

Implementation details

About Dataset

Three types of Iris:

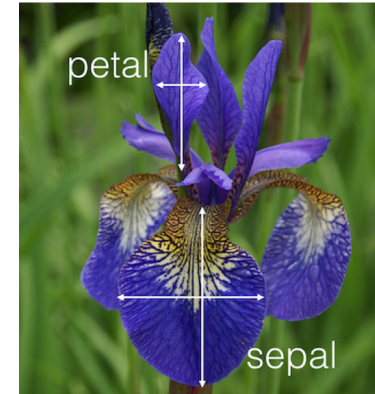
- class 0: 'setosa'
- class 1: 'versicolor'
- class 2: 'virginica'

Four features:

- 'sepal length (cm)',
- 'sepal width (cm)',
- 'petal length (cm)',
- 'petal width (cm)'

Data:

- #150 items
- ...with equal portion of classes 50/50/50



Our pipeline

Normalized Dataset

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|-----|-------------------|------------------|-------------------|------------------|--------|
| 115 | 6.4 | 3.2 | 5.3 | 2.3 | 2 |
| 95 | 5.7 | 3.0 | 4.2 | 1.2 | 1 |
| 96 | 5.7 | 2.9 | 4.2 | 1.3 | 1 |
| 75 | 6.6 | 3.0 | 4.4 | 1.4 | 1 |
| 149 | 5.9 | 3.0 | 5.1 | 1.8 | 2 |
| 92 | 5.8 | 2.6 | 4.0 | 1.2 | 1 |
| 148 | 6.2 | 3.4 | 5.4 | 2.3 | 2 |
| 114 | 5.8 | 2.8 | 5.1 | 2.4 | 2 |

Original Dataset

Shuffled, Splitted



| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|----|-------------------|------------------|-------------------|------------------|--------|
| 9 | 4.9 | 3.1 | 1.5 | 0.1 | 0 |
| 65 | 6.7 | 3.1 | 4.4 | 1.4 | 1 |
| 94 | 5.6 | 2.7 | 4.2 | 1.3 | 1 |
| 66 | 5.6 | 3.0 | 4.5 | 1.5 | 1 |
| 6 | 4.6 | 3.4 | 1.4 | 0.3 | 0 |

Train

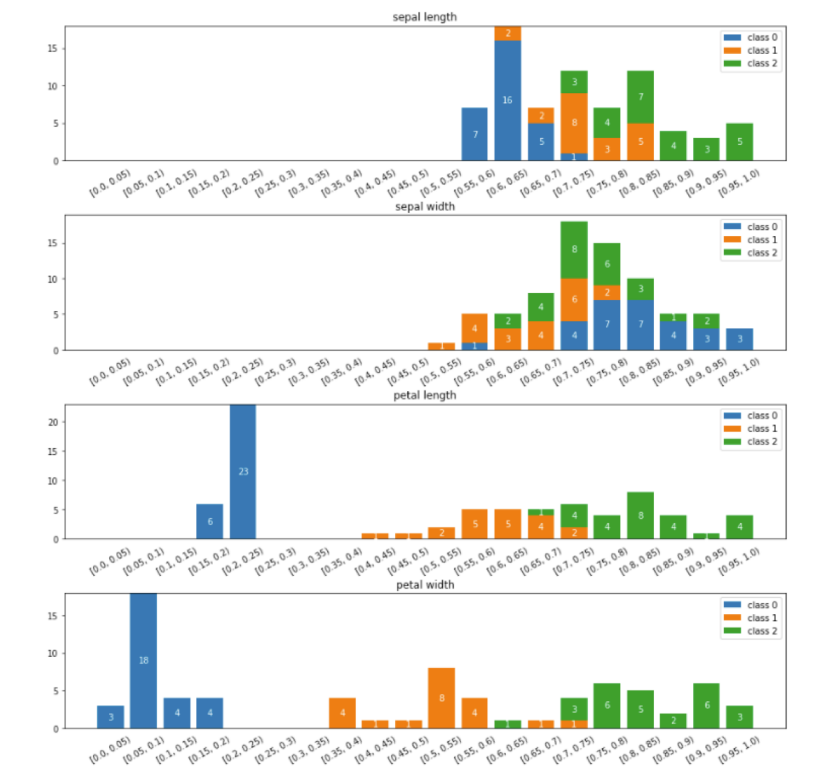
| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|----|-------------------|------------------|-------------------|------------------|--------|
| 83 | 6.0 | 2.7 | 5.1 | 1.6 | 1 |
| 54 | 6.5 | 2.8 | 4.6 | 1.5 | 1 |

