

ML & DL [1]

GDSC - AI-ML_Team_6

Oct. 13. 2021

Python Basics

Install Packages & Modules

- Use Anaconda prompt or Terminal
- `pip install (package name)`
- `conda install (package name)`
- To check installation, use `(pip/conda) search (package name)`

Activating Environment

- To create environment, conda create -n (environment name)
- To activate it, conda activate (environment name)
- To exit to base, conda deactivate
- Each environment do not share the packages -> should install again
- To work in various package versions, use environment

Useful Packages

- Numpy : linear algebra, random (np)
- Pandas : dataframe and managing file (pd)
- Matplotlib.pyplot : draw graphs (plt)
- Seaborn: more various graphs (sns)
- Os : interact with OS, ex) make dir, move dir, current working dir...

Class

-Blueprint of Object

```
In [1]: 1 class MyClass:
        2     def __init__(self, name, std_id):
        3         self.name = name
        4         self.std_id = std_id
        5         self.user_name_ = self.name + '-' + str(self.std_id)
        6
        7     def attendance(self):
        8         print(self.user_name_)
        9
```

Definition

Initialization

Instances

Method

executed in 3ms, finished 00:32:09 2021-10-13

```
In [2]: 1 a = MyClass('yooseung', 20215047)
```

Object

executed in 2ms, finished 00:32:09 2021-10-13

```
In [3]: 1 a.attendance()
        2 a.name
```

Use method & instance by .

executed in 7ms, finished 00:32:09 2021-10-13

yooseung-20215047

'yooseung'

map & sort

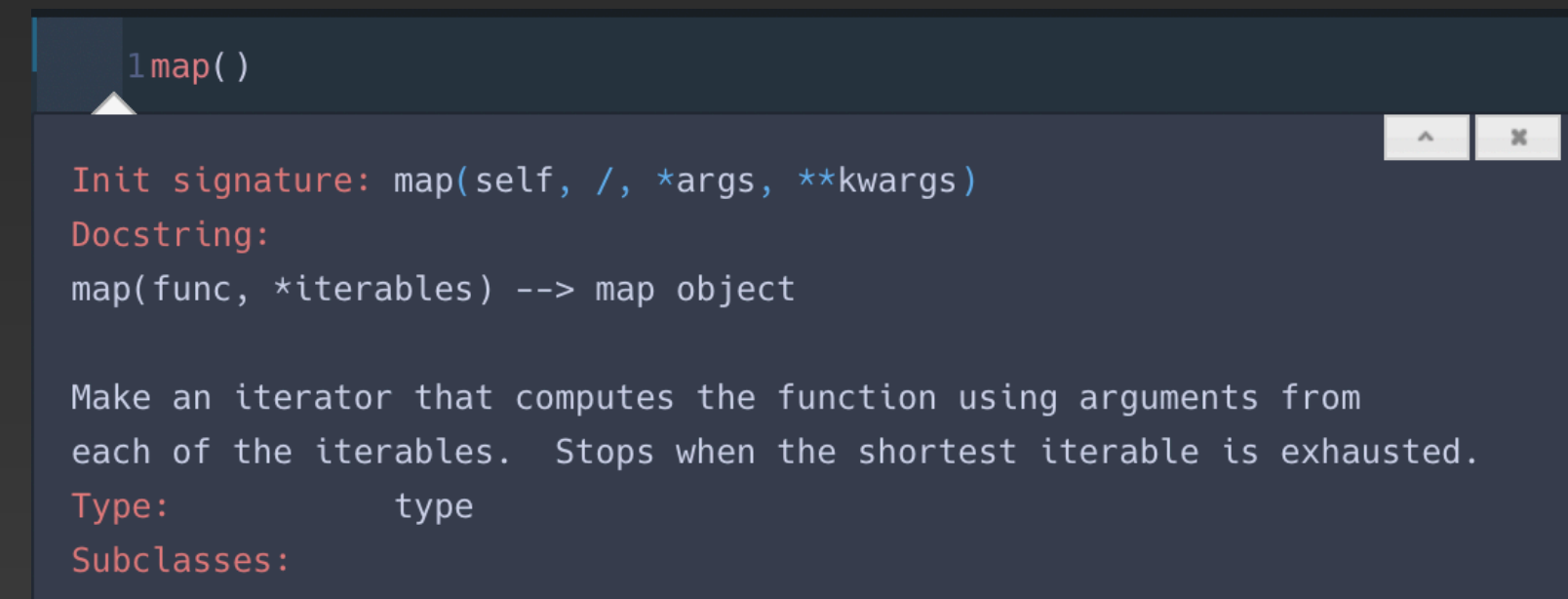
```
1 myList = [1,2,3,4,5]
2 myList = map(lambda x: x**2, myList)
3 print(myList)
4 myList = list(myList)
5 print(myList)           Conditional can be used too
6 bool_list= list(map(lambda x: x % 2 == 1, myList))
7 print(bool_list)
8 myList.sort(reverse = True) In descending order
9 print(myList)
10 myList.sort() In ascending order
11 print(myList)
```

executed in 9ms, finished 20:09:35 2021-10-13

```
<map object at 0x7fb5580e43d0> Map is a object
[1, 4, 9, 16, 25] To see result, use list()
[True, False, True, False, True]
[25, 16, 9, 4, 1]
[1, 4, 9, 16, 25]
```

Shortcuts

- Esc : command mode
 - M : markdown
 - Y : code
 - A/B : add cell Above/Below
 - DD : delete cell
 - Z : undo delete cell
 - C + V : copy and paste
- Enter : edit mode
 - Ctrl + enter : run selected cell
 - Shift + enter : run and move next
 - Shift + tab : cancel tab
 - Shift + tab (inside the word): show detail

