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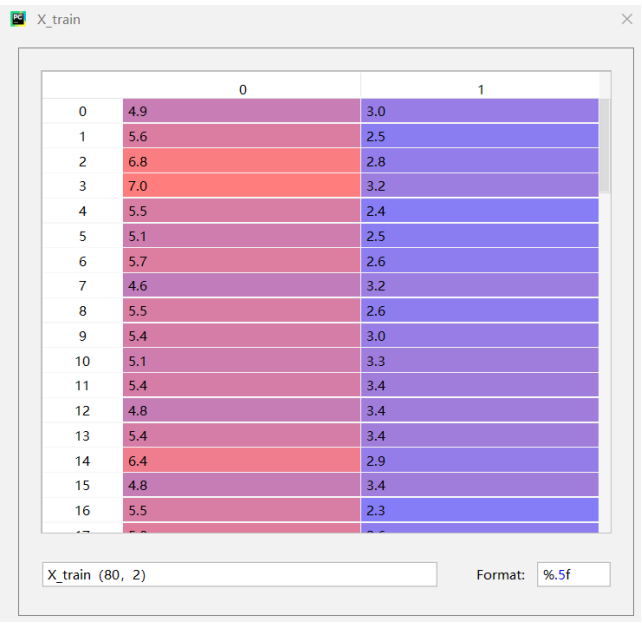
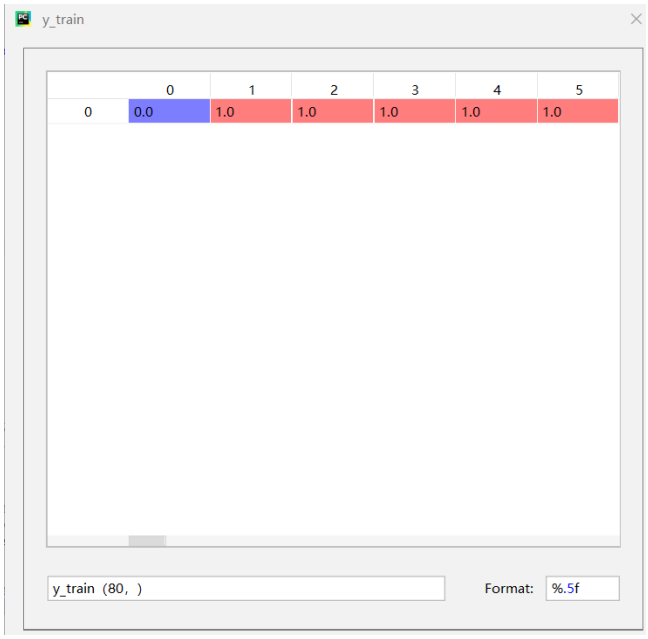
KNN

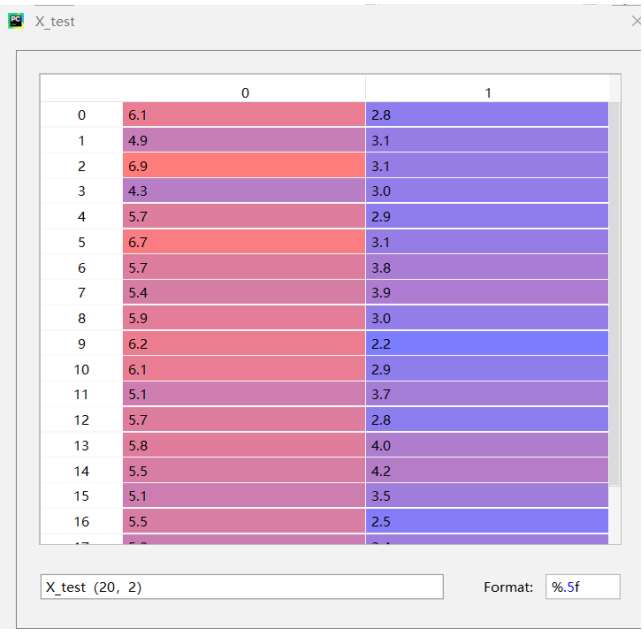
数据(一个feature数据在L_p距离时不好说明)