Test

| | sepal length | sepal width | petal length | petal width | target |
|----|--------------|-------------|--------------|-------------|--------|
| 4 | 0.784810 | 0.536585 | 0.652174 | 0.60 | 1 |
| 35 | 0.632911 | 0.780488 | 0.173913 | 0.08 | 0 |
| 50 | 0.632911 | 0.804878 | 0.202899 | 0.08 | 0 |
| 46 | 0.974684 | 0.682927 | 0.971014 | 0.80 | 2 |
| 37 | 0.810127 | 0.707317 | 0.623188 | 0.52 | 1 |
| 52 | 0.721519 | 0.682927 | 0.594203 | 0.52 | 1 |
| 40 | 0.620253 | 0.585366 | 0.478261 | 0.40 | 1 |
| 16 | 0.569620 | 0.560976 | 0.188406 | 0.12 | 0 |

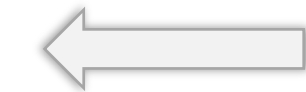


Our pipeline



| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|-----|-------------------|------------------|-------------------|------------------|--------|
| 115 | 6.4 | 3.2 | 5.3 | 2.3 | 2 |
| 95 | 5.7 | 3.0 | 4.2 | 1.2 | 1 |
| 96 | 5.7 | 2.9 | 4.2 | 1.3 | 1 |
| 75 | 6.6 | 3.0 | 4.4 | 1.4 | 1 |
| 149 | 5.9 | 3.0 | 5.1 | 1.8 | 2 |
| 92 | 5.8 | 2.6 | 4.0 | 1.2 | 1 |
| 148 | 6.2 | 3.4 | 5.4 | 2.3 | 2 |
| 114 | 5.8 | 2.8 | 5.1 | 2.4 | 2 |

Original Dataset



Shuffled, Splitted



Normalized Dataset

| | sepal length | sepal width | petal length | petal width | target |
|----|--------------|-------------|--------------|-------------|--------|
| 4 | 0.784810 | 0.536585 | 0.652174 | 0.60 | 1 |
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| 50 | 0.632911 | 0.804878 | 0.202899 | 0.08 | 0 |
| 46 | 0.974684 | 0.682927 | 0.971014 | 0.80 | 2 |
| 37 | 0.810127 | 0.707317 | 0.623188 | 0.52 | 1 |
| 52 | 0.721519 | 0.682927 | 0.594203 | 0.52 | 1 |
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| 16 | 0.569620 | 0.560976 | 0.188406 | 0.12 | 0 |



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| 65 | 6.7 | 3.1 | 4.4 | 1.4 | 1 |
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Train

Problem statement

```
print('params: ', iris_bc.X_test[0], 'class: ', iris_bc.y_test[0])
```

```
params: [5.8 2.8 5.1 2.4] class: 2
```

```
iris_bc.normalize(iris_bc.X_test[0])
```

```
array([0.73417722, 0.68292683, 0.73913043, 0.96      ])
```

```
iris_bc.predict(iris_bc.X_test[0], verbose = True)
```

```
[ (0.7, 0.75), (0.65, 0.7), (0.7, 0.75), (0.95, 1.0) ]
```

so, the problem statement:

What's the probability, that **X_test[0]** belongs to **class N**, if:

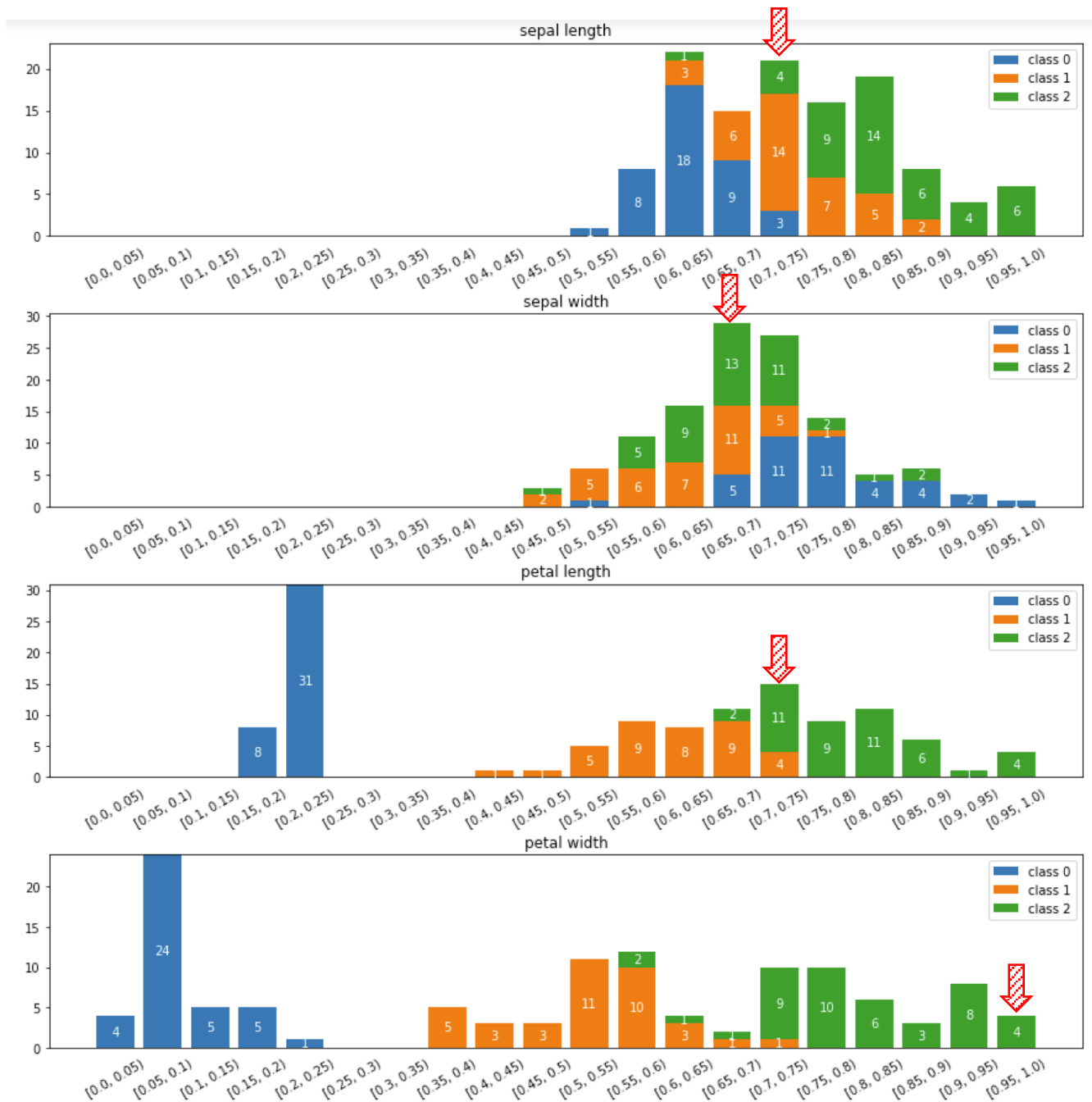
- **F1** is here **(0.7, 0.75)** and
- **F2** is here **(0.65, 0.7)** and
- **F3** is here **(0.7, 0.75)** and
- **F4** is here **(0.95, 1.0)**

Or...