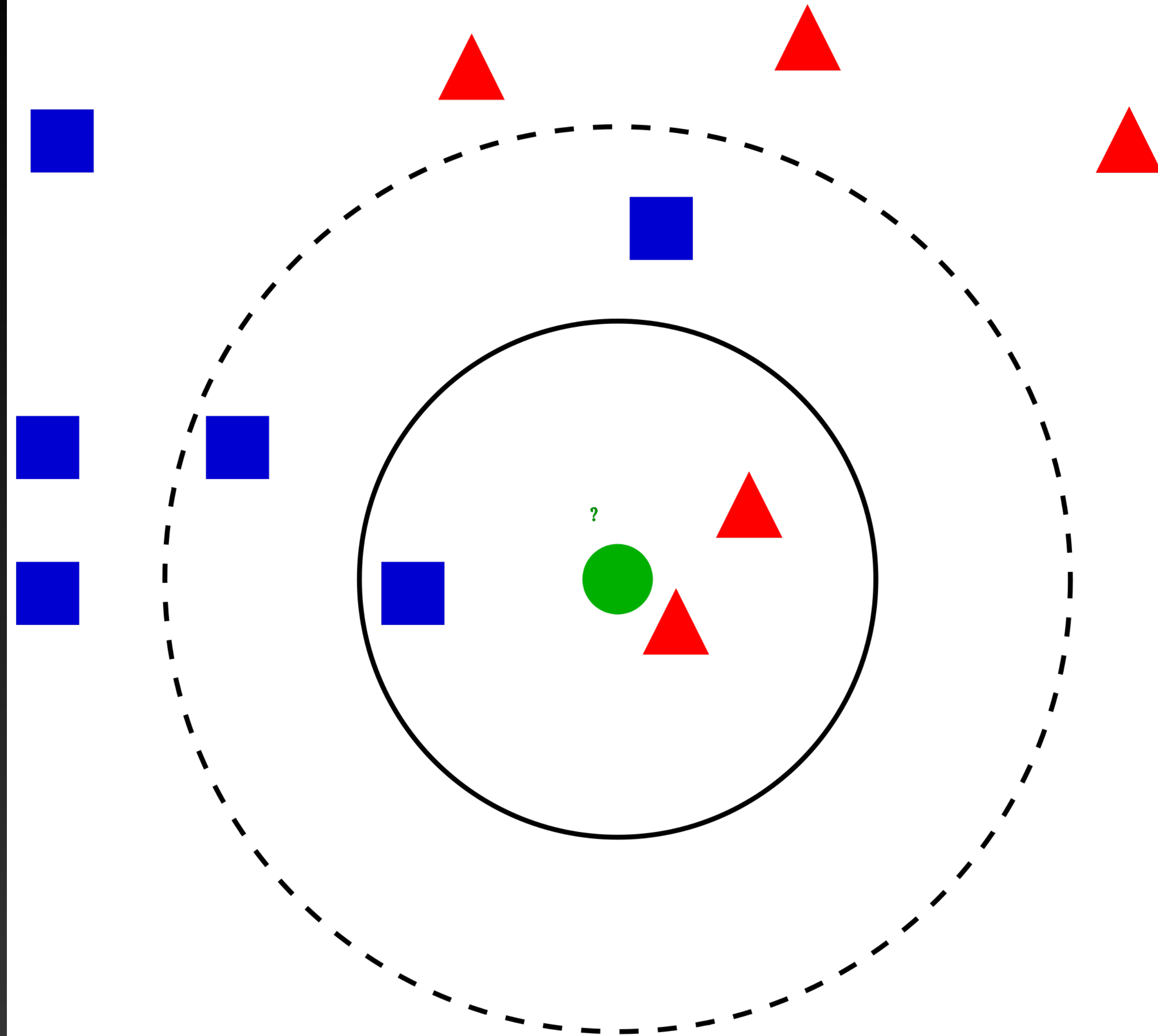


```
1 map( )  
  
Init signature: map(self, /, *args, **kwargs)  
Docstring:  
map(func, *iterables) --> map object  
  
Make an iterator that computes the function using arguments from  
each of the iterables. Stops when the shortest iterable is exhausted.  
Type:          type  
Subclasses:
```


1. Machine Learning

KNN

- Find K nearest Neighbors
- Determine the value with them
- For example, circle will be predicted as red triangle