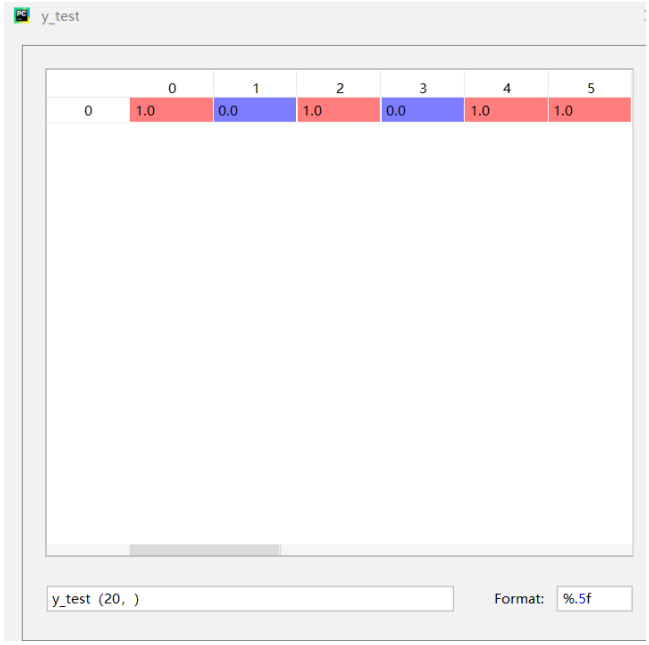
	0	1
0	4.9	3.0
1	5.6	2.5
2	6.8	2.8
3	7.0	3.2
4	5.5	2.4
5	5.1	2.5
6	5.7	2.6
7	4.6	3.2
8	5.5	2.6
9	5.4	3.0
10	5.1	3.3
11	5.4	3.4
12	4.8	3.4
13	5.4	3.4
14	6.4	2.9
15	4.8	3.4
16	5.5	2.3



	0	1	2	3	4	5
0	0.0	1.0	1.0	1.0	1.0	1.0



	0	1
0	6.1	2.8
1	4.9	3.1
2	6.9	3.1
3	4.3	3.0
4	5.7	2.9
5	6.7	3.1
6	5.7	3.8
7	5.4	3.9
8	5.9	3.0
9	6.2	2.2
10	6.1	2.9
11	5.1	3.7
12	5.7	2.8
13	5.8	4.0
14	5.5	4.2
15	5.1	3.5
16	5.5	2.5



	0	1	2	3	4	5
0	1.0	0.0	1.0	0.0	1.0	1.0

两个问题：

- 给定单个test sample，预测相应的label（分类）
- 计算test dataset分类正确率

两个函数的输入输出：

```
    def predict(self, x_test):
        '''

        :param x_test: ndarray (features_n,)
        :return: predict_label , real number
        '''
```

```
    def score(self, X_test, y_test):
        '''

        :param X_test: ndarray, (test_size,feature_n)
        :param y_test: ndarray, (test_size,)
        :return: accuracy: real number
        '''
```

两个函数的实现：

predict function

> 预备补充知识
>
> - 监督学习基本假设：联合概率分布
> - $P(Y|X)=\frac{P(X,Y)}{P(X)}$
> - 判别与生成

knn基本原理

- 选择距离最近的k个样本
- k个样本中频数最高的label作为$\hat{y}_{test}$

分析：

- 谁和谁的距离:
  x_test(features_n,)与X_train(train_size = m,features)的 m 个距离，选最近的k个距离
- 距离怎么度量:
  $(\sum_{l=1}^{n}|x_{i}^{(l)}-x_{j}^{(l)}|^{p})^{\frac{1}{p}} \Longrightarrow$np.linalg.norm()

```
 distance = np.linalg.norm(x_test - self.X_train[i], ord = self.p)
```

