

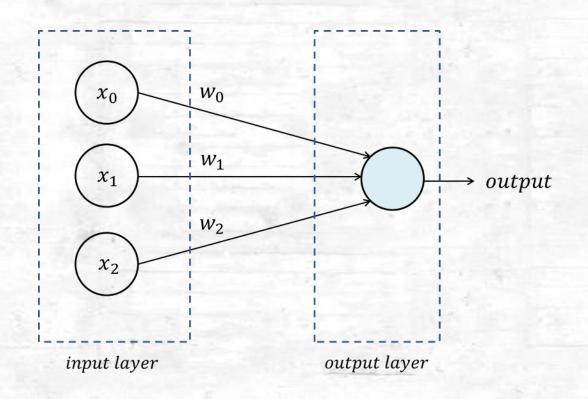
Single Layer Perceptron

Simple Deep Learning Model

First Neuromorphic Approach for solving problems

Simple and Intuitive

Basic of MLP / CNN / RNN ···



-Main Goal [Predict Rings of Abalone]

Before The Begin…

Keywords

Regression

Mean Square Error

Loss Function

Gradient Descent Algorithm

Backward Propagation

Partial derivative

Hyperparameter

Non-linear Information

Keywords

Regression

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Loss Function

Gradient Descent Algorithm

Backward Propagation

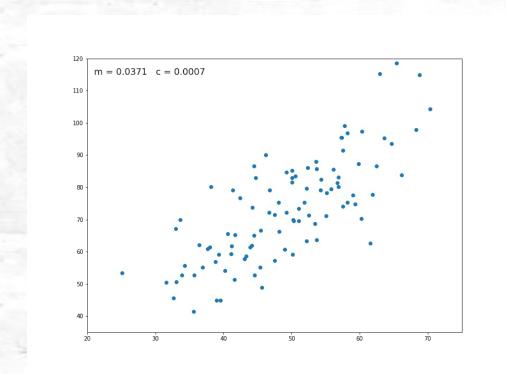
Partial derivative

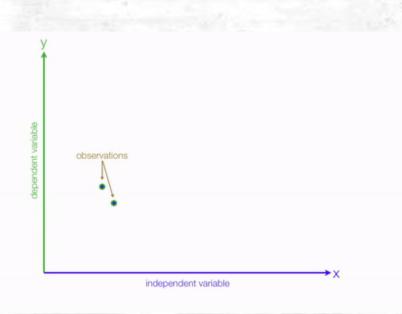
Hyperparameter

Non-linear Information

Regression

: Regression analysis is a set of statistical processes for estimating the relationships between a dependent variableand one or more independent variables





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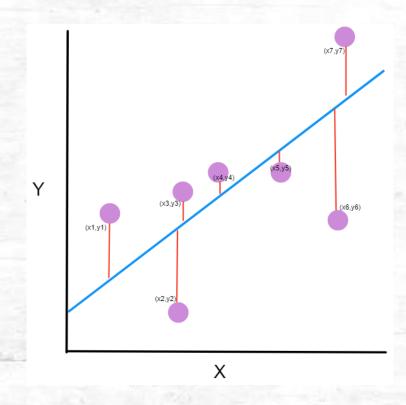
Partial derivative

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Mean Square Error

:MSE(Mean Square Error) used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed.



MSE =
$$\frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$
.

Keywords

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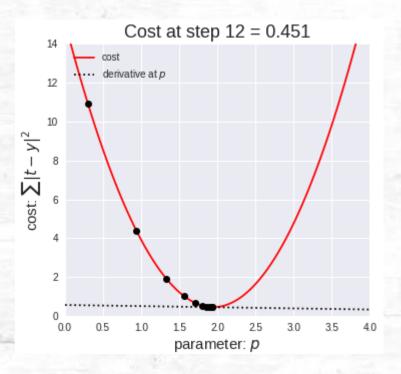
Partial derivative