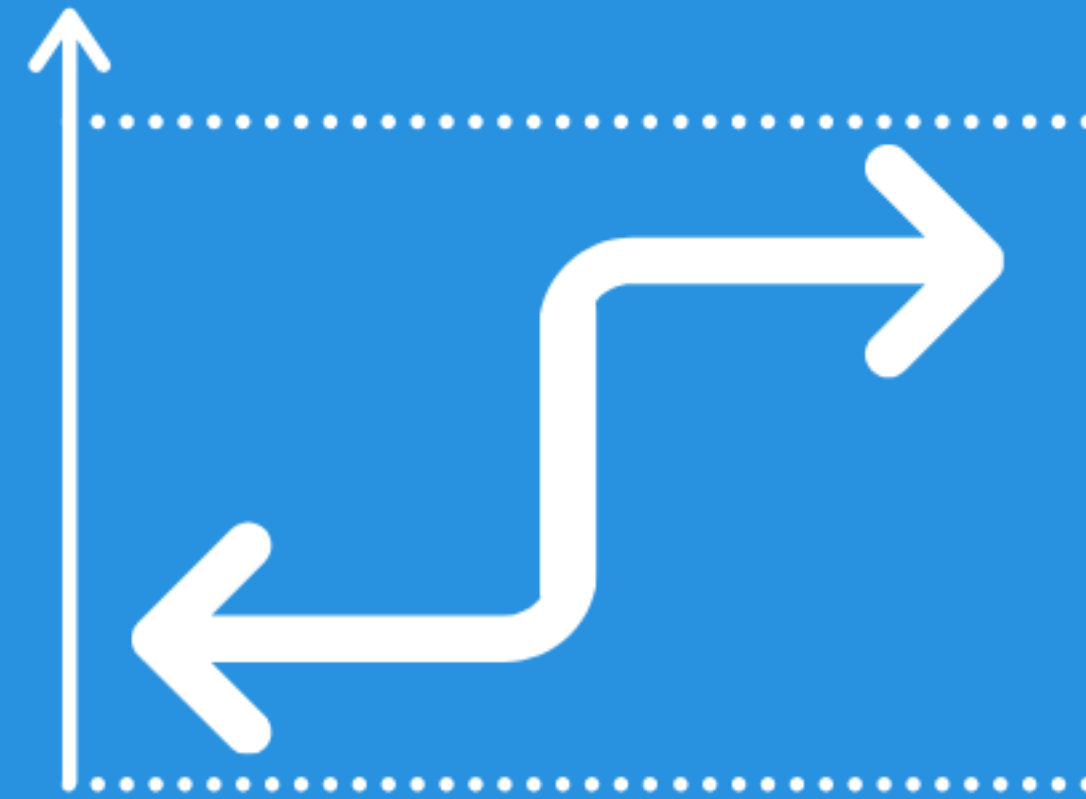


Regression



**LINEAR
REGRESSION**

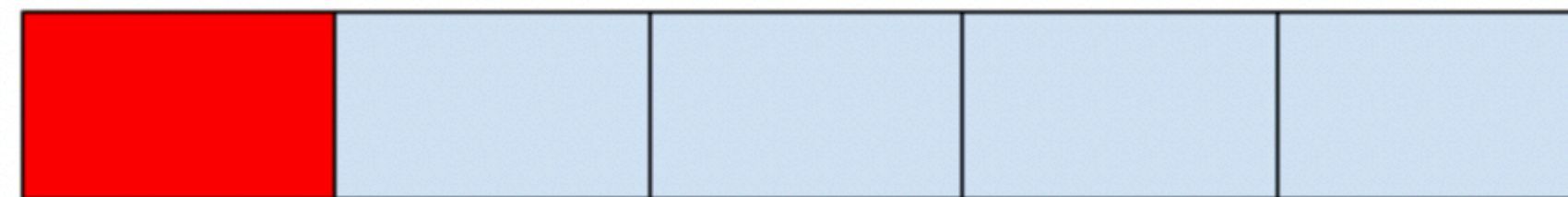
VS



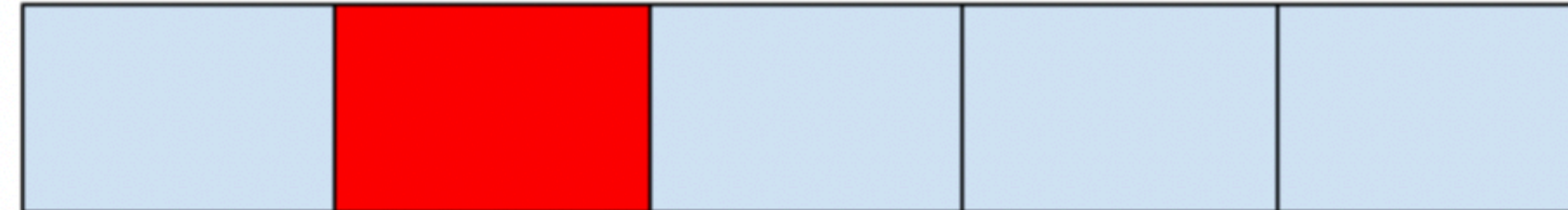
**LOGISTIC
REGRESSION**

Cross Validation

K-Fold Cross Validation



$K = 5$

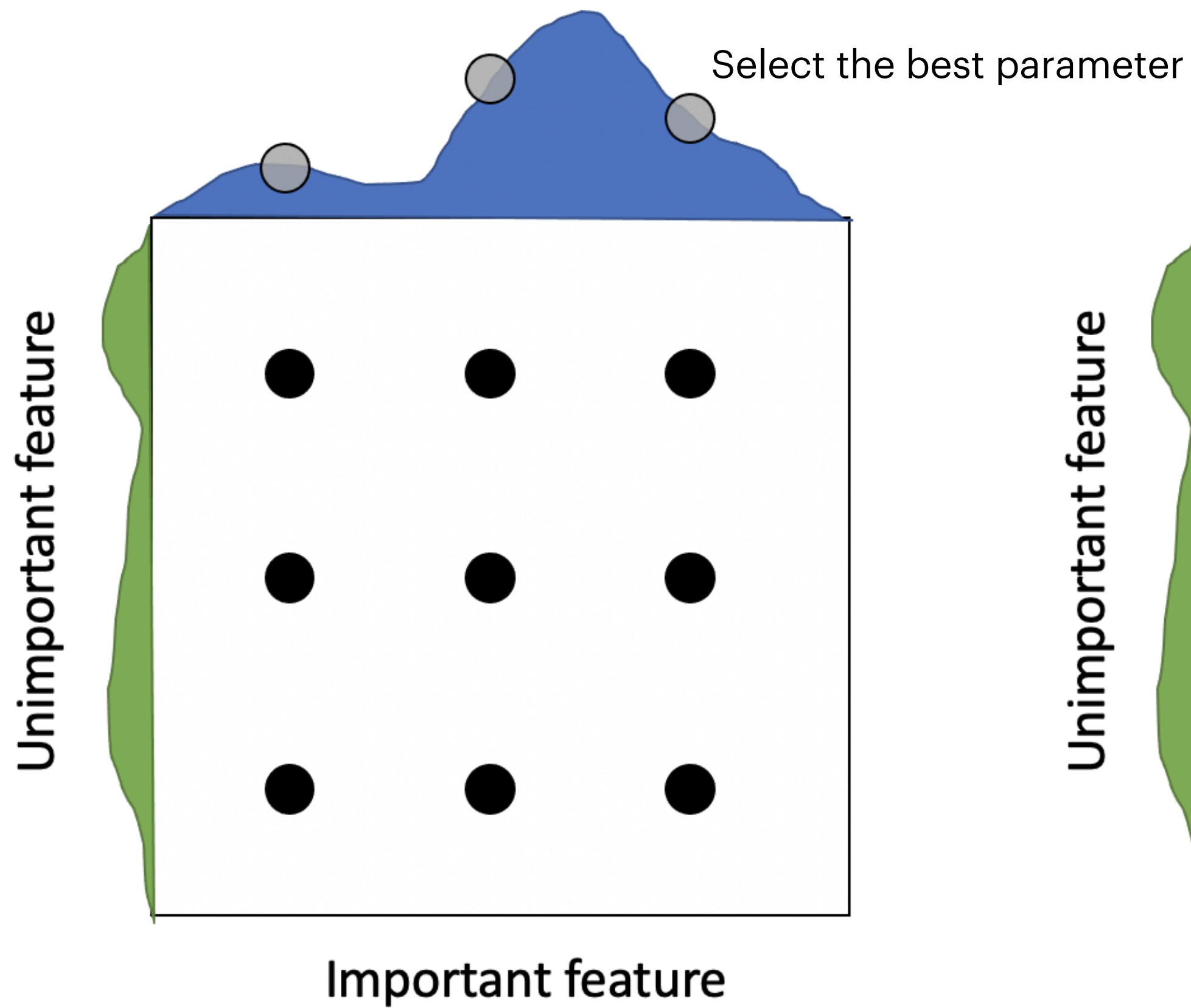


Confusion Matrix

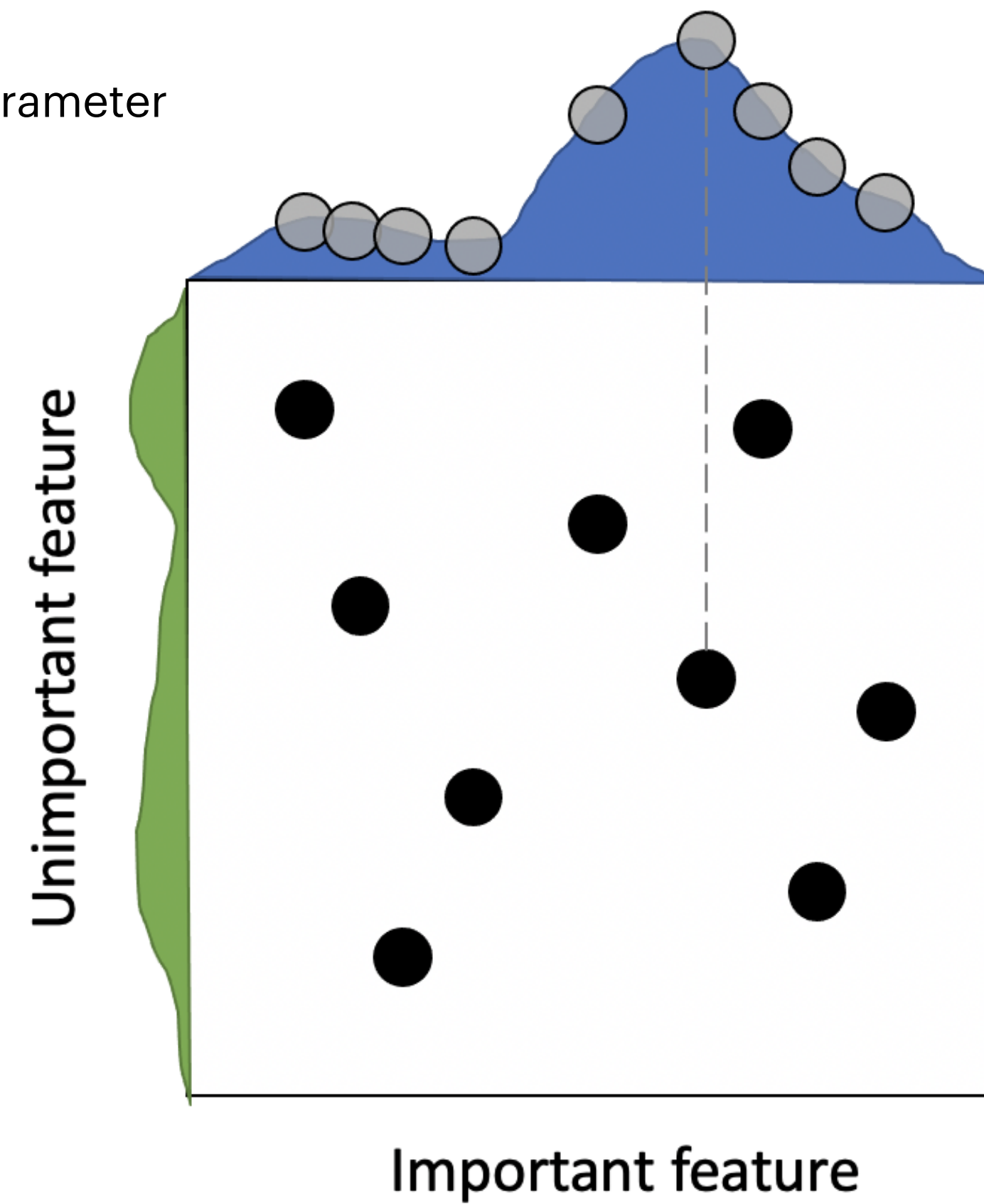
		True Class	
		Positive	Negative
Predicted Class	Positive	TP	FP
	Negative	FN	TN

Grid Search

Grid Search
with 3x3 grid



Randomized Search
with 9 iterations



GridSearchCV

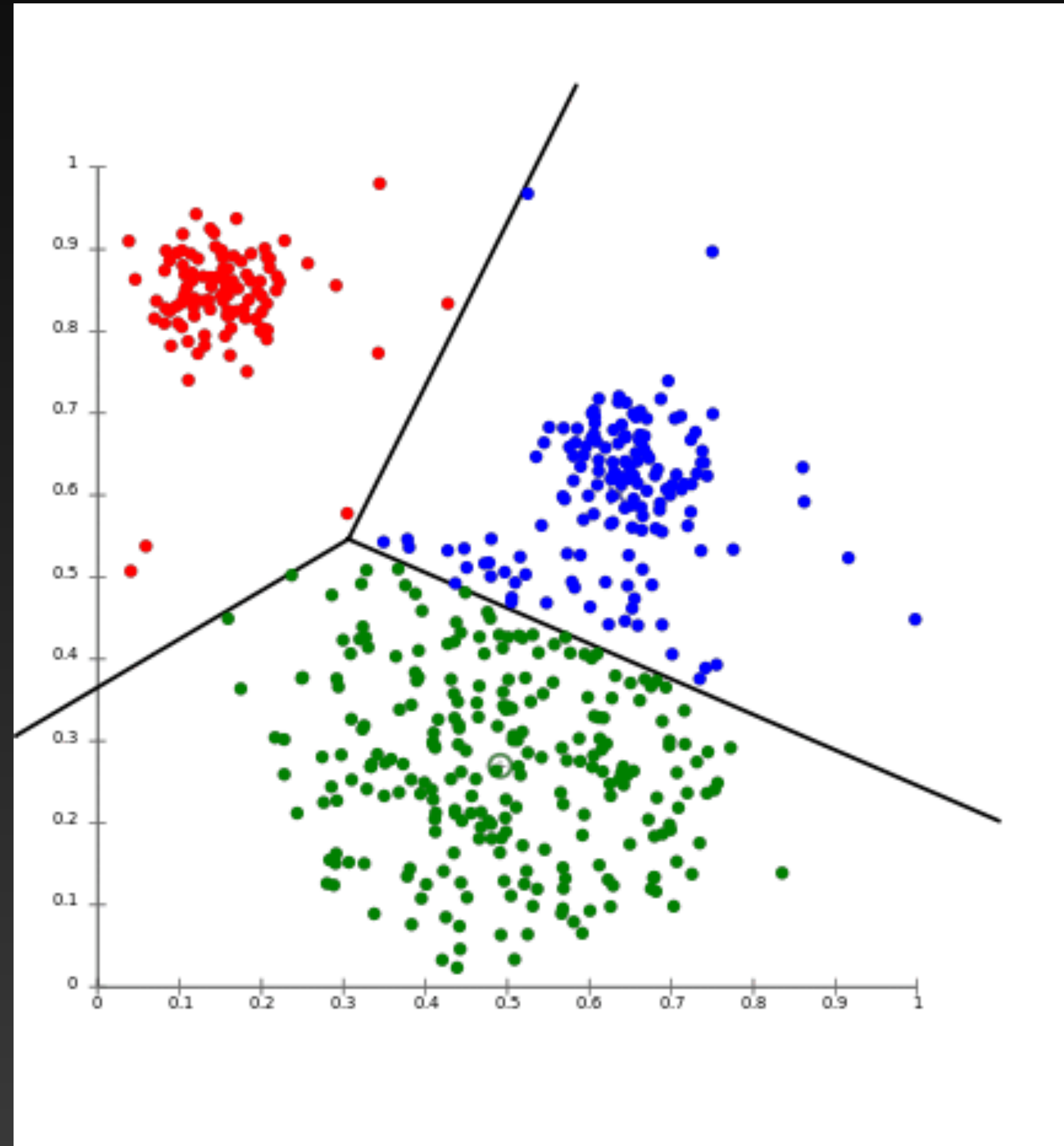
- knn = KNeighborsClassifier()
- knn_cv = GridSearchCV (knn, grid, cv = 3)
Array 1 ~ 50
Estimator
- knn_cv.cv_results_
K = 4 -> Rank 1

```
'rank_test_score': array([25,  9,  3,  1,  5,  2, 25,  4, 40, 10, 27,  8, 35, 17, 24, 17, 38,
 29, 29, 11, 29, 11, 19, 11, 19, 11, 39, 11, 19,  6, 11,  6, 29, 19,
 29, 19, 29, 36, 36, 28, 41, 41, 48, 41, 48, 41, 41, 41, 47],