- 怎么选出k个最近的样本（举个栗子解释）----搜索——两个for loop

```
knn_list = [] #存储(distance,label)
```

```
        for i in range(self.n):

            distance = np.linalg.norm(x_test - self.X_train[i], ord = self.p)

            knn_list.append((distance, self.y_train[i]))
```

```
        for i in range(self.n, len(self.X_train)):

            distance = np.linalg.norm(x_test - self.X_train[i], ord=self.p)

            #knn_list [(distance1,label1),(distance2,label2),...]

            if max(knn_list, key=lambda x: x[0])[0] > distance:
                knn_list[knn_list.index(max(knn_list, key=lambda x: x[0]))] =
(distance,self. y_train[i])
```

max(a, b, c, ...[, key=func])

```
In [6]: lis1 = ['1', '100', '111', '2']
```

- max compares the items using their original values (strings are compared lexicographically so you'd get '2' as output)

```
In [8]: max(lis1)
Out[8]: '2'
```

- to compare the items by their integer value use key with a simple lambda

```
In [4]: max(lis1, key=lambda x:int(x))  # compare `int` version of each item
Out[4]: '111'
```

```
In [9]: lis2 = [(1,'a'), (3,'c'), (4,'e'), (-1,'z')]
```

- By default max will compare the items by the first index. If the first index is the same then it'll compare the second index

```
In [11]: max(lis2)
Out[11]: (4, 'e')
```

- what if you wanted to compare each item by the value at index 1?

```
In [37]: max(lis2, key = lambda x: x[1])
Out[37]: (-1, 'z')
```

Built-in Functions:https://docs.python.org/3/library/functions.html

Built-in Functions				
abs()	delattr()	hash()	memoryview()	set()
all()	dict()	help()	min()	setattr()
any()	dir()	hex()	next()	slice()
ascii()	divmod()	id()	object()	sorted()
bin()	enumerate()	input()	oct()	staticmethod()
bool()	eval()	int()	open()	str()
breakpoint()	exec()	isinstance()	ord()	sum()
bytearray()	filter()	issubclass()	pow()	super()
bytes()	float()	iter()	print()	tuple()
callable()	format()	len()	property()	type()
chr()	frozenset()	list()	range()	vars()
classmethod()	getattr()	locals()	repr()	zip()
compile()	globals()	map()	reversed()	__import__()
complex()	hasattr()	max()	round()	

- 怎么统计：Counter

```
#knn_list [(distance1,label1),(distance2,label2),...(distance_k,label_k)]

        knn_label = [x[-1] for x in knn_list]

#knn_label [label1,label2,...label_k]

        label_count = Counter(knn_label)   #Counter({label1:n1, label2:n2, ...})
        predict_label = sorted(label_count.items(), key= lambda x: x[-1])[-1][0]
        #<scaler variable> C.items()convert to a list of (elem, cnt) pairs
```

Both `list.sort()` and `sorted()` have a *key* parameter to specify a function to be called on each list element prior to making comparisons.

For example, here's a case-insensitive string comparison:

```
>>> sorted("This is a test string from Andrew".split(), key=str.lower)
['a', 'Andrew', 'from', 'is', 'string', 'test', 'This']
```

The value of the *key* parameter should be a function that takes a single argument and returns a key to use for sorting purposes. This technique is fast because the key function is called exactly once for each input record.

A common pattern is to sort complex objects using some of the object's indices as keys. For example:

```
>>> student_tuples = [
...     ('john', 'A', 15),
...     ('jane', 'B', 12),
...     ('dave', 'B', 10),
... ]
>>> sorted(student_tuples, key=lambda student: student[2])   # sort by age
[('dave', 'B', 10), ('jane', 'B', 12), ('john', 'A', 15)]
```