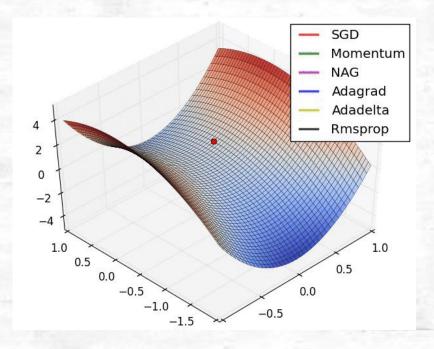
Hyperparameter

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Loss Function (Cost Function)

: Maps an event or values of one or more variables onto a real number intuitively representing some "cost" associated with the event. An optimization problem seeks to minimize a loss function





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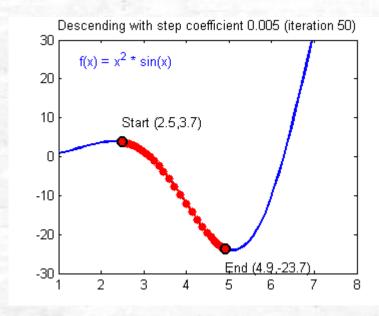
Partial derivative

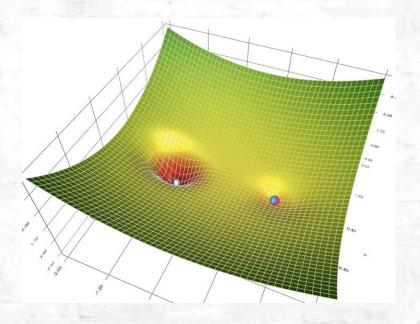
Hyperparameter

Non-linear Information

Gradient Descent Algorithm

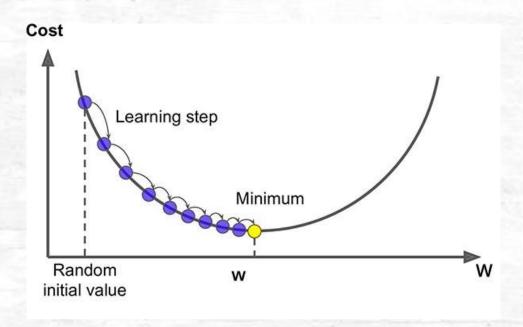
: Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function.





Gradient Descent Algorithm

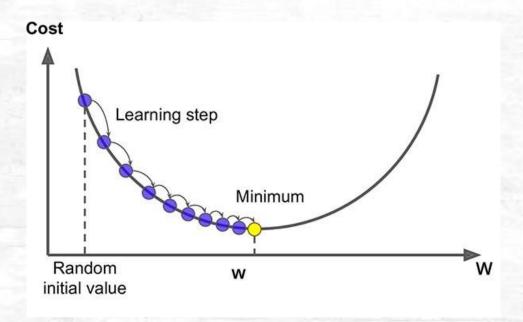
: Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function.



$$x_{i+1} = x_i - \alpha \frac{\partial f(x)}{\partial x}$$

Gradient Descent Algorithm

: Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function.



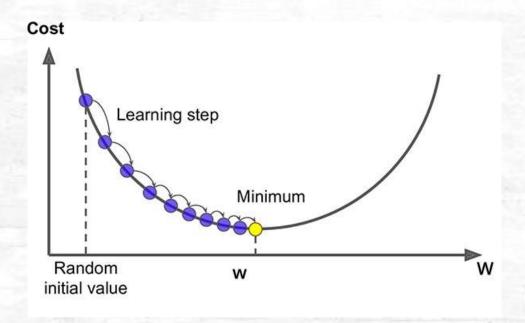
$$x_{i+1} = x_i - \alpha \frac{\partial f(x)}{\partial x}$$

Why Not?

$$x_{i+1} = x_i - \alpha \frac{df(x)}{dx}$$

Gradient Descent Algorithm

: Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function.



$$x_{i+1} = x_i - \alpha \frac{\partial f(x)}{\partial x}$$

Why Not?