 dtype=int32)}
```

```
'split0_test_score': array([0.41346154, 0.41346154, 0.43269231, 0.41346154, 0.41346154,
 0.40384615, 0.41346154, 0.42307692, 0.41346154, 0.42307692,
 0.42307692, 0.40384615, 0.40384615, 0.40384615, 0.40384615,
 0.40384615, 0.39423077, 0.39423077, 0.39423077, 0.39423077,
 0.39423077, 0.39423077, 0.39423077, 0.39423077, 0.39423077,
 0.39423077, 0.40384615, 0.39423077, 0.39423077, 0.39423077,
 0.39423077, 0.39423077, 0.38461538, 0.38461538, 0.38461538,
 0.38461538, 0.38461538, 0.38461538, 0.38461538, 0.38461538,
 0.38461538, 0.38461538, 0.38461538, 0.39423077]),
'split1_test_score': array([0.90291262, 0.88349515, 0.88349515, 0.91262136, 0.90291262,
 0.9223301 , 0.88349515, 0.88349515, 0.87378641, 0.87378641,
 0.87378641, 0.89320388, 0.88349515, 0.88349515, 0.88349515,
 0.88349515, 0.87378641, 0.88349515, 0.88349515, 0.89320388,
 0.87378641, 0.89320388, 0.89320388, 0.90291262, 0.89320388,
