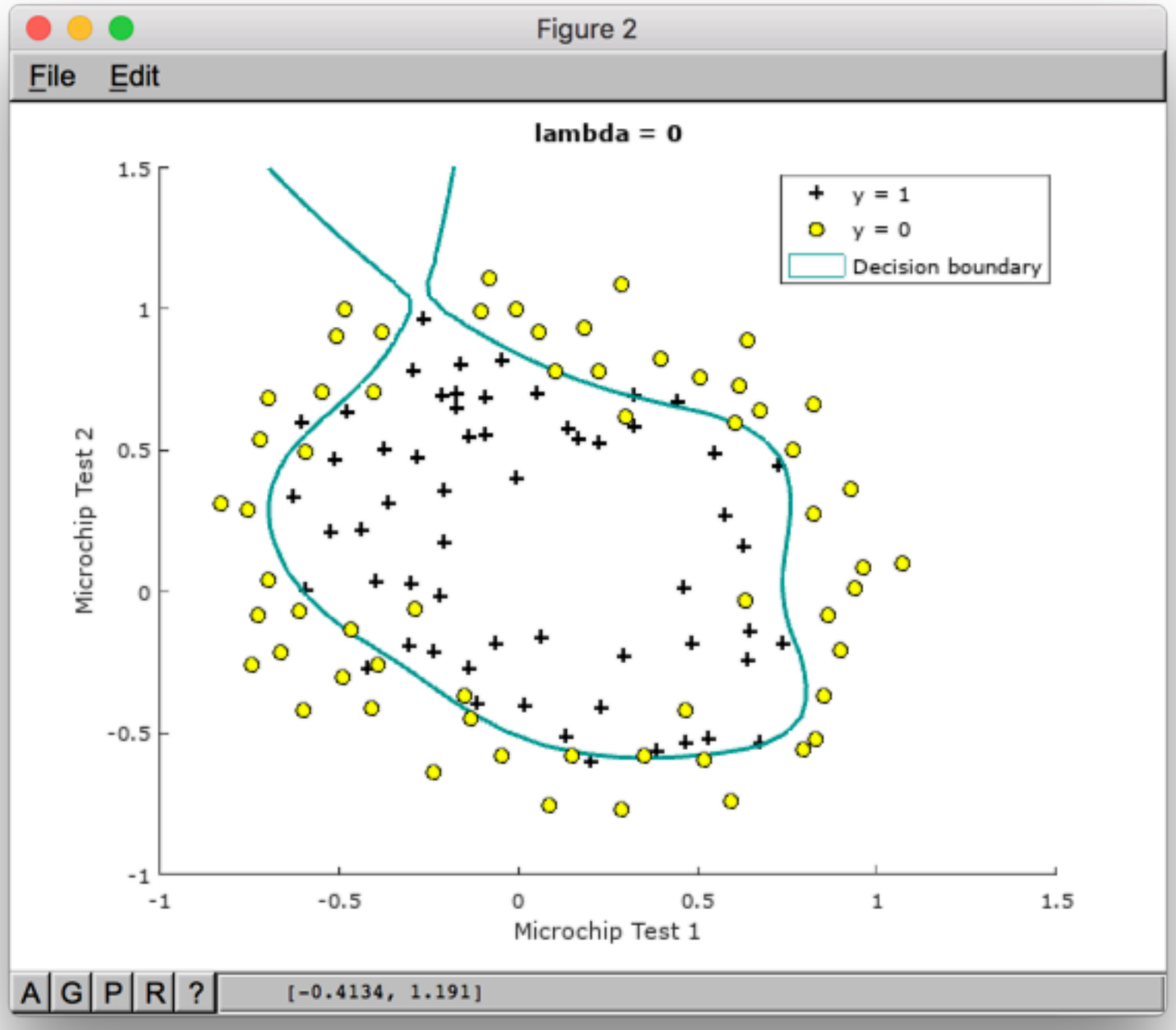


Figure 2
File Edit
lambda = 0
y = 1
y = 0
Decision boundary
Microchip Test 2
Microchip Test 1
1.5
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-1
-1
-0.5
0
0.5
1
1.5
A G P R ?
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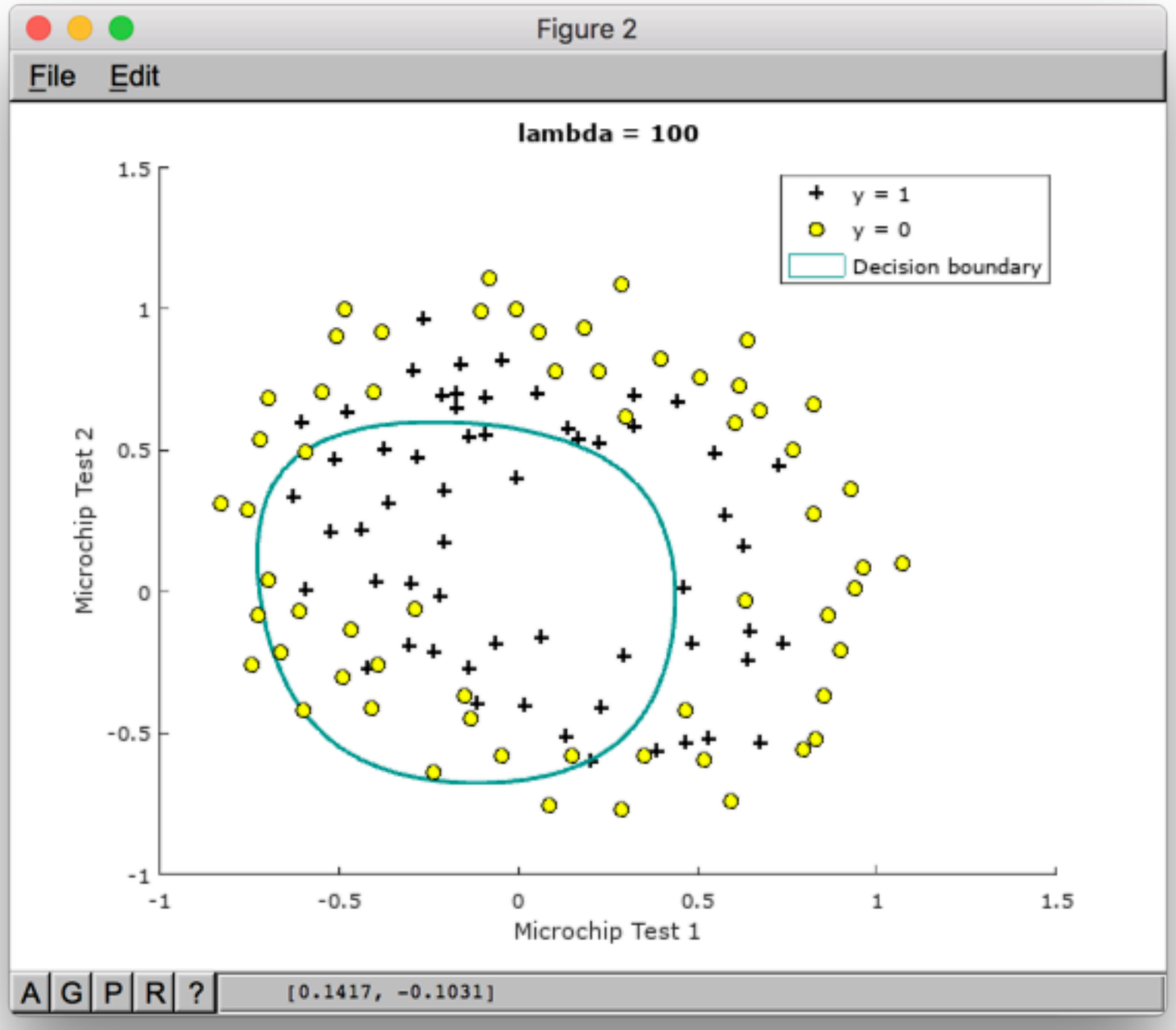
Figure 2
File Edit
lambda = 100
y = 1
y = 0
Decision boundary
1.5
1
0.5
0
-0.5
-1
-1
-0.5
0
0.5
1
1.5
Microchip Test 2
Microchip Test 1
A G P R ?
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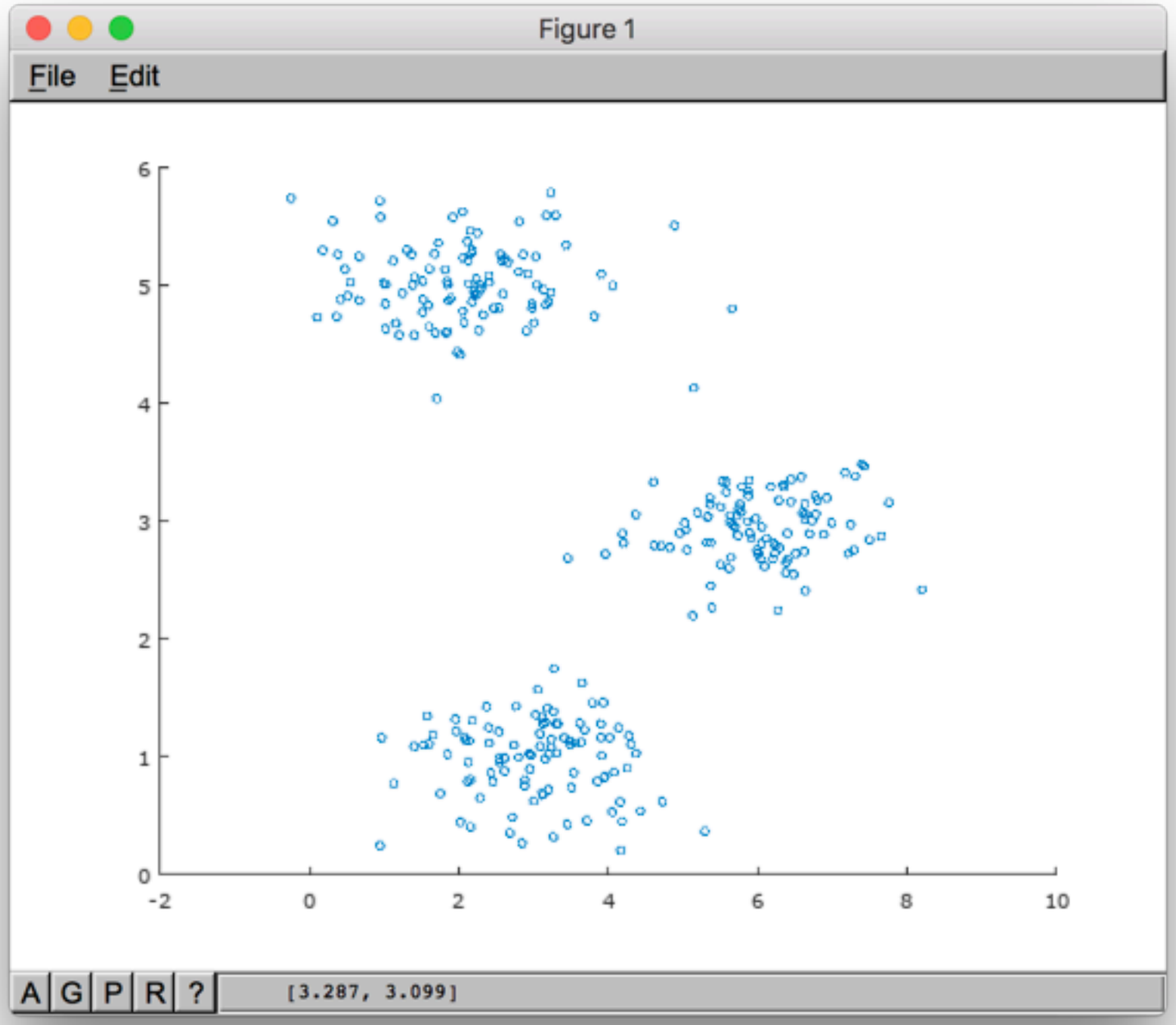
Figure 1
File Edit
6
5
4
3
2
1
0
-2
0
2
4
6
8
10
A G P R ?
[3.287, 3.099]