$$x_{i+1} = x_i - \alpha \frac{df(x)}{dx}$$

Complex

Keywords

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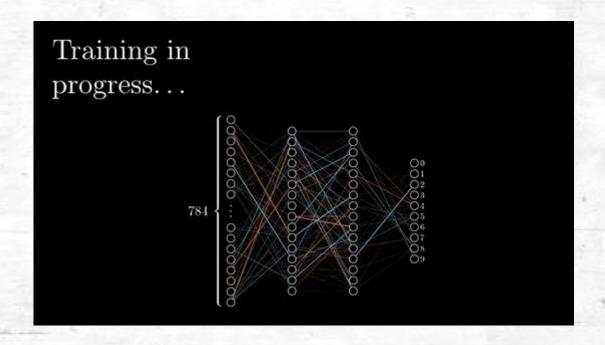
Partial derivative

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Backward Propagation

: Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function.



Loss Function Gradient
$$=\frac{\partial L}{\partial x}$$

Keywords

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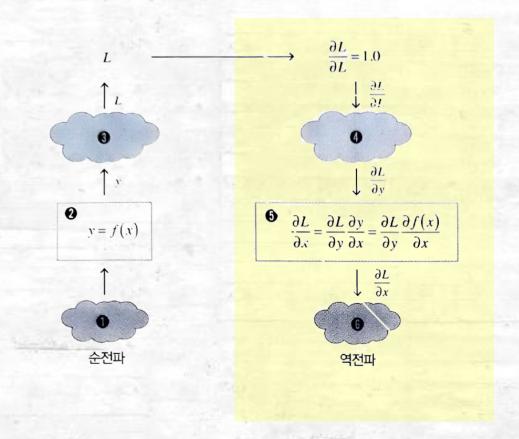
Partial derivative

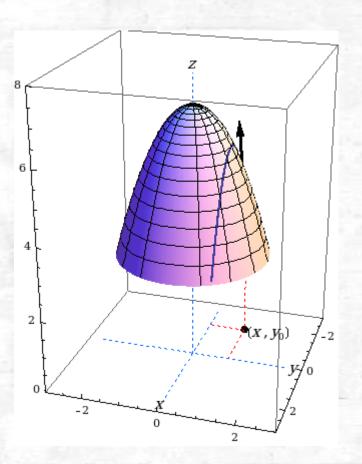
Hyperparameter

Non-linear Information

Partial derivative

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial x} \to differential \ equation$$





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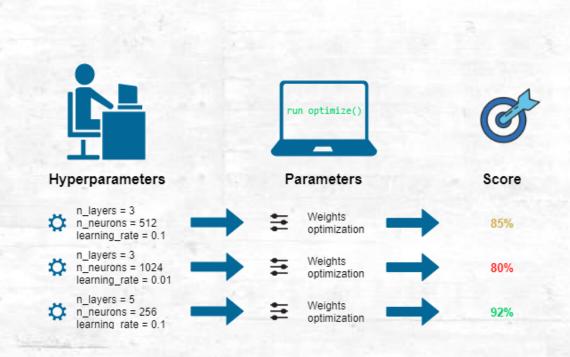
Partial derivative

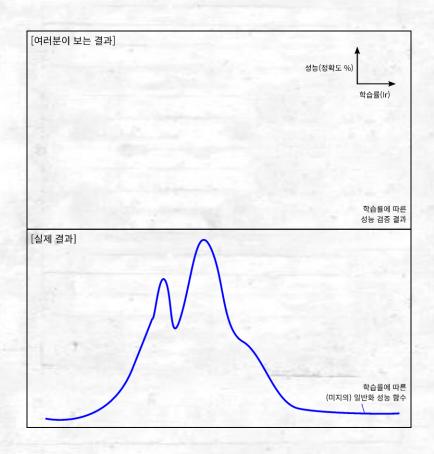
Hyperparameter

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Hyperparameter

: hyperparameter is a parameter whose value is used to control the learning process. By contrast, the values of other parameters (typically node weights) are derived via training.