 0.90291262, 0.88349515, 0.90291262, 0.90291262, 0.90291262,
 0.91262136, 0.91262136, 0.89320388, 0.89320388, 0.88349515,
 0.89320388, 0.88349515, 0.88349515, 0.88349515, 0.88349515,
 0.86407767, 0.86407767, 0.85436893, 0.86407767, 0.85436893,
 0.86407767, 0.86407767, 0.86407767, 0.85436893]),
'split2_test_score': array([0.86407767, 0.90291262, 0.9223301 , 0.94174757, 0.89320388,
 0.91262136, 0.88349515, 0.91262136, 0.87378641, 0.90291262,
 0.88349515, 0.90291262, 0.88349515, 0.90291262, 0.89320388,
 0.90291262, 0.89320388, 0.89320388, 0.89320388, 0.90291262,
 0.90291262, 0.90291262, 0.89320388, 0.89320388, 0.89320388,
 0.89320388, 0.87378641, 0.89320388, 0.88349515, 0.90291262,
 0.88349515, 0.89320388, 0.88349515, 0.89320388, 0.89320388,
 0.89320388, 0.89320388, 0.89320388, 0.89320388, 0.90291262,
 0.89320388, 0.89320388, 0.88349515, 0.89320388, 0.88349515,
 0.89320388, 0.89320388, 0.89320388, 0.88349515]),
```