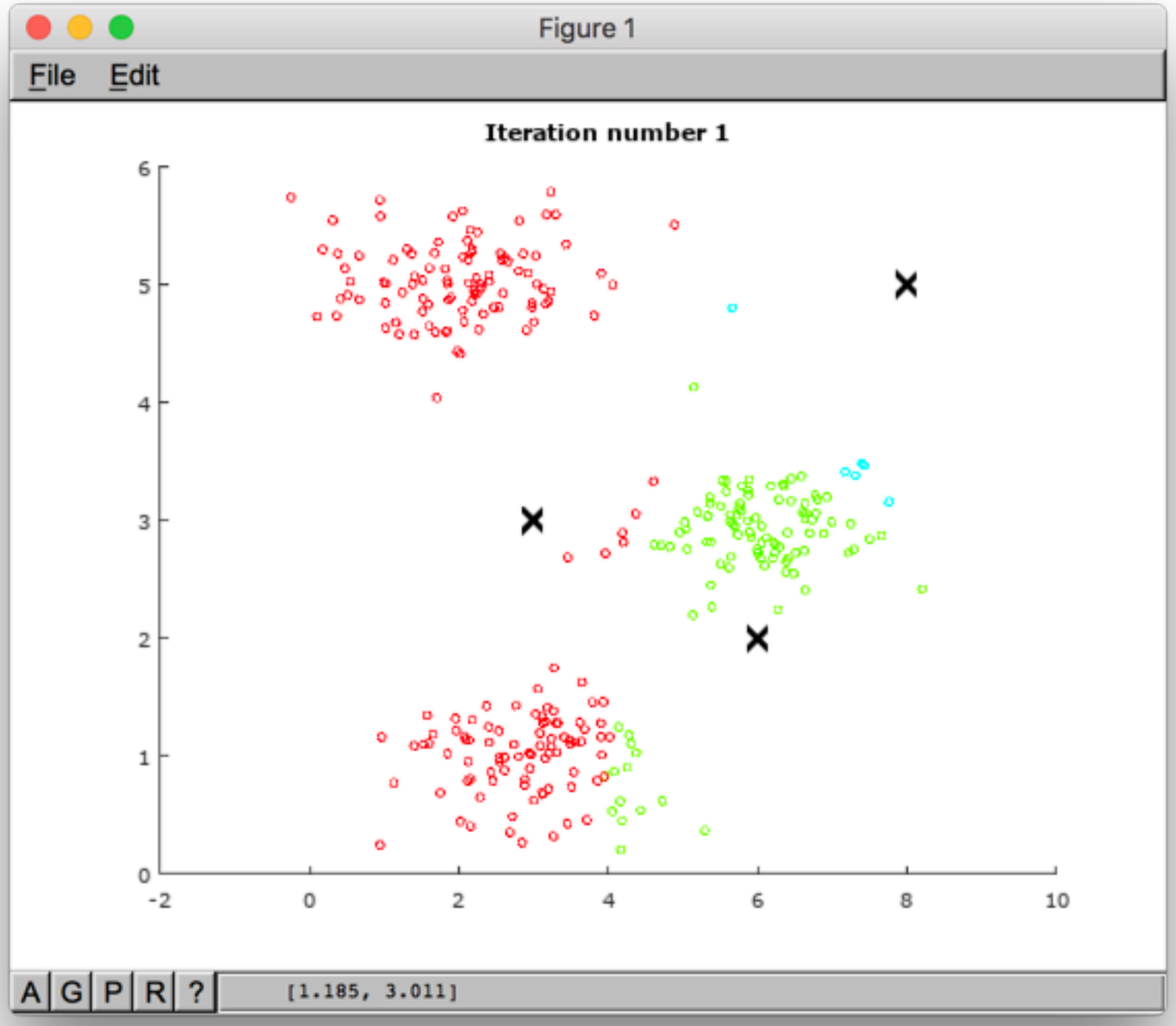
Figure 1
File Edit
Iteration number 1
6
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4
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2
1
0
-2
0
2
4
6
8
10
A G P R ?
[1.185, 3.011]