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Hyperparameter

Non-linear Information

Non-linear Information & One-hot Vector

Label Encoding

Food Name	Categorical #	Calories		
Apple	1	95		
Chicken	2	231		
Broccoli	3	50		

One Hot Encoding

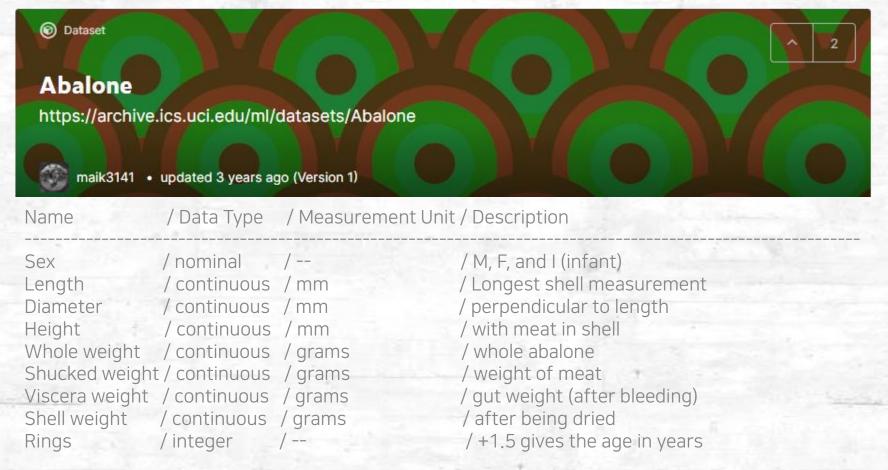
Apple	Chicken	Broccoli	Calories
1	0	0	95
0	1	0	231
0	0	1	50

Non-linear Information & One-hot Vector

-Main Goal [Predict Rings of Abalone]

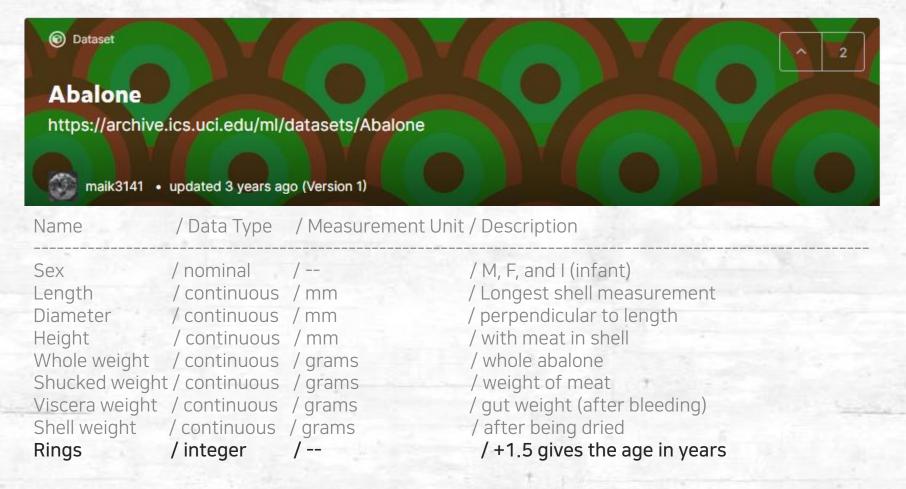
Welcome Back!

-Main Goal [Predict Rings of Abalone]



https://archive.ics.uci.edu/ml/datasets/abalone

-Main Goal [Predict Rings of Abalone]



- Implement

Abablone_exec

```
import numpy as np
import csv
import time

np.random.seed(1234)
def randomize(): np.random.seed(time.time())

RND_MEAN = 0
RND_STD = 0.0030

LEARNING_RATE = 0.001
```

- Implement

Abablone_exec

- Implement

Abablone_exec

Init_model

```
def init_model():
    global weight, bias, input_cnt, output_cnt
    weight = np.random.normal(RND_MEAN, RND_STD,[input_cnt, output_cnt]) //Start point is also crucial
    bias = np.zeros([output_cnt])
```