Cv = 3 -> Three test sets

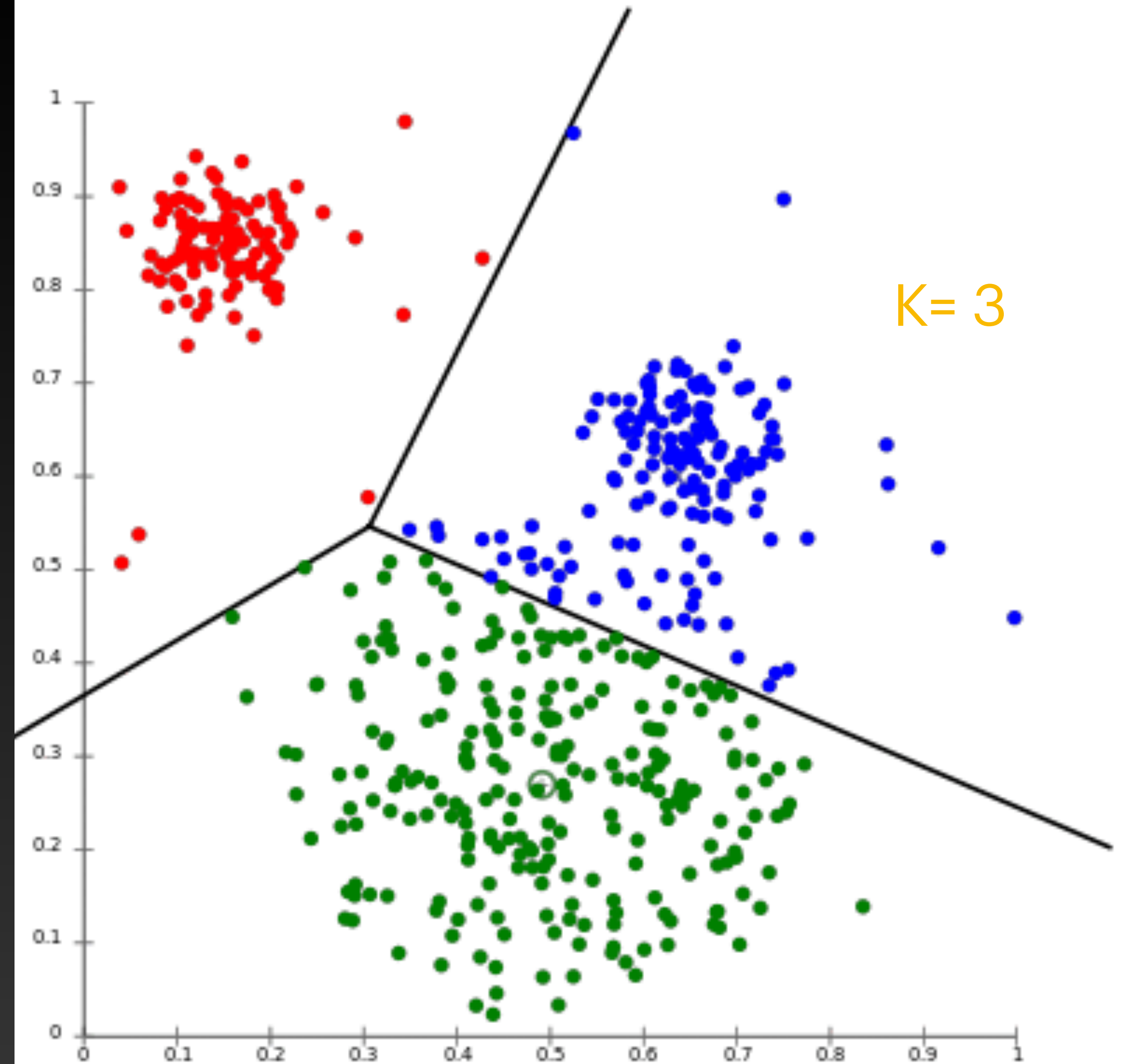
K-Mean Clustering



$K = 3$

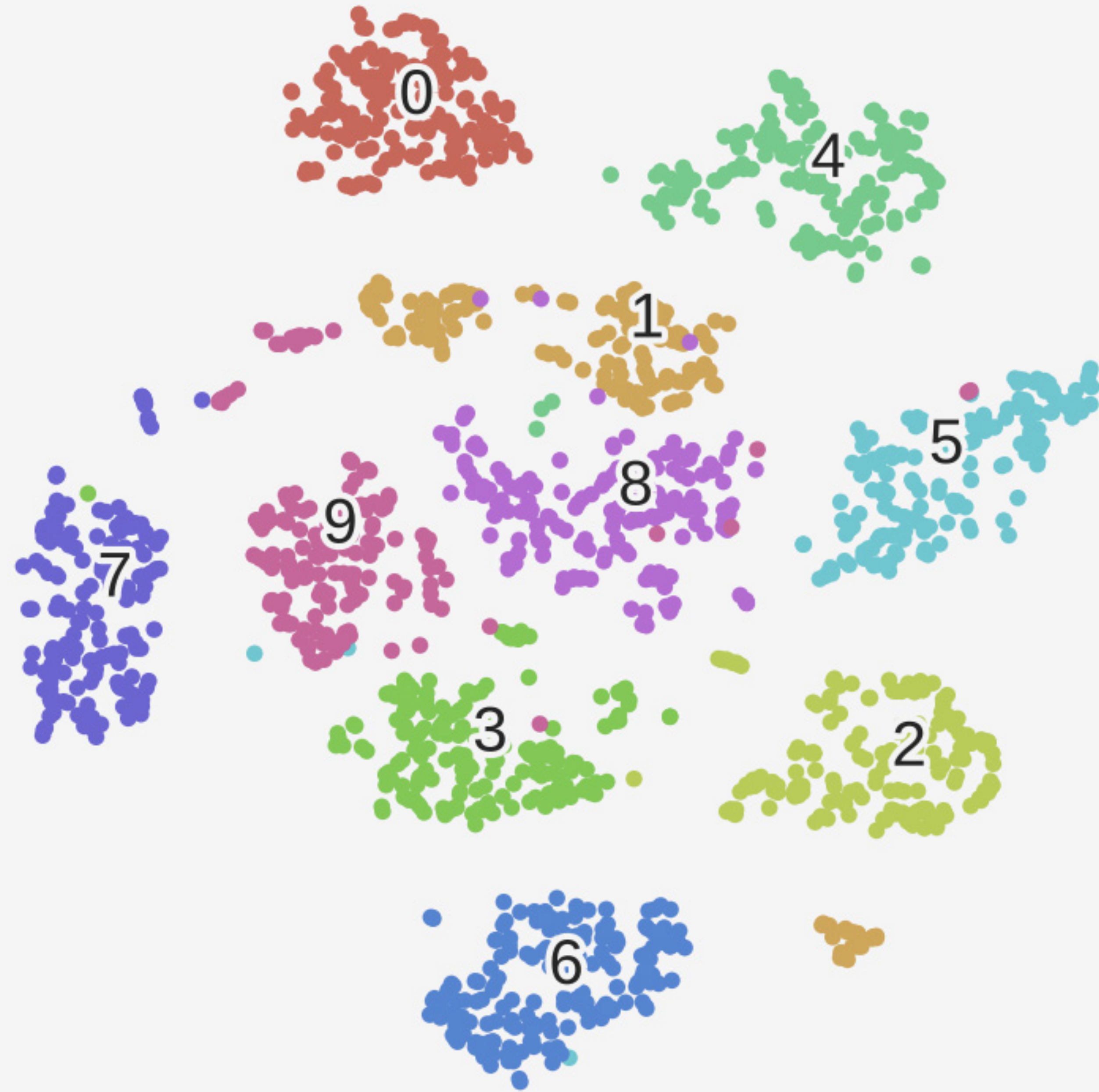
K-Mean Clustering

- Cluster in to K groups
- In the way of minimizing the variance of each points



T-SNE

- Convert high-dimension graph to low-dimension graph
- Using T-distribution



2. Deep Learning Tutorial

Forward Propagation

input	weight	activation	output.
$[x_1, x_2, \dots, x_n]$	$[w_1, w_2, \dots, w_n]$	sigmoid ($\sigma(z)$)	$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix}$

$$\Rightarrow z = w^T \cdot x = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \cdot [x_1, x_2, \dots, x_n] = \begin{bmatrix} w_1 x_1 \\ w_2 x_2 \\ \vdots \\ w_n x_n \end{bmatrix}$$

$$\Rightarrow \sigma(z) = \begin{bmatrix} \sigma(z_1) \\ \sigma(z_2) \\ \vdots \\ \sigma(z_n) \end{bmatrix} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix}$$

\hat{y} labels.

Error Loss Function

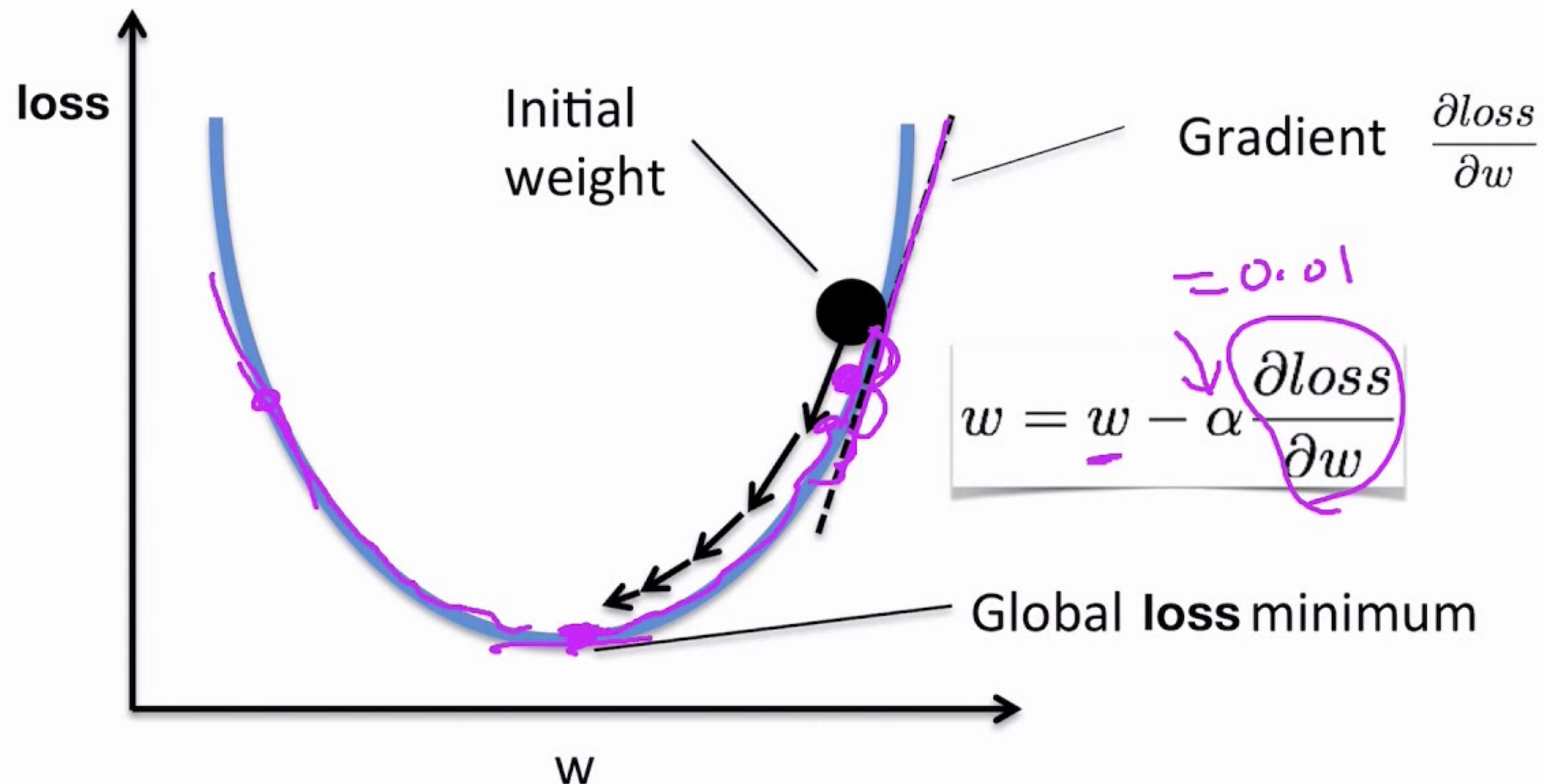
$$f(y, \hat{y}) := -(1-y) \log(1-\hat{y}) - y \log \hat{y}$$