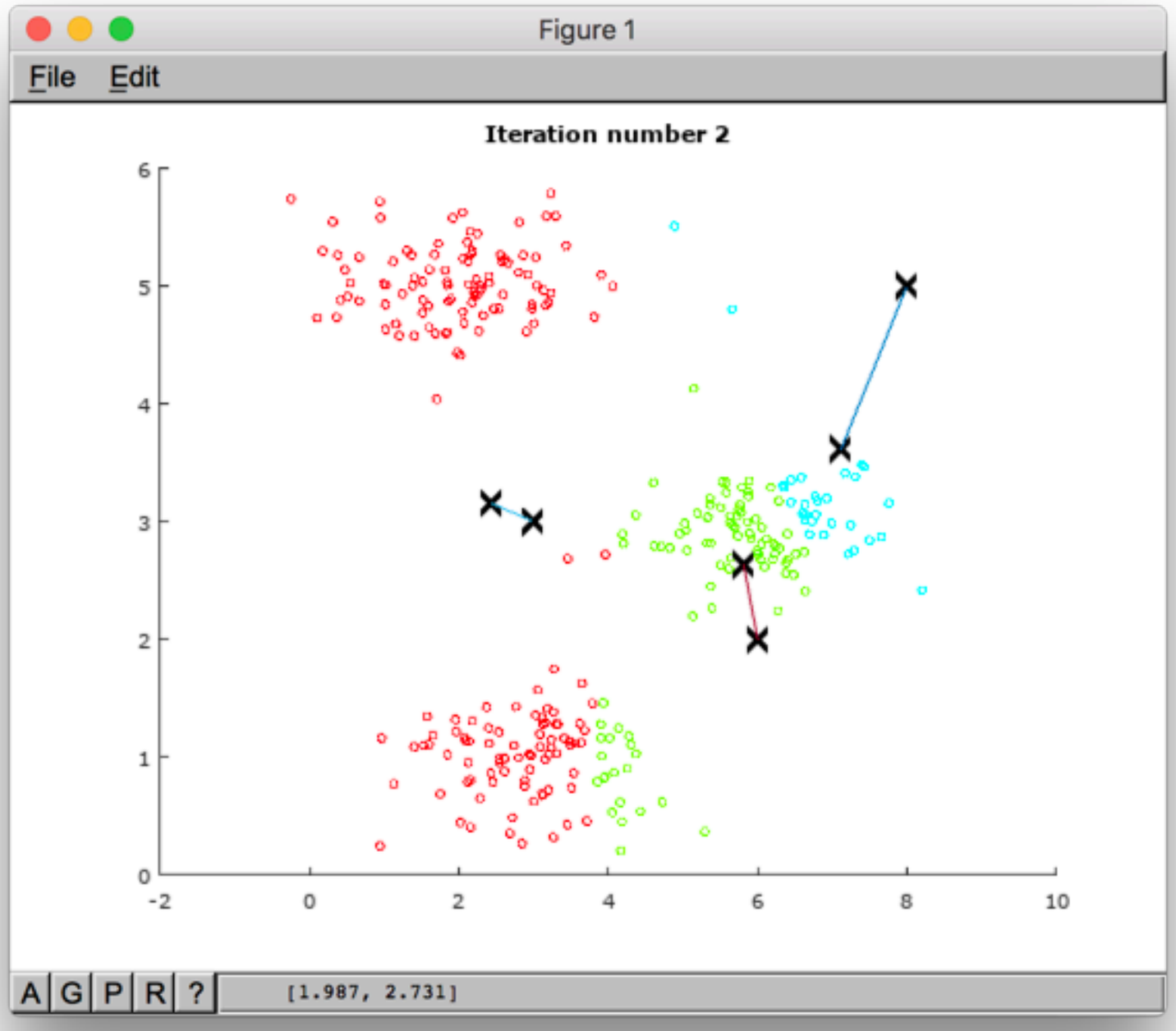
Figure 1
File Edit
Iteration number 2
6
5
4
3
2
1
0
-2
0
2
4
6
8
10
A G P R ?
[1.987, 2.731]

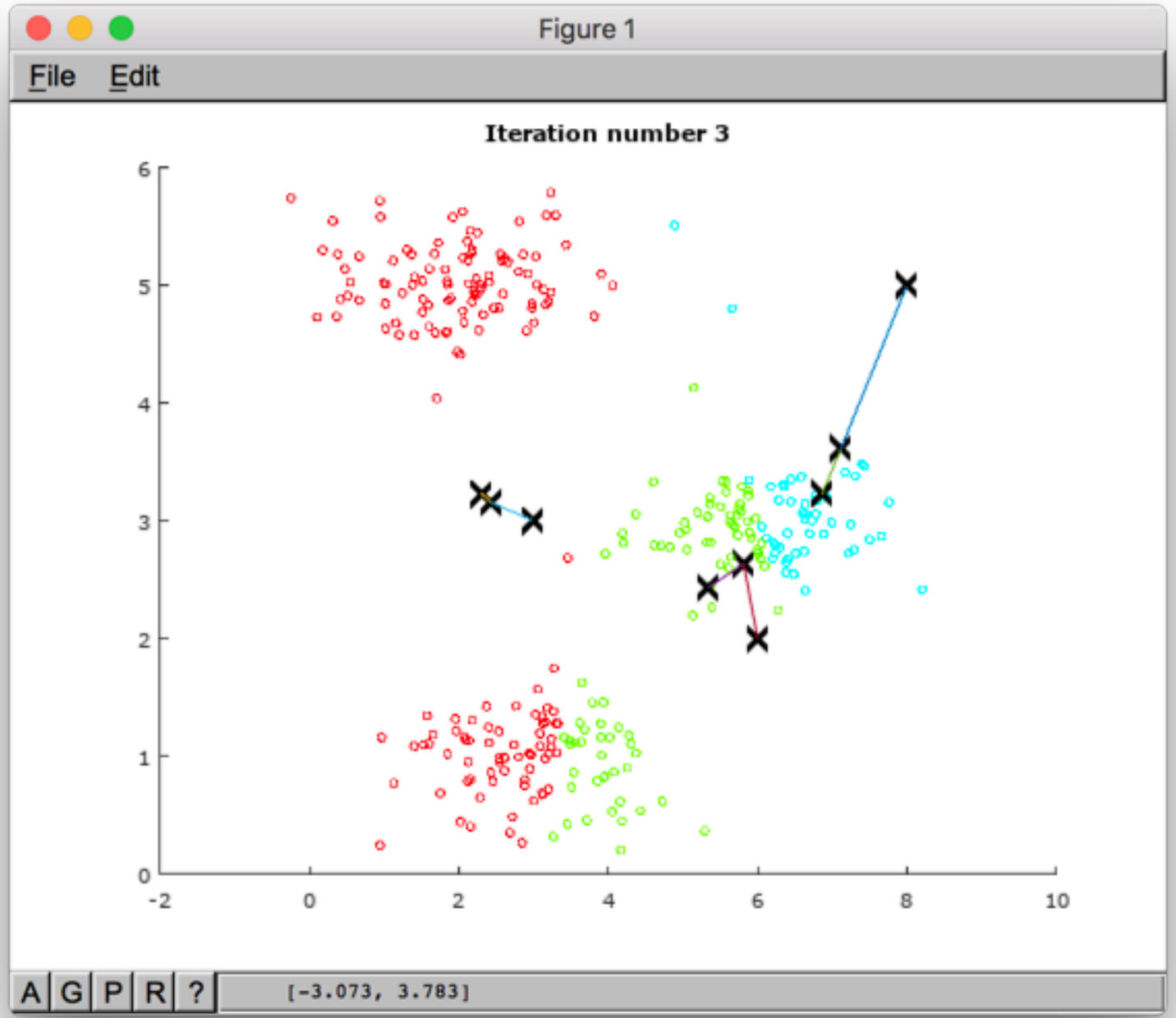
Figure 1
File Edit
Iteration number 3
6
5
4
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2
1
0
-2
0
2
4
6
8
10
A G P R ?
[-3.073, 3.783]