- Implement

```
Abablone_exec
```

Init_model

Load_abalone_dataset

```
def load_abalone_dataset():
    with open('../../data/chap01/abalone.csv') as csvfile:
        csvreader = csv.reader(csvfile)
       next(csvreader, None)
       rows = []
        for row in csyreader:
            rows.append(row)
    global data, input_cnt, output_cnt
    input_cnt, output_cnt = 10, 1
    data = np.zeros([len(rows), input_cnt+output_cnt])
    for n, row in enumerate(rows):
                                         //One-hot Encoding
        if row[0] == '|': data[n, 0] = 1
       if row[0] == 'M': data[n, 1] = 1
       if row[0] == 'F': data[n, 2] = 1
       data[n, 3:] = row[1:]
```

- Implement

Abablone_exec

Init_model

Load_abalone_dataset

Train_and_test

```
def train_and_test(epoch_count, mb_size, report):
    step_count = arrange_data(mb_size)//Mini batch setup
    test_x, test_y = get_test_data()
    for epoch in range(epoch_count)://Set Epoch
        losses, accs = [], []
        for n in range(step_count): //Number of Minibatch
            train_x, train_y = get_train_data(mb_size, n) //Define minibatch
            loss, acc = run_train(train_x, train_y)//Actual Train step
            Tosses.append(Toss)
           accs.append(acc)
        if report > 0 and (epoch+1) % report == 0: //Report state (when Condition is True)
            acc = run_test(test_x, test_y)
           print('Epoch {}: loss={:5.3f}, accuracy={:5.3f}/{:5.3f}'. #
                  format(epoch+1, np.mean(losses), np.mean(accs), acc))
    final_acc = run_test(test_x, test_y)
    print('\mathbf{m}Final Test: final accuracy = \{:5.3f\}'.format(final_acc))
```

- Implement

Abablone_exec

Init_model

Load_abalone_dataset

Train_and_test

Arrange_data

Get_train_data

Get_test_data

```
def arrange_data(mb_size)://Shuffling process
   global data, shuffle_map, test_begin_idx
   shuffle_map = np.arange(data.shape[0])//Make id number
   np.random.shuffle(shuffle_map)//shuffle
   step_count = int(data.shape[0] * 0.8) // mb_size//minibatch
   test_begin_idx = step_count * mb_size
   return step_count//return number of minibatch
def get_test_data()://Data spliter
   global data, shuffle_map, test_begin_idx, output_cnt
   test_data = data[shuffle_map[test_begin_idx:]]
   return test_data[:, :-output_cnt], test_data[:, -output_cnt:]
def get_train_data(mb_size, nth)://Data spliter
   global data, shuffle_map, test_begin_idx, output_cnt
   if nth == 0:
       np.random.shuffle(shuffle_map[:test_begin_idx])
   train_data = data[shuffle_map[mb_size*nth:mb_size*(nth+1)]]
   return train_data[:, :-output_cnt], train_data[:, -output_cnt:]
```

- Implement

Abablone_exec

Init_model

Load_abalone_dataset

Train_and_test

Arrange_data

Get_train_data

Get_test_data

Run_train

Run_test

- Implement

Abablone_exec

Init_model | Load_abalone_dataset | Train_and_test

Arrange_data

Get_train_data

Get_test_data

Run_train

Run_test

Forward_neuralnet

Backprop_neuralnet

```
def forward_neuralnet(x):
     global weight, bias
     output = np.matmul(x, weight) + bias //Make output
     return output, x
                                  output = x(input \ matrix) * w(weight \ matrix) + b(bias)
def backprop_neuralnet(G_output, x)://Backward Process (Get G_output [loss gradient of forward output 'output']
     global weight, bias
     g_output_w = x.transpose() //partial gradient between x and output
                        \longrightarrow [10, N], when N is size of mini batch
                                                                        Weight matrix W loss cost gradient W [Weight Loss Gradient]
[10,1]G_{w} = np.matmul(g_output_w, G_output)[N,1]
                                                                        \frac{\partial L}{\partial B_i} = T_{k1}G_{1j} + T_{k2}G_{2j} + \dots + T_{km}G_{mj} \rightarrow \frac{\partial L}{\partial W} = TG = X^TG
                                                                                                                                        * T = X^T
     G_b = np.sum(G_output, axis=0)
                                                                        bias matrix B loss cost gradient B [Bias Loss Gradient]
     weight -= LEARNING_RATE * G_w
                                                                        \frac{\partial E}{\partial B_i} = G_{1j} + G_{2j} + \dots + G_{mj}
     bias -= LEARNING_RATE * G_b
                                                                                                     Get these values simply by get sum of the each G matrix's row
     //subtraction by Learning Rate
     //(Ref. Partial derivative)
```