$$P(C = 0 \mid x_1 = F1, x_2 = F2, x_3 = F3, x_4 = F4) = ?$$

$$P(C = 1 \mid x_1 = F1, x_2 = F2, x_3 = F3, x_4 = F4) = ?$$

$$P(C = 2 \mid x_1 = F1, x_2 = F2, x_3 = F3, x_4 = F4) = ?$$



Bayes Theorem

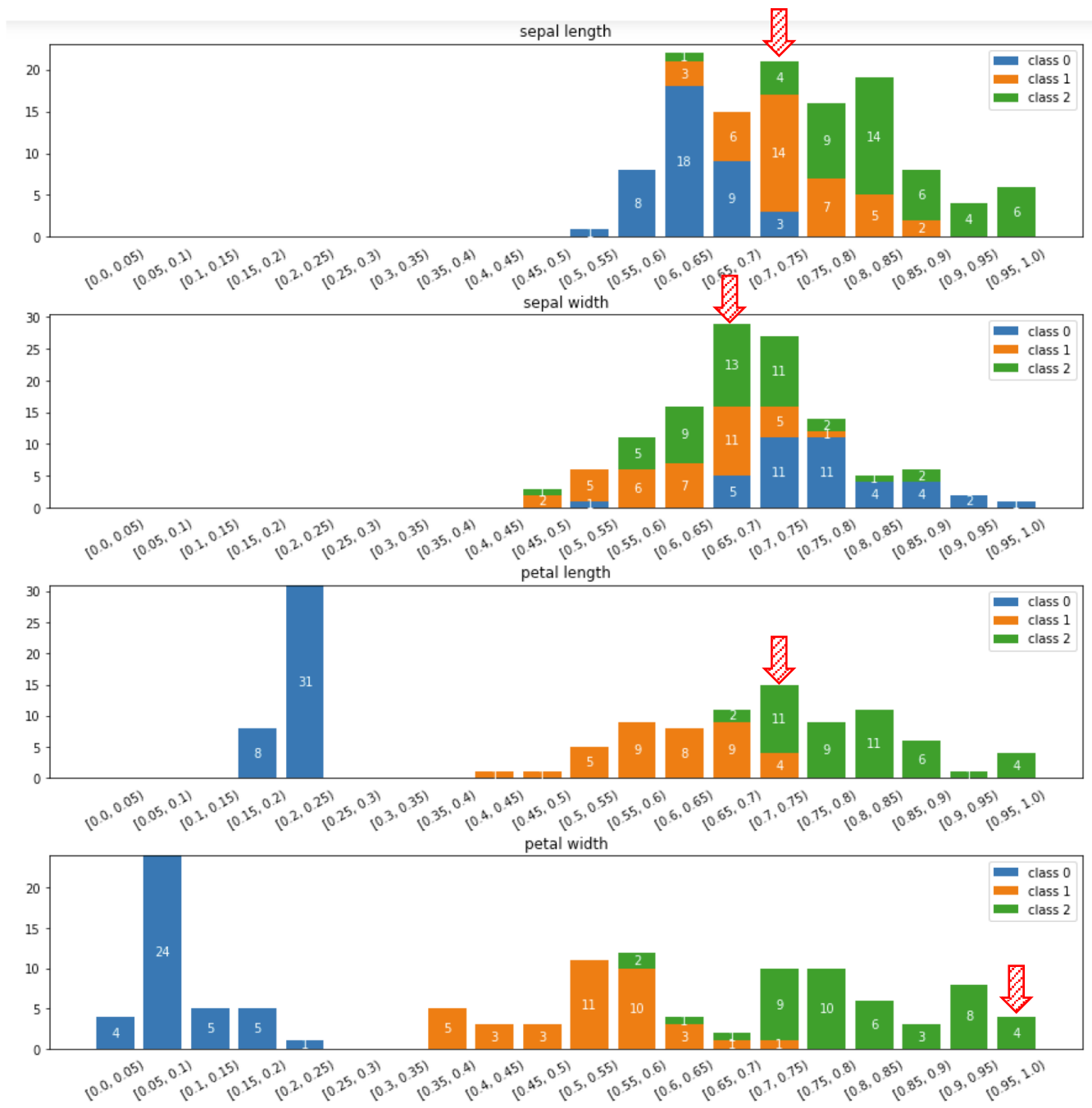
$$P(C = 0 \mid x_1 = F_1, x_2 = F_2, x_3 = F_3, x_4 = F_4) = ?$$