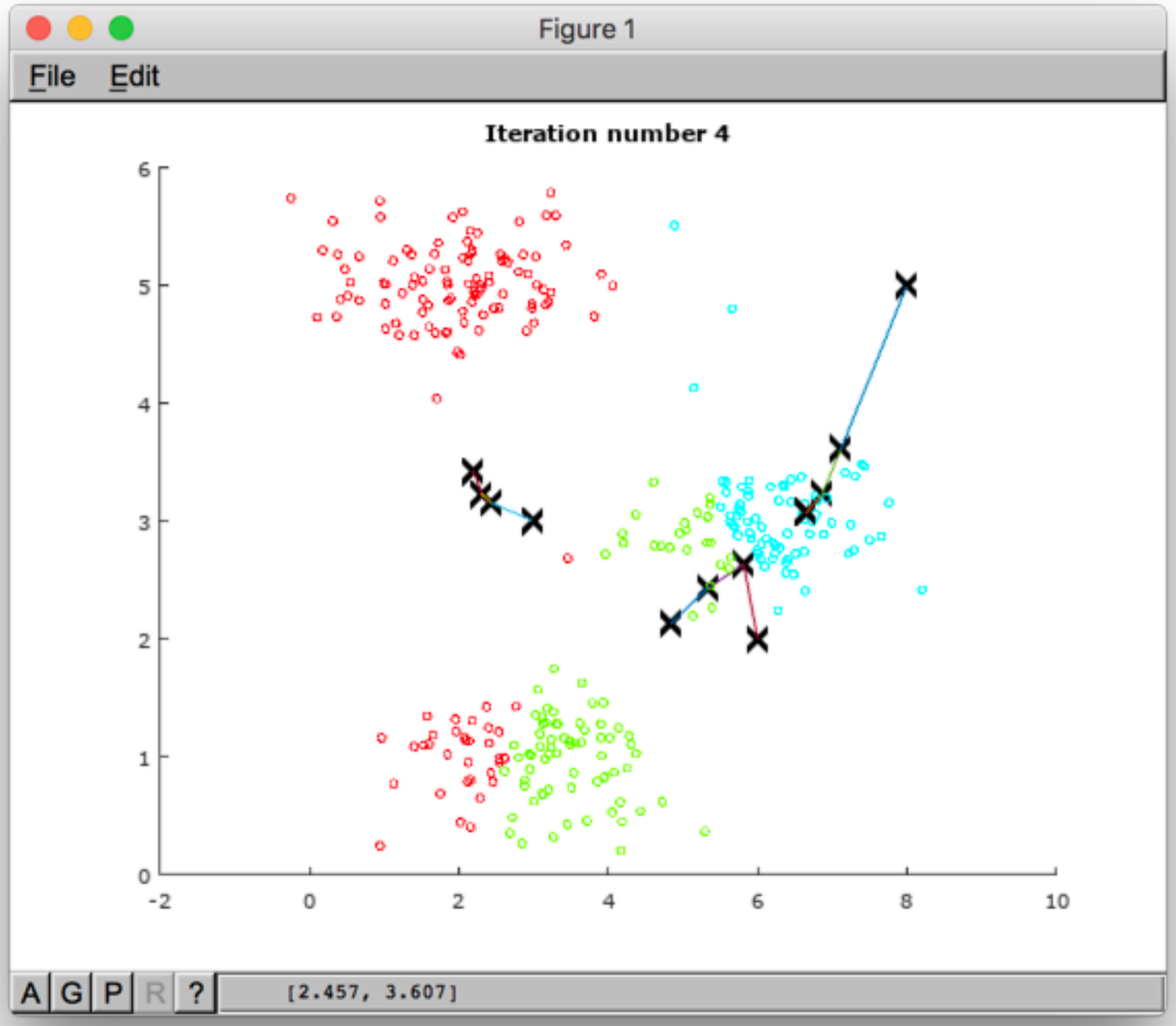


Figure 1
File Edit
Iteration number 4
6
5
4
3
2
1
0
-2
0
2
4
6
8
10
A G P R ?
[2.457, 3.607]

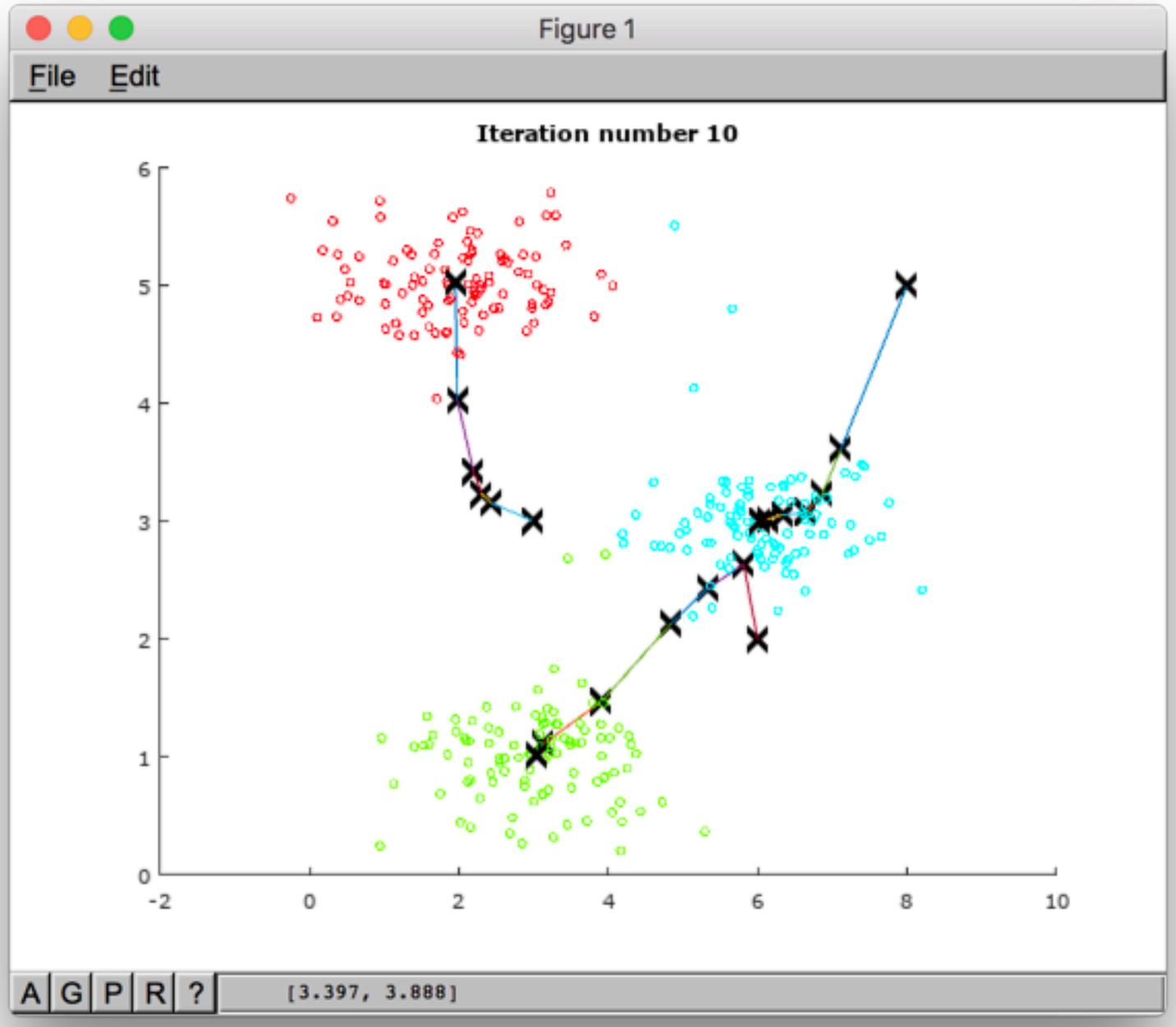


Figure 1
File Edit
Iteration number 10
6
5
4
3
2
1
0
-2
0
2
4
6
8
10
A G P R ?
[3.397, 3.888]

# K-means

```
% Initialize centroids
centroids = kMeansInitCentroids(X, K);
for iter = 1:iterations
    % Cluster assignment step: Assign each data point to the
    % closest centroid. idx(i) corresponds to c^(i), the index
    % of the centroid assigned to example i
    idx = findClosestCentroids(X, centroids);

    % Move centroid step: Compute means based on centroid
    % assignments
    centroids = computeMeans(X, idx, K);
end
```