return G_output

- Implement Abablone_exec Init_model Load_abalone_dataset Train_and_test Arrange_data Get_train_data Run_train Get test data Run_test Forward_neuralnet Backprop_neuralnet Forward postproc Backprop_postproc def forward_postproc(output, y)://Get MSE Matrix [N,1] diff = output - y -Matrix [N,1] square = np.square(diff) ← -Single Scalar loss = np.mean(square) ← return loss, diff def backprop_postproc(G_loss, diff)://Backward Process shape = diff.shape g_loss_square = np.ones(shape) / np.prod(shape) Also Can be represent as g_square_diff = 2 * diff $g_diff_output = 1$ def backprop_postproc_oneline(G_loss, diff): return 2 * diff / np.prod(diff.shape) G_square = g_loss_square * G_loss//Mean, Square, Loss backward step G_diff = g_square_diff * G_square G_output = g_diff_output * G_diff

- Implement

Abablone_exec

Init_model Load_abalone_dataset Train_and_test

Arrange_data Get_train_data Get_test_data Run_train Run_test

Forward_neuralnet Backprop_neuralnet Forward_postproc Backprop_postproc Eval_accuracy

```
def eval_accuracy(output, y): //eval process
  mdiff = np.mean(np.abs((output - y)/y))
  return 1 - mdiff
```

Forward_postproc

Eval_accuracy

Forward_neuralnet

- Implement

```
Epoch 9740: loss=4.750, accuracy=0.842/0.837
Epoch 9760: loss=4.750, accuracy=0.842/0.838
Epoch 9780: loss=4.750, accuracy=0.842/0.838
Epoch 9800: loss=4.750, accuracy=0.842/0.838
Epoch 9820: loss=4.750, accuracy=0.842/0.837
Epoch 9840: loss=4.750, accuracy=0.842/0.837
Epoch 9860: loss=4.750, accuracy=0.842/0.838
Epoch 9880: loss=4.750, accuracy=0.842/0.838
Epoch 9800: loss=4.749, accuracy=0.842/0.838
Epoch 9920: loss=4.749, accuracy=0.842/0.838
Epoch 9940: loss=4.749, accuracy=0.842/0.838
Epoch 9960: loss=4.749, accuracy=0.842/0.838
Epoch 9980: loss=4.749, accuracy=0.842/0.838
Epoch 9980: loss=4.749, accuracy=0.842/0.838
```

Epoch 10000: loss=4.749, accuracy=0.842/0.838

Final Test: final accuracy = 0.838

abalone_exec(epoch_count = 100, mb_size = 50, report = 20)

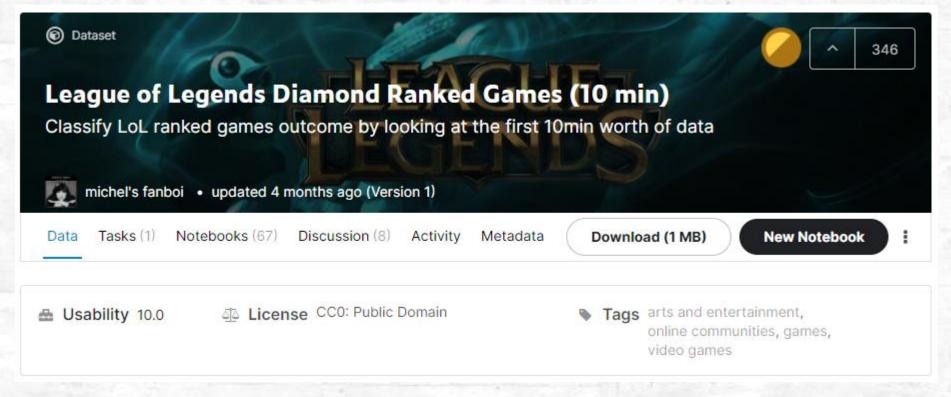
Predict 'Rings' label in abalone dataset Get more than 0.80 Acc