$$P(C = 1 \mid x_1 = F_1, x_2 = F_2, x_3 = F_3, x_4 = F_4) = ?$$

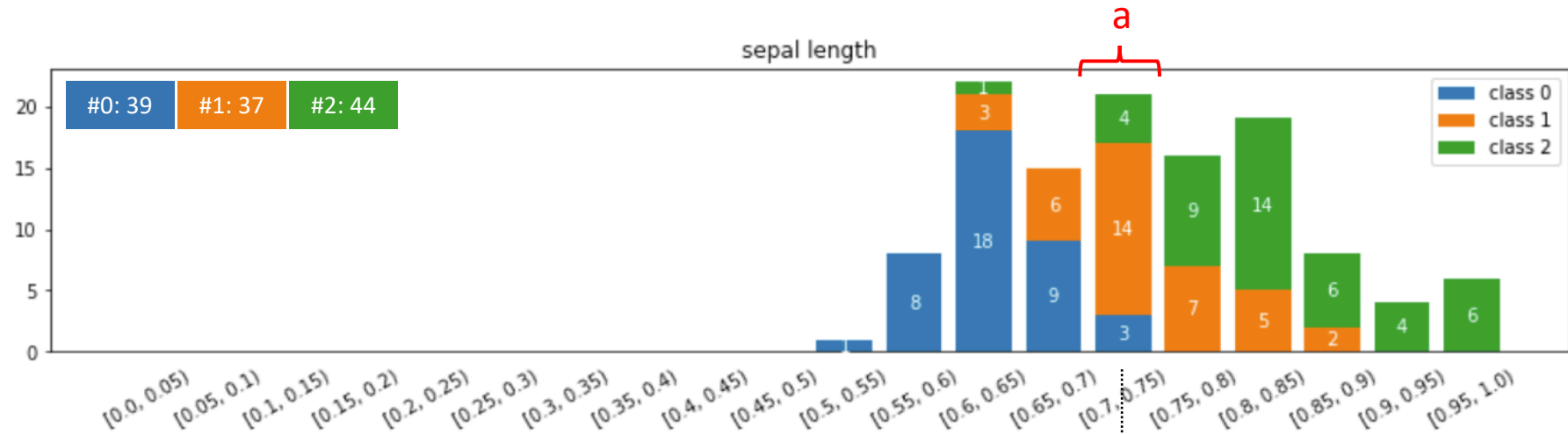
$$P(C = 2 \mid x_1 = F_1, x_2 = F_2, x_3 = F_3, x_4 = F_4) = ?$$

let's check it for more simple case for only feature:

$$P(C = 0 \mid x_1 = F_1) = ?$$



Bayes Theorem

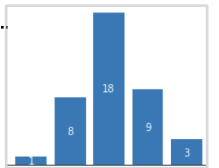


let's check it for more simple case for only feature:

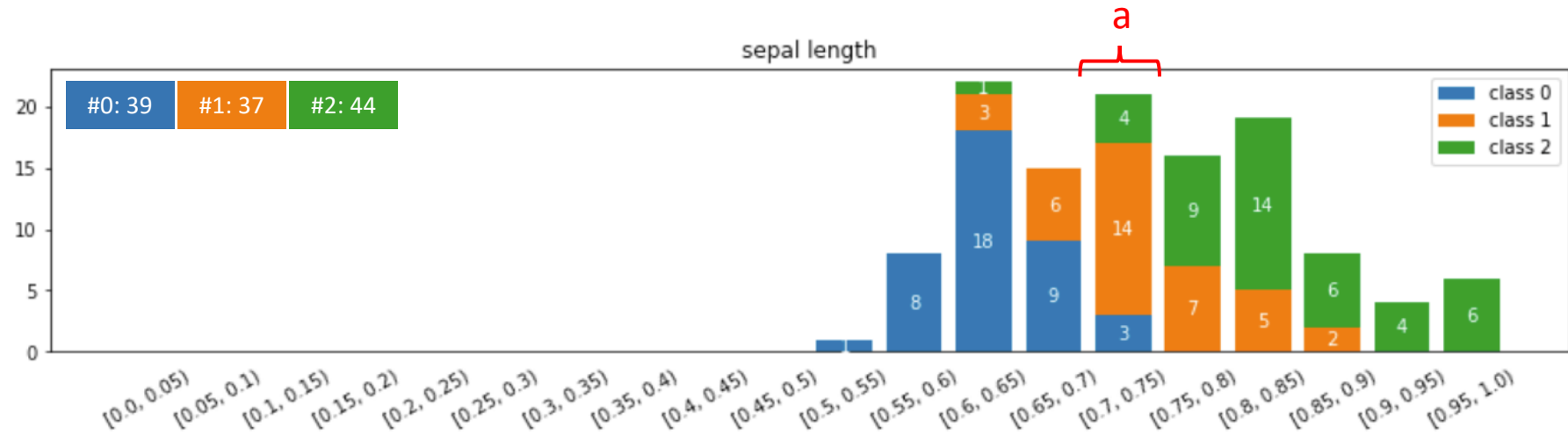
$$P(x1 = \textcolor{red}{a} | C = 0) = \frac{N(x1 = \textcolor{red}{a} | C = 0)}{N(C = 0)}$$