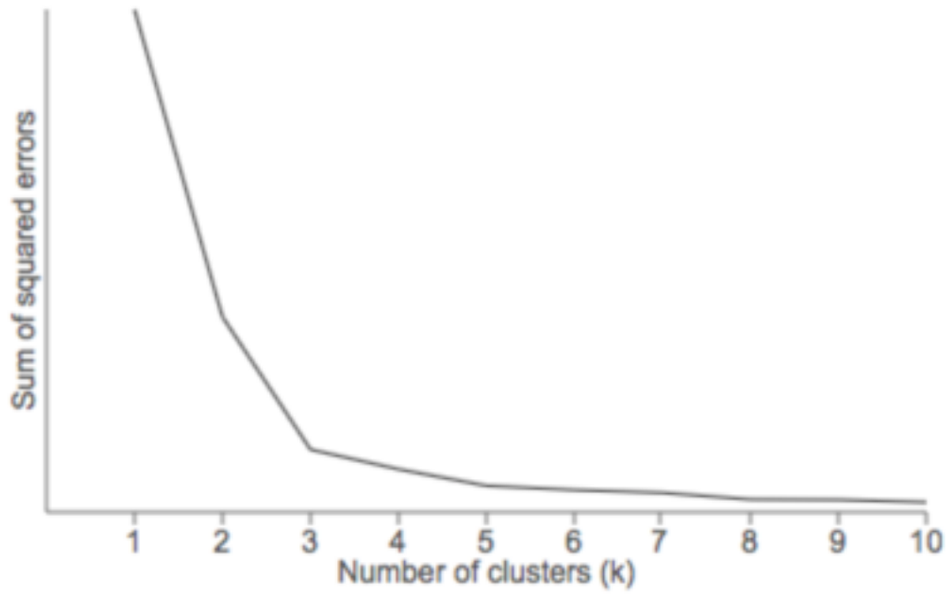
## find closest centroids

$$c^{(i)} := j \quad \text{that minimizes} \quad ||x^{(i)} - \mu_j||^2,$$

## compute means

$$\mu_k := \frac{1}{|C_k|} \sum_{i \in C_k} x^{(i)}$$

## elbow method



I LOVE IT WHEN

YOU CALL ME BIG DATA

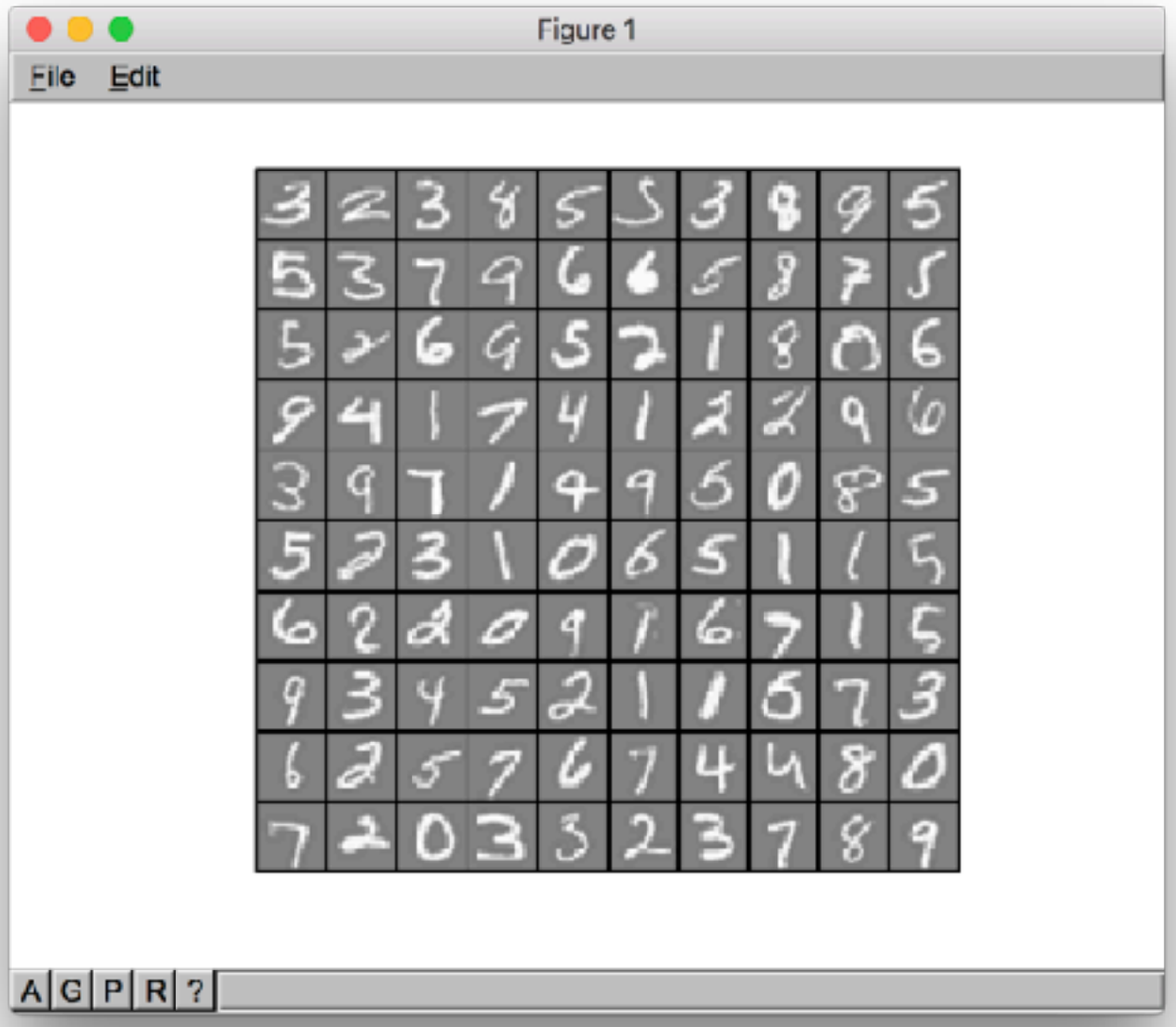
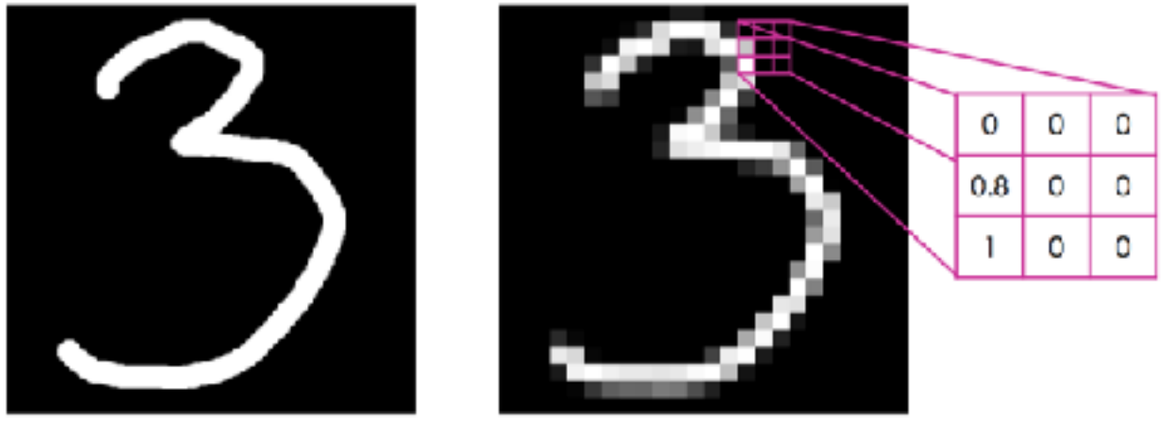
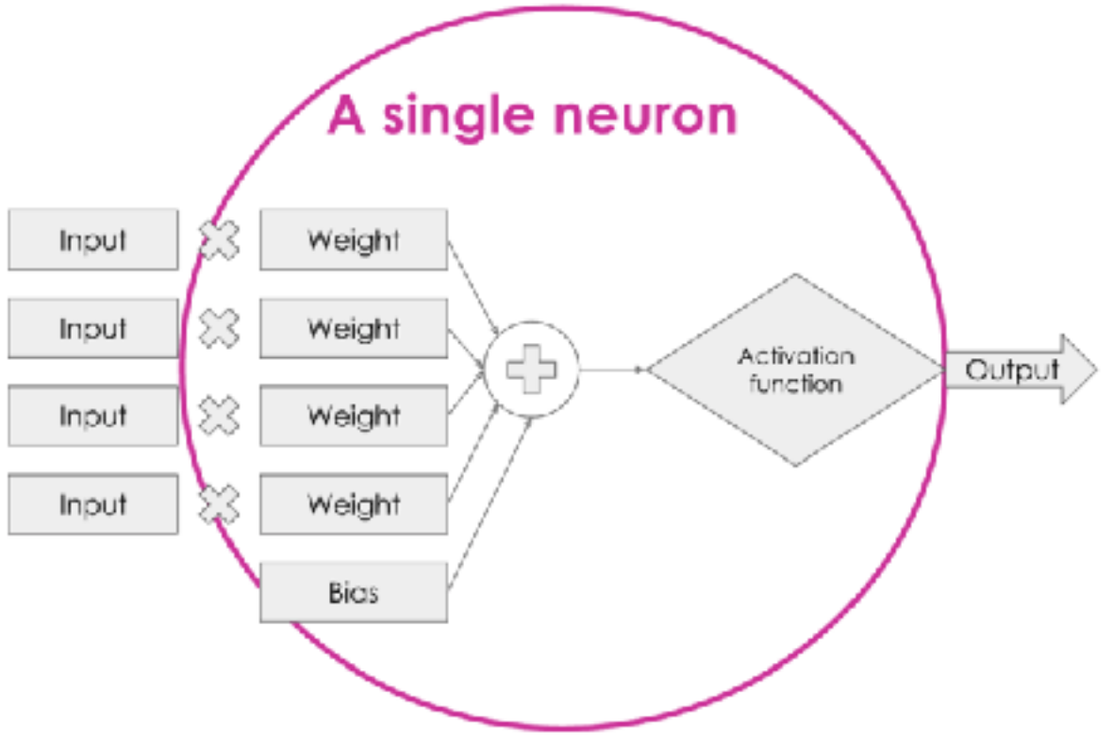
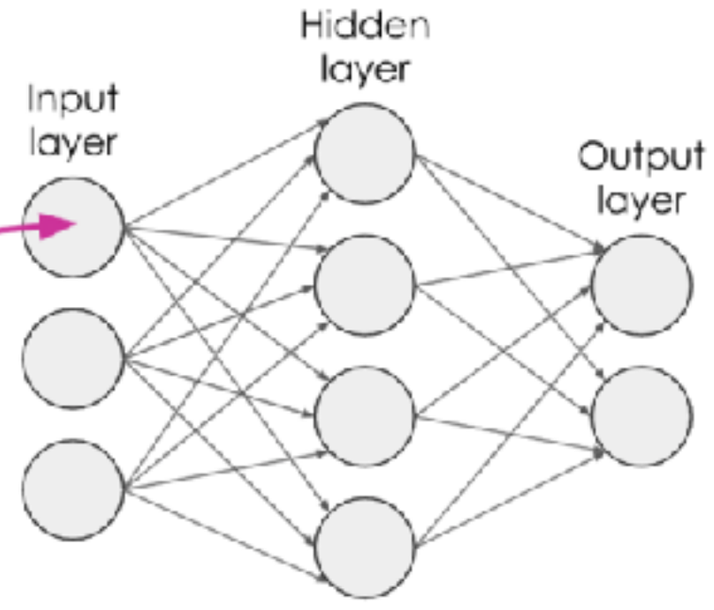