A list comprehension consists of brackets containing an expression followed by a `for` clause, then zero or more `for` or `if` clauses. The result will be a new list resulting from evaluating the expression in the context of the `for` and `if` clauses which follow it. For example, this listcomp combines the elements of two lists if they are not equal:

```
>>> [(x, y) for x in [1,2,3] for y in [3,1,4] if x != y]
[(1, 3), (1, 4), (2, 3), (2, 1), (2, 4), (3, 1), (3, 4)]
```

and it's equivalent to:

```
>>> combs = []
>>> for x in [1,2,3]:
...     for y in [3,1,4]:
...         if x != y:
...             combs.append((x, y))
...
>>> combs
[(1, 3), (1, 4), (2, 3), (2, 1), (2, 4), (3, 1), (3, 4)]
```

sorted:https://docs.python.org/release/3.7.4/howto/sorting.html#sortinghowto

list_comprehension:https://docs.python.org/3.8/tutorial/datastructures.html#list-comprehensions

Counter:https://docs.python.org/3/library/collections.html?highlight=counter#collections.Counter

score function

```
 def score(self,X_test, y_test):

        correct_number = 0

        for x, y in zip(X_test, y_test):

            if  self.predict(x) == y:
                correct_number += 1

        accuracy = correct_number/len(X_test)
```

> zip:https://docs.python.org/3.8/library/functions.html#zip

final version

```
class Knn:
    def __init__(self, X_train, y_train, n_neighbors=5, p=2):
        self.X_train = X_train
        self.y_train = y_train
        self.n = n_neighbors
        self.p = p

    def predict(self, x_test):
        '''

        :param x_test: ndarray (feature_n,)
        :return: predict_label , real number
        '''
        knn_list = []

        for i in range(self.n):
            distance = np.linalg.norm(x_test - self.X_train[i], ord=self.p)

            knn_list.append((distance, self.y_train[i]))

        for i in range(self.n, len(self.X_train)):

            distance = np.linalg.norm(x_test - self.X_train[i], ord=self.p)

            if max(knn_list, key=lambda x: x[0])[0] > distance:
                knn_list[knn_list.index(max(knn_list, key=lambda x: x[0]))] =
(distance,self. y_train[i])

        knn_label = [x[-1] for x in knn_list]
        label_count = Counter(knn_label)
        predict_label = sorted(label_count.items(), key=lambda x: x[-1])[-1][0]
#高阶函数
```

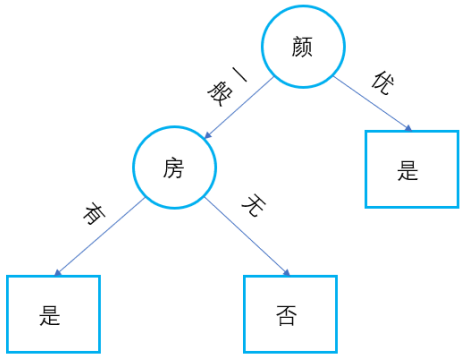
```
        return predict_label

    def score(self, X_test, y_test):
        '''

        :param X_test: ndarray, (test_size,feature_n)
        :param y_test: ndarray, (test_size,)
        :return: accuracy: real number
        '''

        correct_number = 0

        for x, y in zip(X_test, y_test):

            if self.predict(x) == y:
                correct_number += 1

        accuracy = correct_number / len(X_test)

        return accuracy
```

- 待改进与完善：搜索（感兴趣可实现）

DecisionTree

- 决策树——我的理解
- 实现思路
- 代码实现

决策树是什么



ID	年龄	有工作	有房	长相	类别
1	少年	否	否	一般	是
2	少年	否	否	好	是
3	少年	是	否	好	是
4	少年	是	是	一般	是
5	少年	否	否	一般	否
6	中年	否	否	一般	是
7	中年	否	否	好	是
8	中年	是	是	好	是
9	中年	否	是	非常好	否
10	中年	否	是	非常好	否
11	老年	否	是	非常好	是
12	老年	否	是	好	是
13	老年	是	否	好	否
14	老年	是	否	非常好	否
15	老年	否	否	一般	否