$$P(C = 0) = \frac{N(C = 0)}{N}$$

$$P(C = 0 | x1 = \textcolor{red}{a}) = \frac{P(x1 = \textcolor{red}{a} | C = 0) * P(C = 0)}{\sum_{i=1}^{\#Classes} P(x1 = \textcolor{red}{a} | C = i) P(C = i)}$$



Bayes Theorem



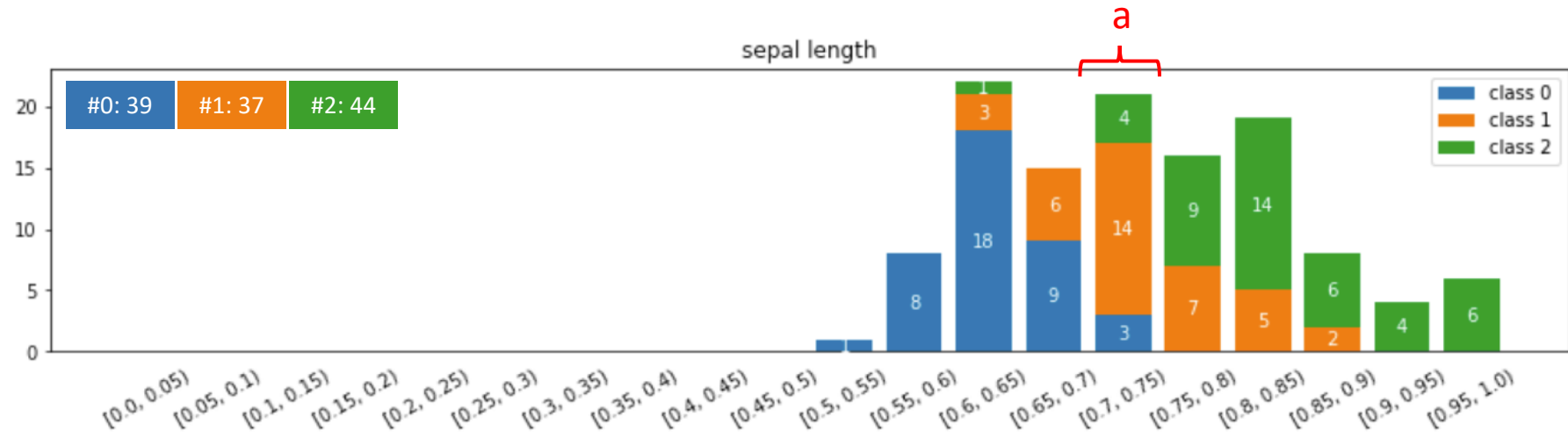
let's check it for more simple case for only feature:

$$P(x_1 = \textcolor{red}{a} | C = 0) = \frac{N(x_1 = \textcolor{red}{a} | C = 0)}{N(C = 0)} = \frac{3}{39}$$

$$P(C = 0) = \frac{N(C = 0)}{N} = \frac{39}{120}$$

$$P(C = 0 | x_1 = \textcolor{red}{a}) = \frac{P(x_1 = \textcolor{red}{a} | C = 0) * P(C = 0)}{\sum_{i=1}^{\#Classes} P(x_1 = \textcolor{red}{a} | C = i) P(C = i)}$$