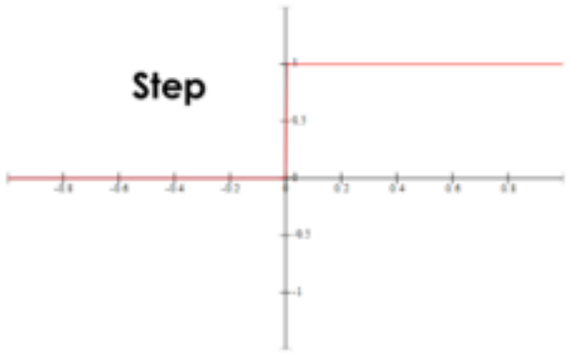
Figure 1
File Edit
A G P R ?


0 0 0
0.8 0 0
1 0 0

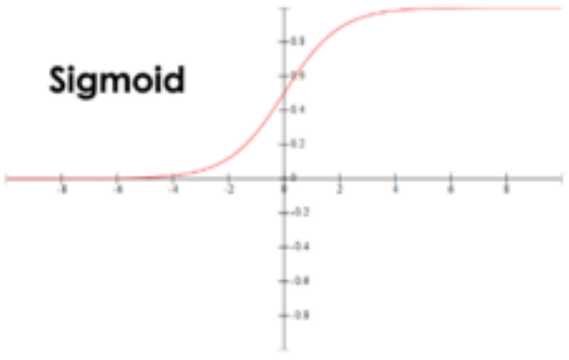


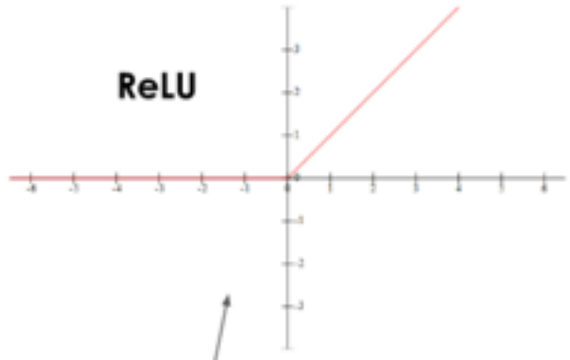

Each of these blobs is a neuron



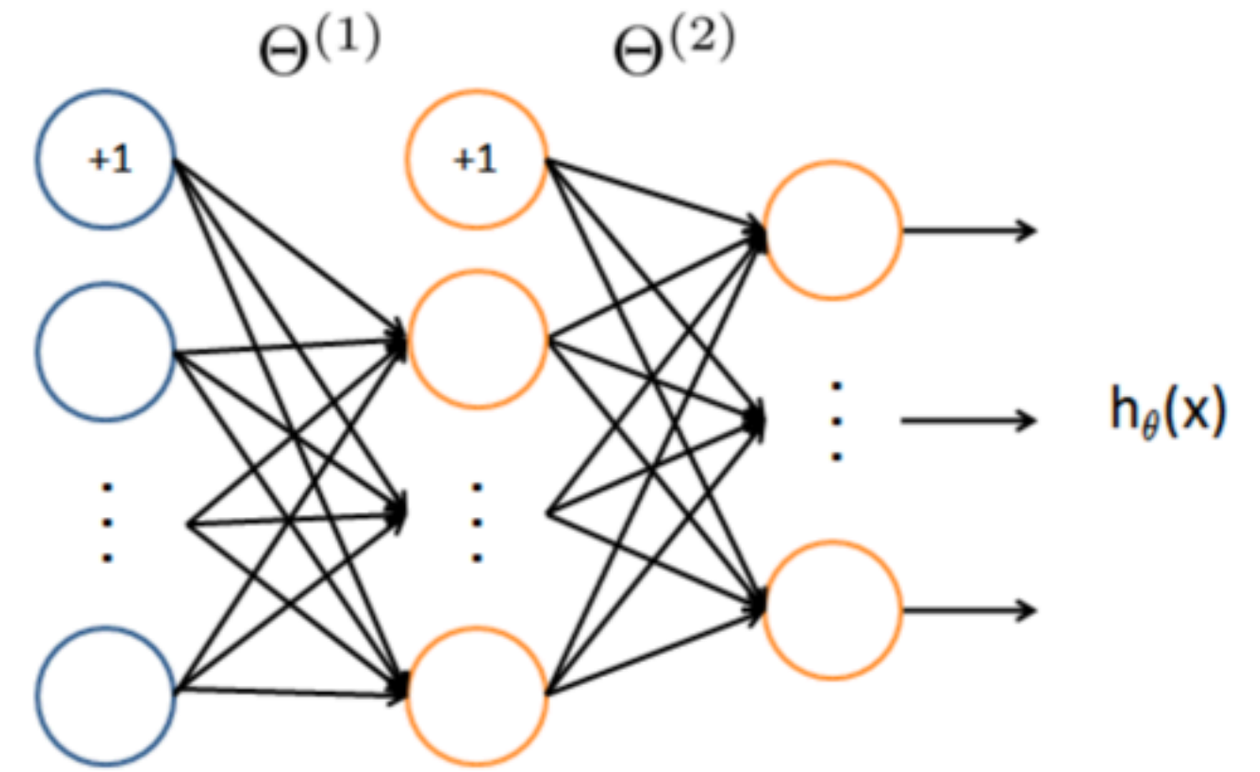

Popular historically




Popular these days

# Neural network model




$a^{(1)} = x$ (add $a_0^{(1)}$)

$z^{(2)} = \Theta^{(1)} a^{(1)}$

$a^{(2)} = g(z^{(2)})$ (add $a_0^{(2)}$)