→ where y : actual value
 \hat{y} : predicted value.

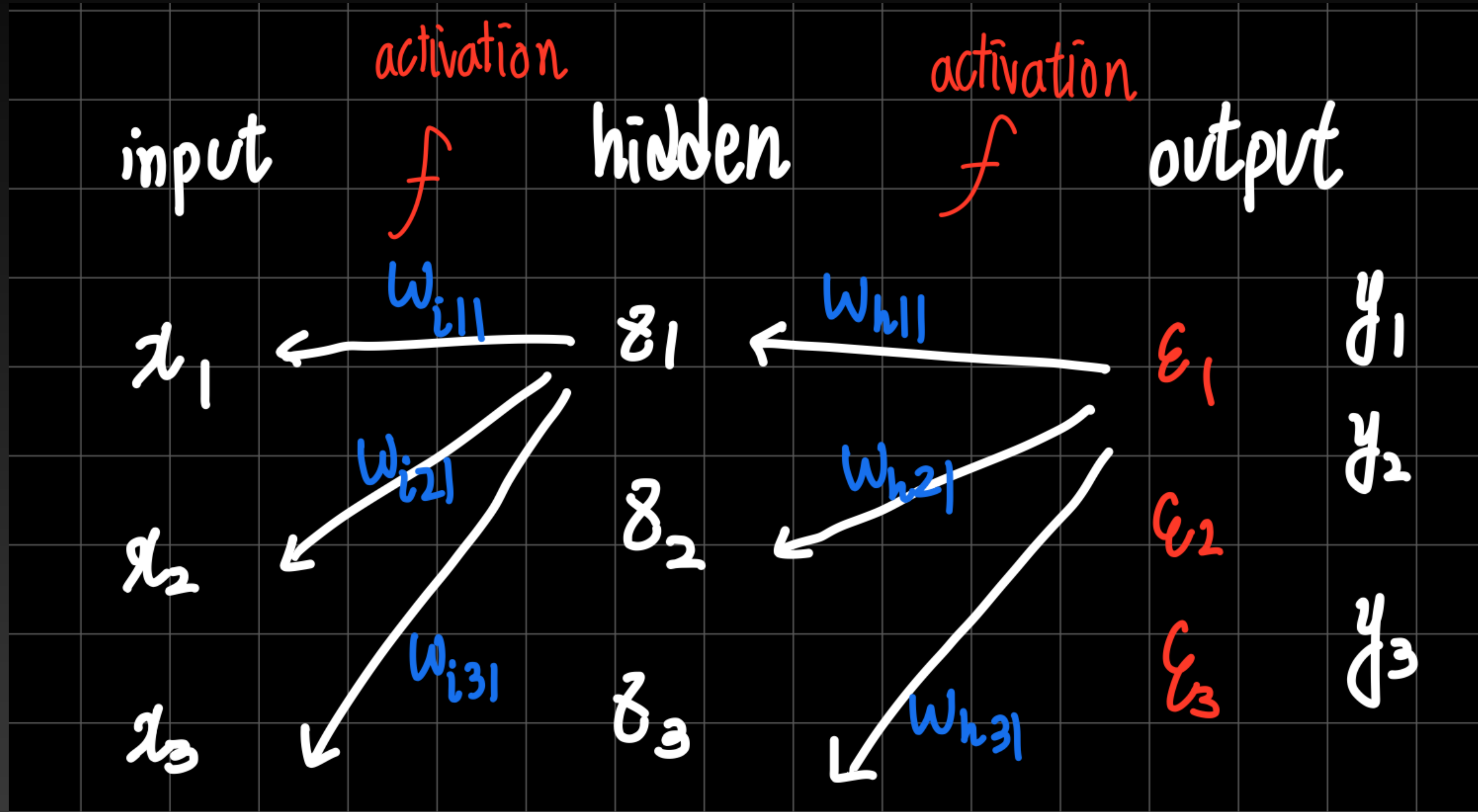
output	actual	loss	cost
$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix}$	$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$	$\begin{bmatrix} f(y_1, \hat{y}_1) \\ f(y_2, \hat{y}_2) \\ \vdots \\ f(y_n, \hat{y}_n) \end{bmatrix}$	$\sum_{i=1}^n f(y_i, \hat{y}_i)$