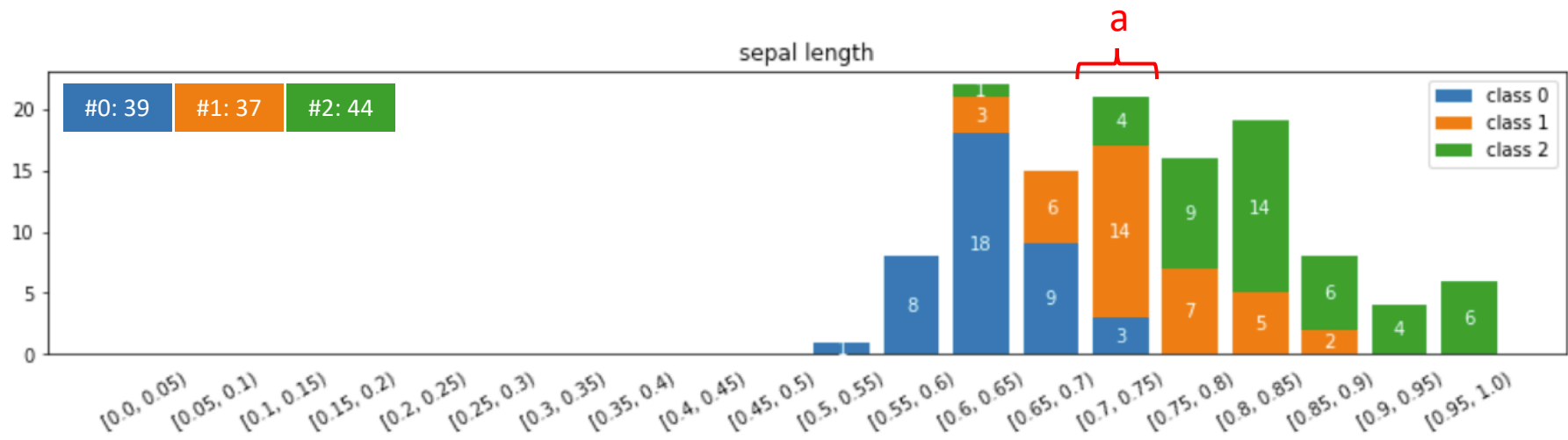
Bayes Theorem



let's check it for more simple case for only feature:

$$\begin{aligned}
 P(x_1 = \mathbf{a} | C = 0) &= \frac{N(x_1 = \mathbf{a} | C = 0)}{N(C = 0)} = \frac{3}{39} \\
 P(C = 0) &= \frac{N(C = 0)}{N} = \frac{39}{120} \\
 P(C = 0 | x_1 = \mathbf{a}) &= \frac{P(x_1 = \mathbf{a} | C = 0) * P(C = 0)}{\sum_{i=1}^{\#Classes} P(x_1 = \mathbf{a} | C = i) P(C = i)} \\
 &= \frac{\frac{3}{39} * \frac{39}{120}}{\frac{3}{39} * \frac{39}{120} + \frac{14}{37} * \frac{37}{120} + \frac{4}{44} * \frac{44}{120}} = \frac{3}{3 + 14 + 4} = 0,14
 \end{aligned}$$

Bayes Theorem



Back to complex case:

| | Class 0 | Class 1 | Class 2 |
|----|-------------------------------------|------------|-------------|
| F1 | [[0.14285714 0.66666667 0.19047619] | | |
| F2 | [0.001 | 0.4375 | 0.5625] |
| F3 | [0.001 | 0.26666667 | 0.73333333] |
| F4 | [0.001 | 0.001 | 1.]] |