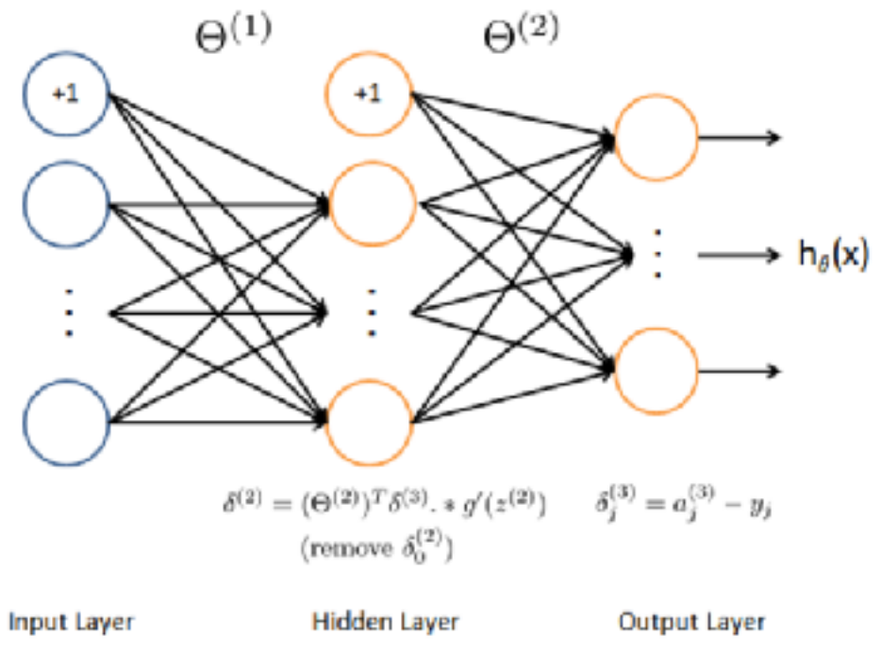
$z^{(3)} = \Theta^{(2)} a^{(2)}$

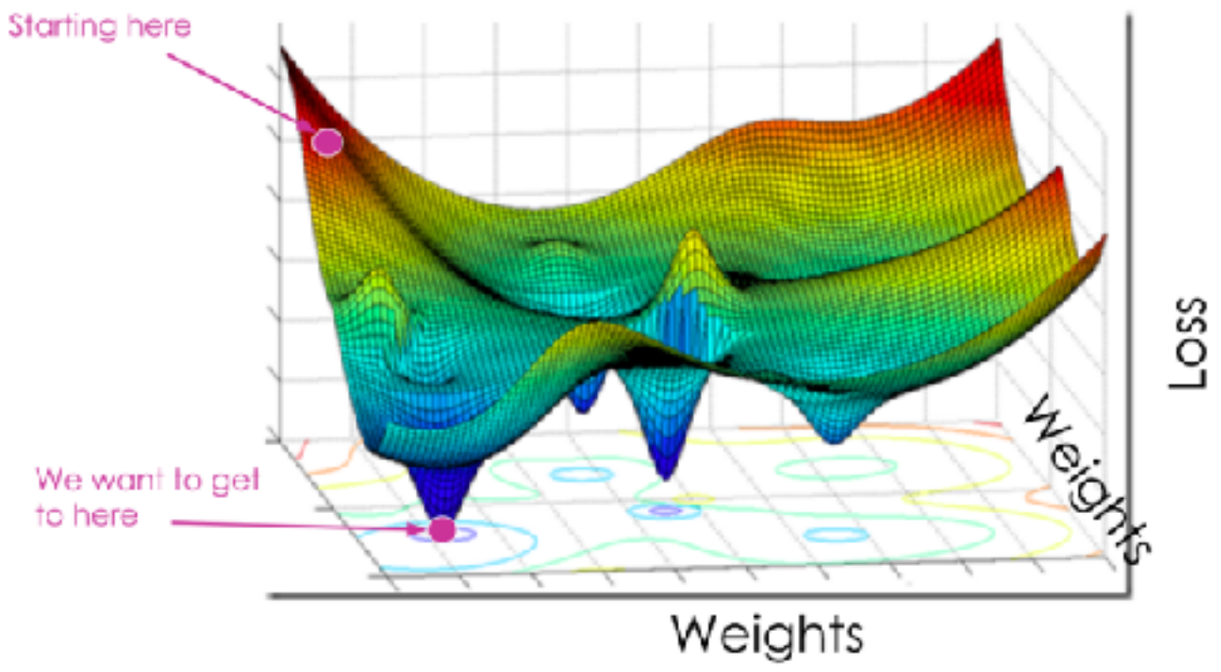
$a^{(3)} = g(z^{(3)}) = h_\theta(x)$

Input Layer | Hidden Layer | Output Layer

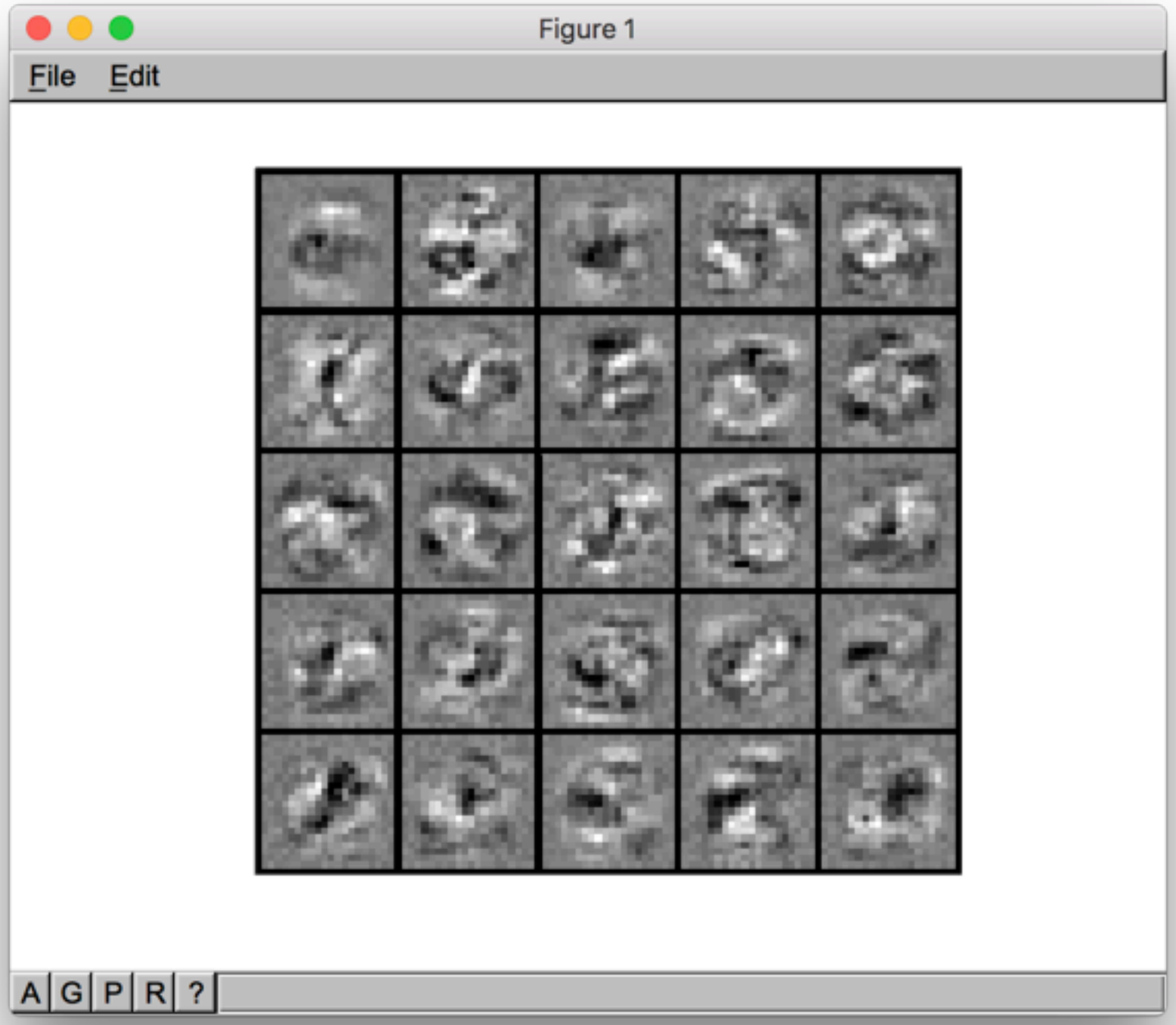
# Training a neural network

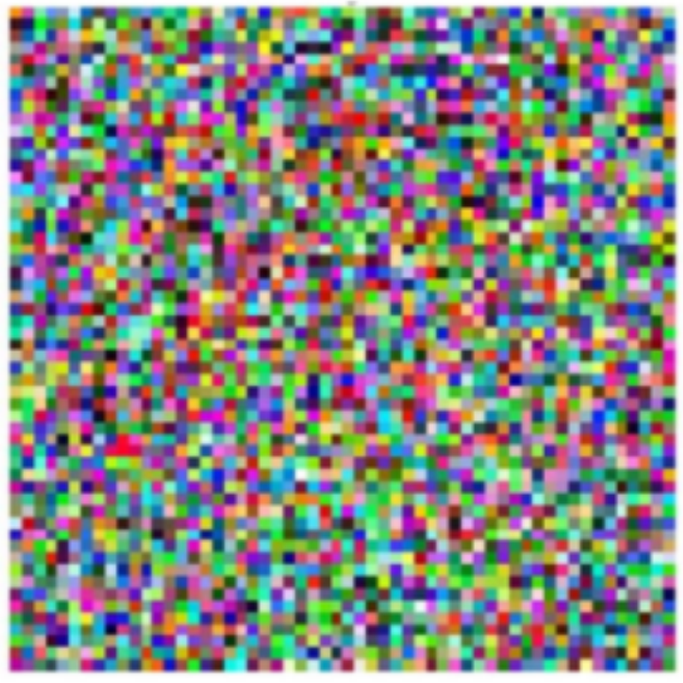
- Randomly initialise the network weights and biases
- For every piece of training data, feed it into the network
- Check whether the network gets it right
- If not, how wrong was it? Or, how right was it?
- Nudge the weights a little to increase the probability of a correct answer
- Repeat