Gradient Descent

Gradient descent algorithm

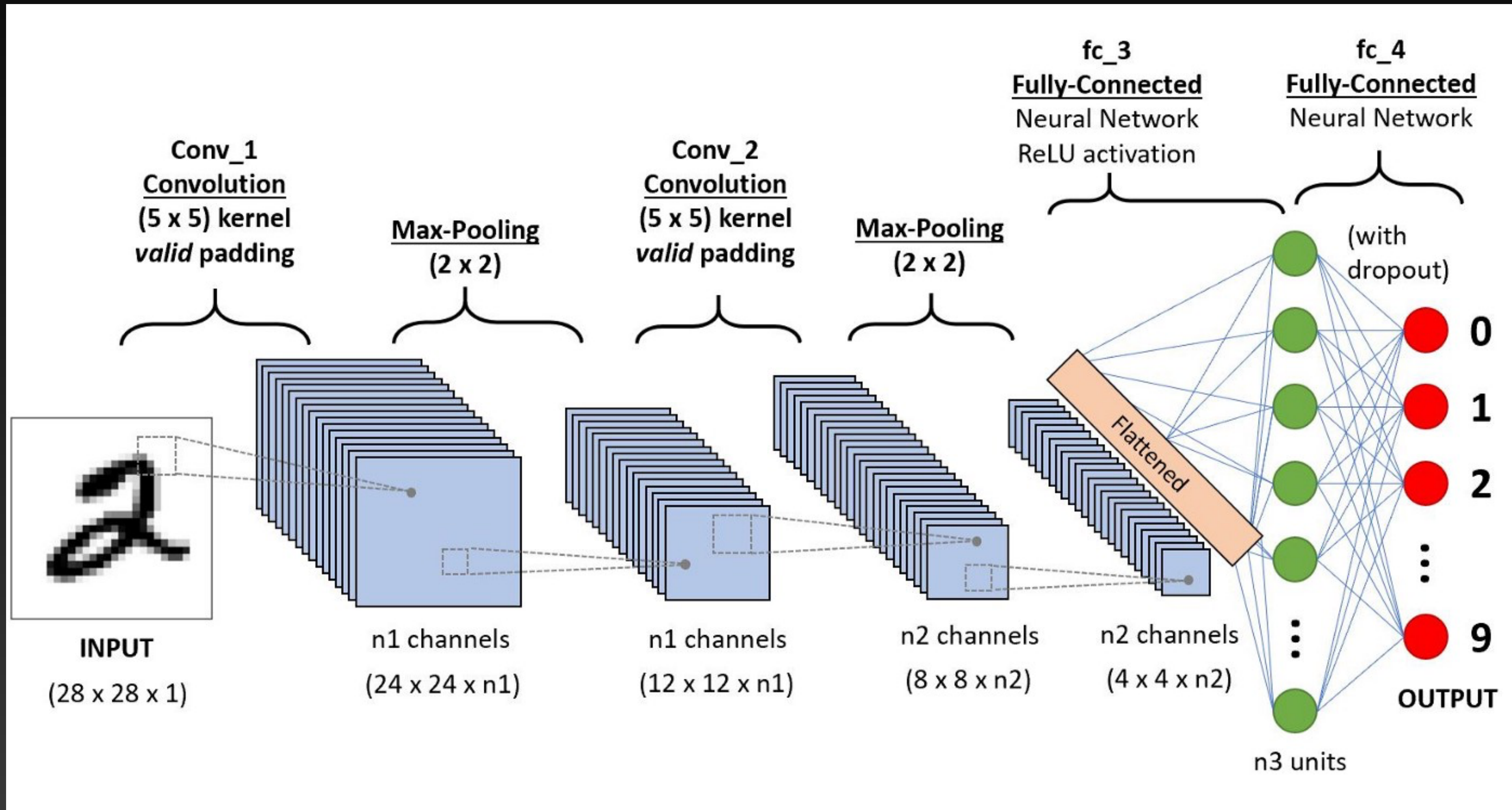


Back propagation

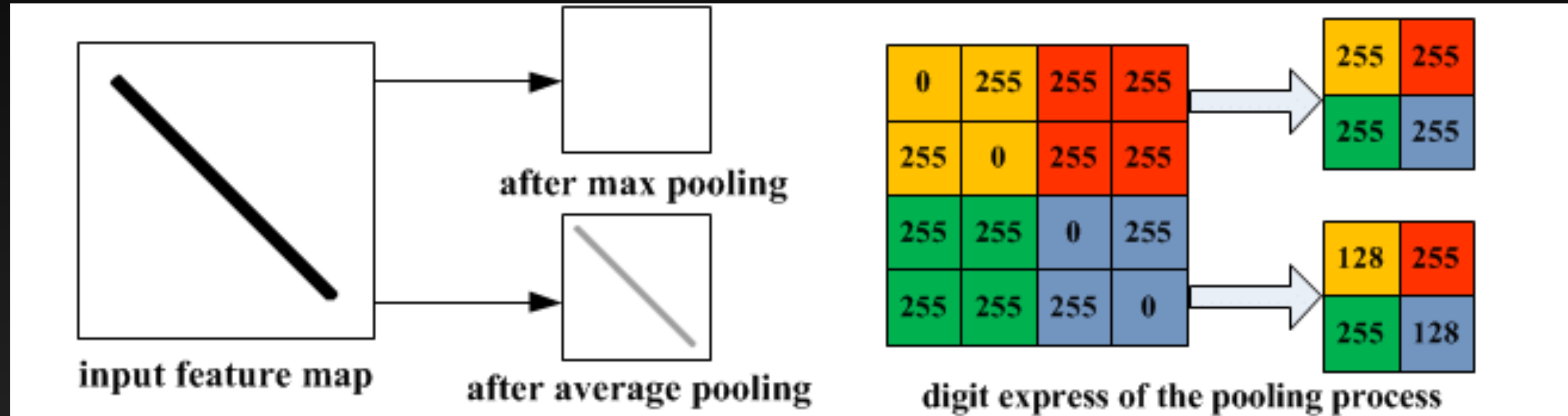


3. Pytorch Tutorial

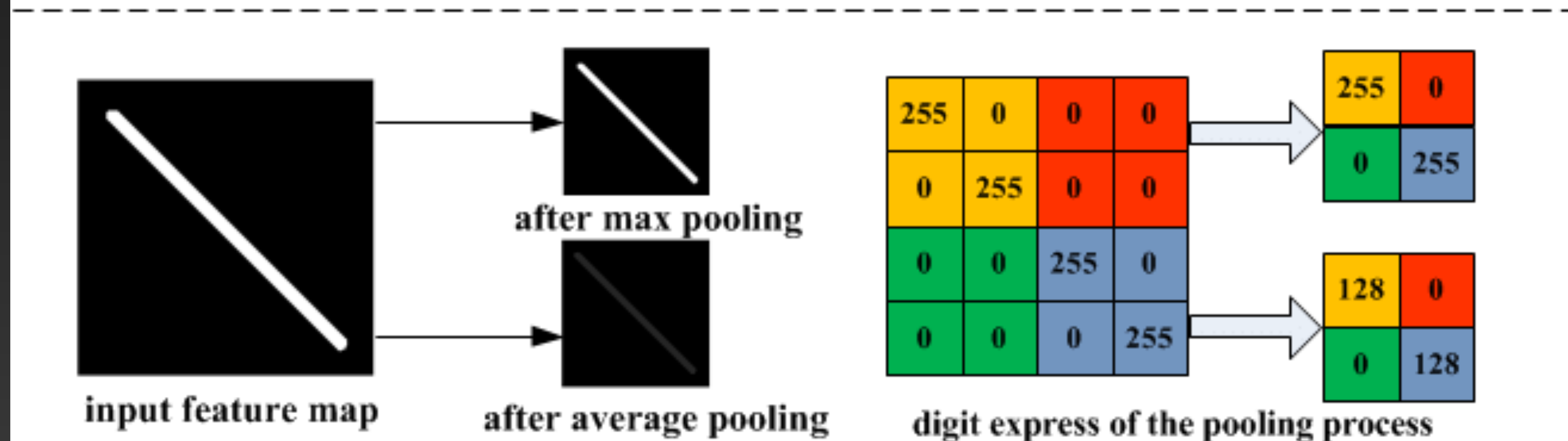
Convolutional Neural Network



Pooling



(a) Illustration of max pooling drawback



(b) Illustration of average pooling drawback

**Just an Implementation
on Pytorch!**