	Α	В	С	D	Е	F	G	Н	1
1	М	0.455	0.365	0.095	0.514	0.2245	0.101	0.15	15
2	М	0.35	0.265	0.09	0.2255	0.0995	0.0485	0.07	7
3	F	0.53	0.42	0.135	0.677	0.2565	0.1415	0.21	9
4	М	0.44	0.365	0.125	0.516	0.2155	0.114	0.155	10
5		0.33	0.255	80.0	0.205	0.0895	0.0395	0.055	7
6		0.425	0.3	0.095	0.3515	0.141	0.0775	0.12	8
7	F	0.53	0.415	0.15	0.7775	0.237	0.1415	0.33	20
8	F	0.545	0.425	0.125	0.768	0.294	0.1495	0.26	16
9	М	0.475	0.37	0.125	0.5095	0.2165	0.1125	0.165	9
10	F	0.55	0.44	0.15	0.8945	0.3145	0.151	0.32	19
11	F	0.525	0.38	0.14	0.6065	0.194	0.1475	0.21	14
12	М	0.43	0.35	0.11	0.406	0.1675	0.081	0.135	10
13	М	0.49	0.38	0.135	0.5415	0.2175	0.095	0.19	11
14	F	0.535	0.405	0.145	0.6845	0.2725	0.171	0.205	10
15	F	0.47	0.355	0.1	0.4755	0.1675	0.0805	0.185	10
16	М	0.5	0.4	0.13	0.6645	0.258	0.133	0.24	12

X label

Y label

-One More! [Predict Anything in dataset]



https://www.kaggle.com/bobbyscience/league-of-legends-diamond-ranked-games-10-mins

-One More! [Predict Anything in dataset]

* LOL_data.csv

- 4	В	С	D	E	F	G	Н	I	J	K	L	M
1	blueWins	blueWardsPlaced	blueWardsDestroyed	blueFirstBlood	blueKills	blueDeath	blueAssists	blueEliteMonsters	blueDrago	blueHerald	blueTower	blueTotalG
2	0	28	2	1	9	6	11	0	0	0	0	17210
3	0	12	1	0	5	5	5	0	0	0	0	14712
4	0	15	0	0	7	11	4	1	1	0	0	16113
5	0	43		0	4	5	5	1	0	1	0	15157
6	0	75		0	6	6	6	0	0	0	0	
7	1	18		0	5	3	6	1	1	0	0	
8	1	18		1	7	6		1	1	0	0	
9	0	16	2	0	5	13	3	0	0	0	0	
10	0	16		0	7	7	8	0	0	0	0	
11	1	13		1	4	5	5	1	1	0	0	
12	0	20		1	4	4	6	0	0	0	0	
13	0	33		1	11	11	7	1	0	1	0	
14	1	18		1	7	1	11	1	1	0	0	
15	0	14		0	4	9	1	1	0		0	14979
16	1	15		1	4	4	4	0	_		0	
17	0	17		0	_	7	3	0			0	
18	1	14	1	1	10	2	8	0			0	
19	0	43	3	0	3	7	3	1	0		0	
20	1	21	4	1	5	4	11	0			0	.0202
21	0		3	0	_	9			0	0	0	
22	1	14		1	11	6			1	0	0	.0000
23	0	13		0	4	13	5	0	0	0	0	
24	0	17				6		0		0	0	
25	0	78	4	0	4	3	4	2	1	1	0	15906

Predict 'any y' label in abalone dataset

Recommend y label

- blueWardsPlaced
- blueTotalGold
- blueAvgLevel
- blueTotalExperience
- blueTotalMinionsKilled
- blueGoldPerMin

Single Layer Perceptron THANKS