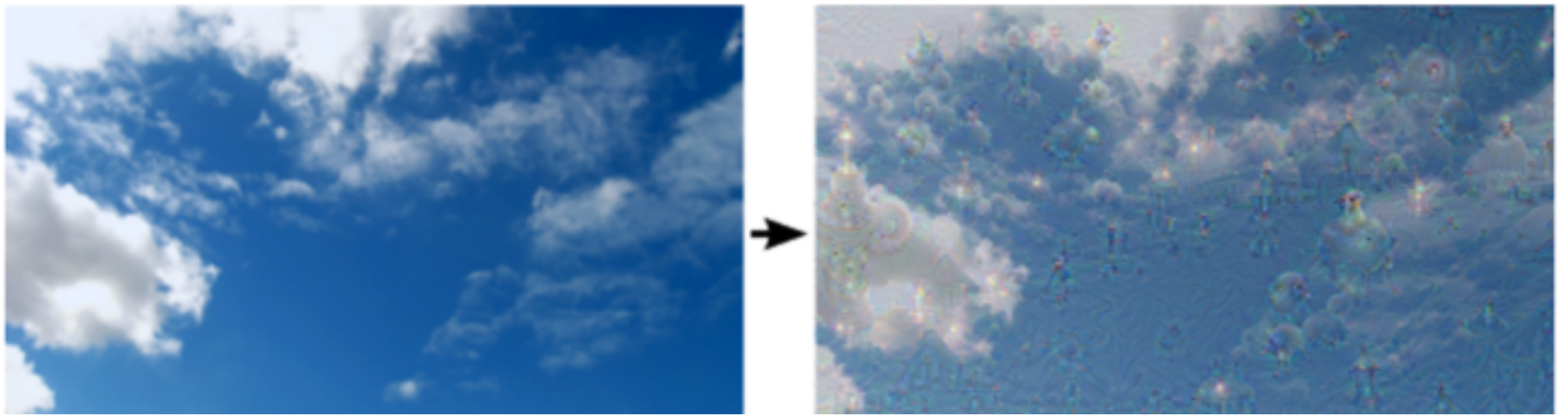



## 50 iterations, 96.1% accuracy





100.0% Goldfish



"Admiral Dog!"

"The Pig-Snail"

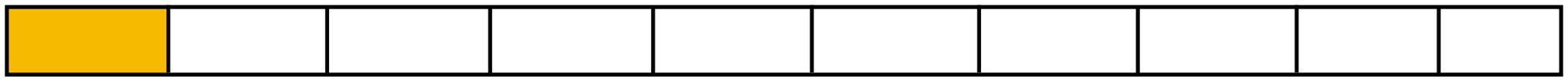
"The Camel-Bird"

"The Dog-Fish"

*Neural net "dreams"— generated purely from random noise, using a network trained on places by MIT Computer Science and AI Laboratory. See our Inceptionism gallery for hi-res versions of the images above and more (Images marked "Places205-GoogLeNet" were made using this network).*

# Model evaluation


## K-fold Cross Validation




Run k testing experiments

- pick testing set
- train
- test on testing set

*Average test results*

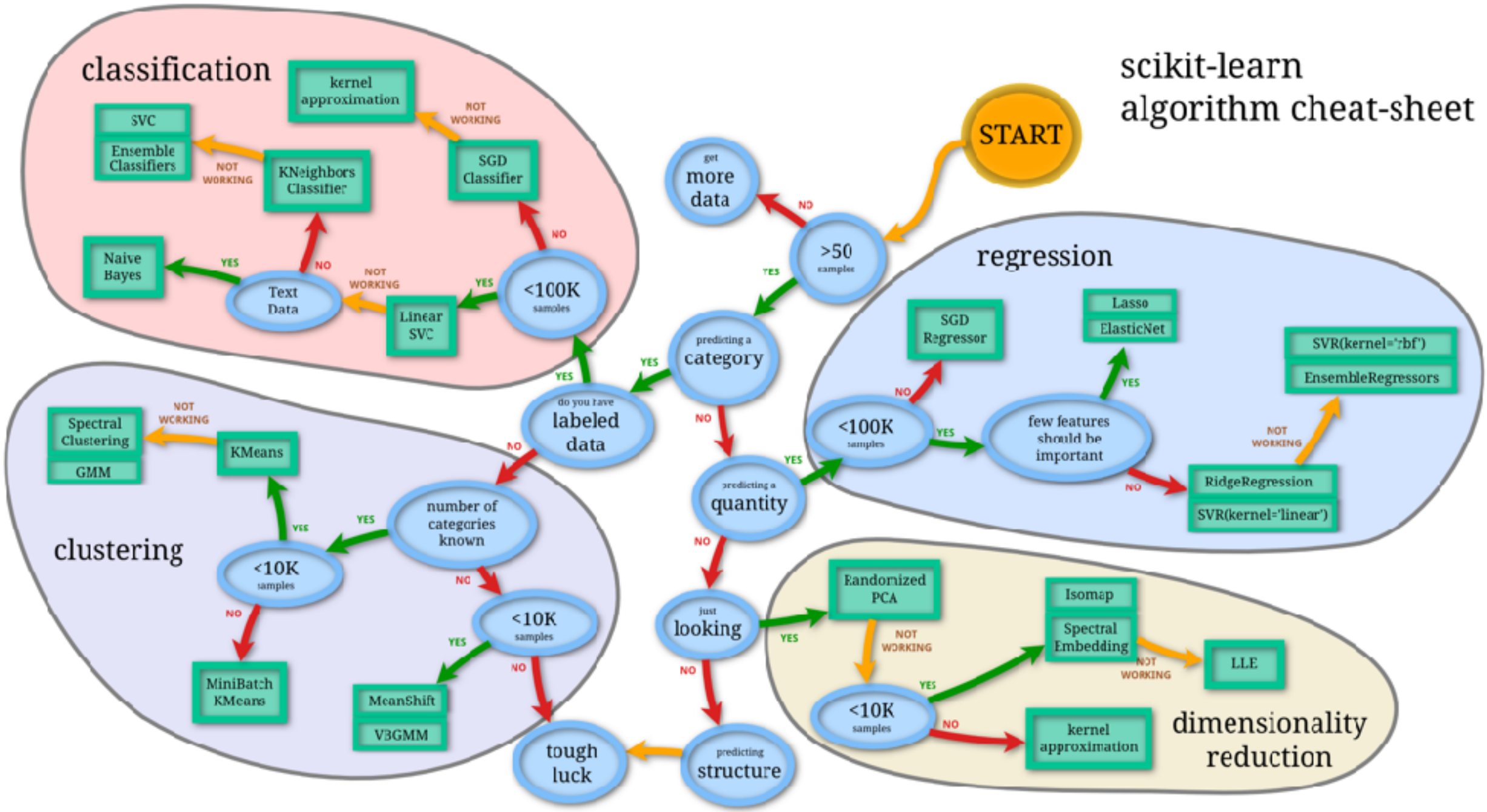
# Debugging a learning algorithm

- Get more training examples
- Try smaller set of features
- Try getting additional features
- Try adding polynomial features
- Try decreasing regularisation parameter
- Try increasing regularisation parameter

1. Gathering data
2. Data preparation
3. Choosing a model
4. Training
5. Evaluation
6. Parameter tuning
7. Prediction

*Repeat*

# scikit-learn algorithm cheat-sheet



https://www.coursera.org/learn/machine-learning

http://cs229.stanford.edu/syllabus.html

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