一些概念

熵(信息论)：

- $H(X) = \sum_{i=1}^{n}p_i(-logp_i)$
- 平均信息量，熵越大，随机性越大

条件熵(公式略，举例计算), 信息增益，ID3,C4.5,CART，基尼指数

```
class Node():
    def __init__(self):
        self.label = None
        self.ax = None
        self.parent = None
        self.children = {}



class DecisionTree():

    def __init__(self,epsilon = 0.1):
        self.root = Node()
        self.epsilon = epsilon

    def entropy(self,labels):
        y = Counter(labels)  # y[k] y_train中值为k的 数量
        len_y = len(labels)

        entropy_d = -sum([y[k] / len_y * log(y[k] / len_y, 2) for k in y.keys()])
# + 1e-10

        return entropy_d

    def cdt_entropy(self, ax, data, labels):

        xc = Counter(data[:, ax])  # X_train某一列进行counter

        sum = 0
        for i, j in zip(xc.keys(), xc.values()):  # 遍历X_train中所有不同取值 i

            tmp = j  # Di = j

            idx = [x for x, y in enumerate(data) if y[ax] == i]  # 返回X_train中值
为i的全部索引

            label_counter = Counter(labels[idx])
            sum1 = 0
            for m, n in zip(label_counter.keys(), label_counter.values()):
                sum1 += (n / tmp) * log(n / tmp, 2)

            sum += tmp / len(labels) * sum1
        cdt_entropy = - sum
        return cdt_entropy
```

```
    def info_gain(self,ax, data, labels):

        return self.entropy(labels) - self.cdt_entropy(ax, data, labels)

    def fqt_label(self,labels): #返回labels中频数最高的label

        fqt = sorted(Counter(labels).items(), key = lambda x:x[-1])[-1][0]

        return fqt


    def bulid_tree(self, curr_node,sub_data,sub_labels,curr_axises):
        '''
        input: dataset, feature/axis, epsilon
        output: T
        :return:
        '''



        unique_label = list(set(sub_labels)) # unique label
        #若所有实例属于同一类，单节点树，返回该label
        if len(unique_label) == 1:
            curr_node.label = unique_label[0]  #而非self.node
            return
        #若feature 为空，将dataset中label 频数最高的作为结点的label

        if not curr_axises:
            curr_node.label = self.fqt_label(sub_labels)
            return

        info_gain_list = []
        for ax in curr_axises:  #获取每个feature的entropy; axises存储
            info_gain = self.info_gain(ax, sub_data, sub_labels)
            info_gain_list.append(info_gain)

        if max(info_gain_list) <self.epsilon:
            curr_node.label = self.fqt_label(sub_labels)

            return
        idx = info_gain_list.index((max(info_gain_list)))  #max information gain
indx
        ag = curr_axises.pop(idx)  #ag = max information gain feature
        curr_node.ax = ag     #记录当前用于分类的feature（max information gain）
        ax_data = sub_data[:, ag] # subdataset when feature = ag(classify feature)
        ax_unique = set(ax_data)

        for ax in ax_unique:
            tmp_idx = np.argwhere(ax_data == ax).flatten()
            child_node = Node() #new empty Node
            child_node.parent = curr_node
            curr_node.children[ax] = child_node
            child_labels = sub_labels[tmp_idx]   ###
            child_data = sub_data[tmp_idx]      ###
            self.bulid_tree(child_node,child_data,child_labels,curr_axises)
```

```
        return

    def fit(self, data, labels):
        features = data.shape[1]  #features 总数
        axies = list(range(features))          ########
        self.bulid_tree(self.root, data, labels, axies)

    def predict(self, test_data, test_labels):
        counts = 0
        test_size = test_labels.size
        for i in range(test_size):  #遍历test样本
            tmp_node = self.root
            while tmp_node.children:
                ax = tmp_node.ax
                val = test_data[i, ax]
                tmp_node = tmp_node.children[val]        #### continus variables
            if tmp_node.label == test_labels[i]:
                counts += 1
        accuracy = format(counts / test_size, '.5f')

        return accuracy
```

算法实现的收获：