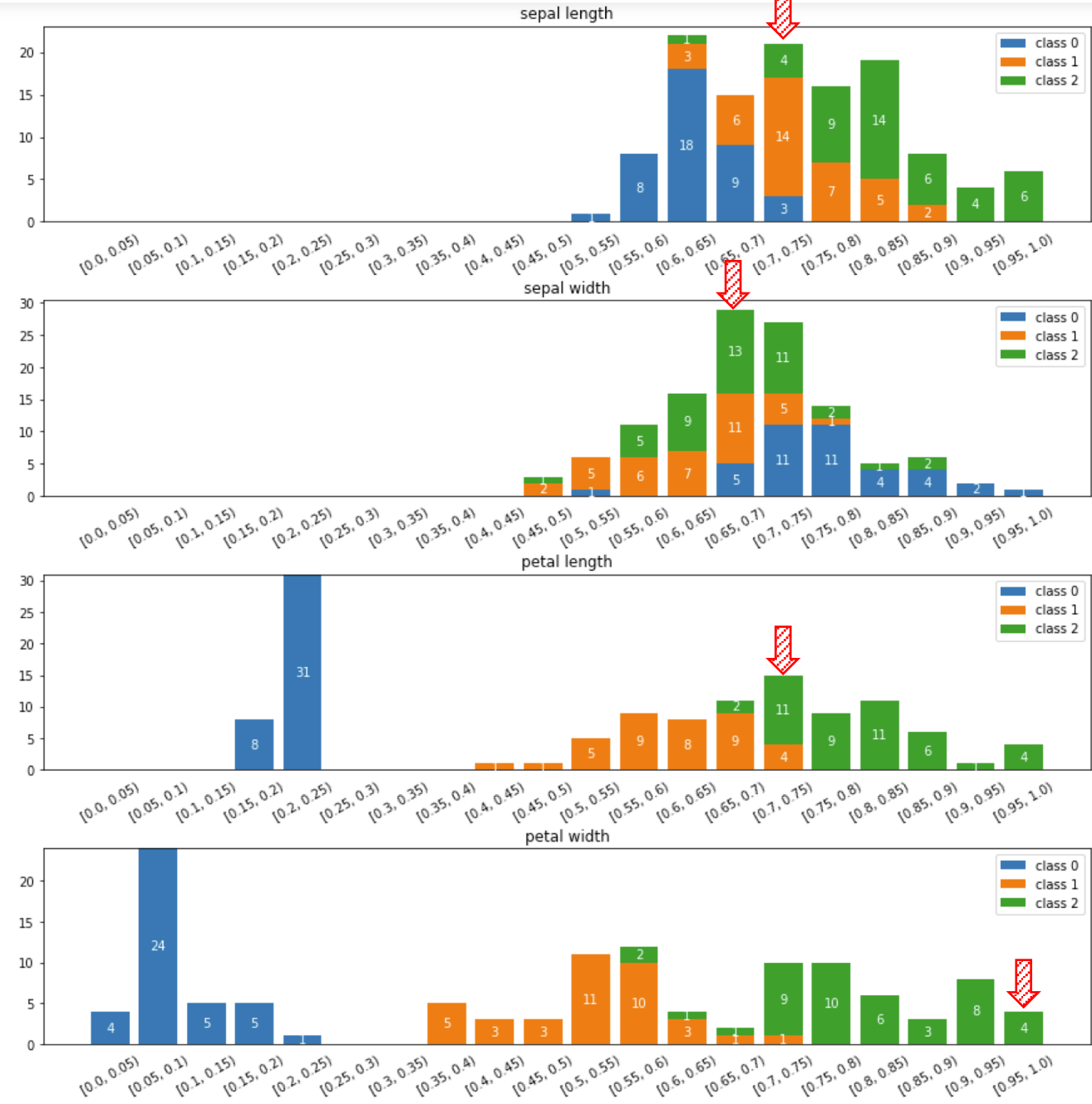
```
iris_bc.normalize(iris_bc.X_test[0])
array([0.73417722, 0.68292683, 0.73913043, 0.96      ])

iris_bc.predict(iris_bc.X_test[0], verbose = True)
[(0.7, 0.75), (0.65, 0.7), (0.7, 0.75), (0.95, 1.0)]
```

| | Class 0 | Class 1 | Class 2 |
|----|-------------------------------------|---------|---------|
| F1 | [[0.14285714 0.66666667 0.19047619] | | |
| F2 | [0.001 0.4375 0.5625] | | |
| F3 | [0.001 0.26666667 0.73333333] | | |
| F4 | [0.001 0.001 1.] | | |

Predicted class: 2, Original class: 2

[1.42857143e-10, 7.77777778e-05, 7.85714286e-02]



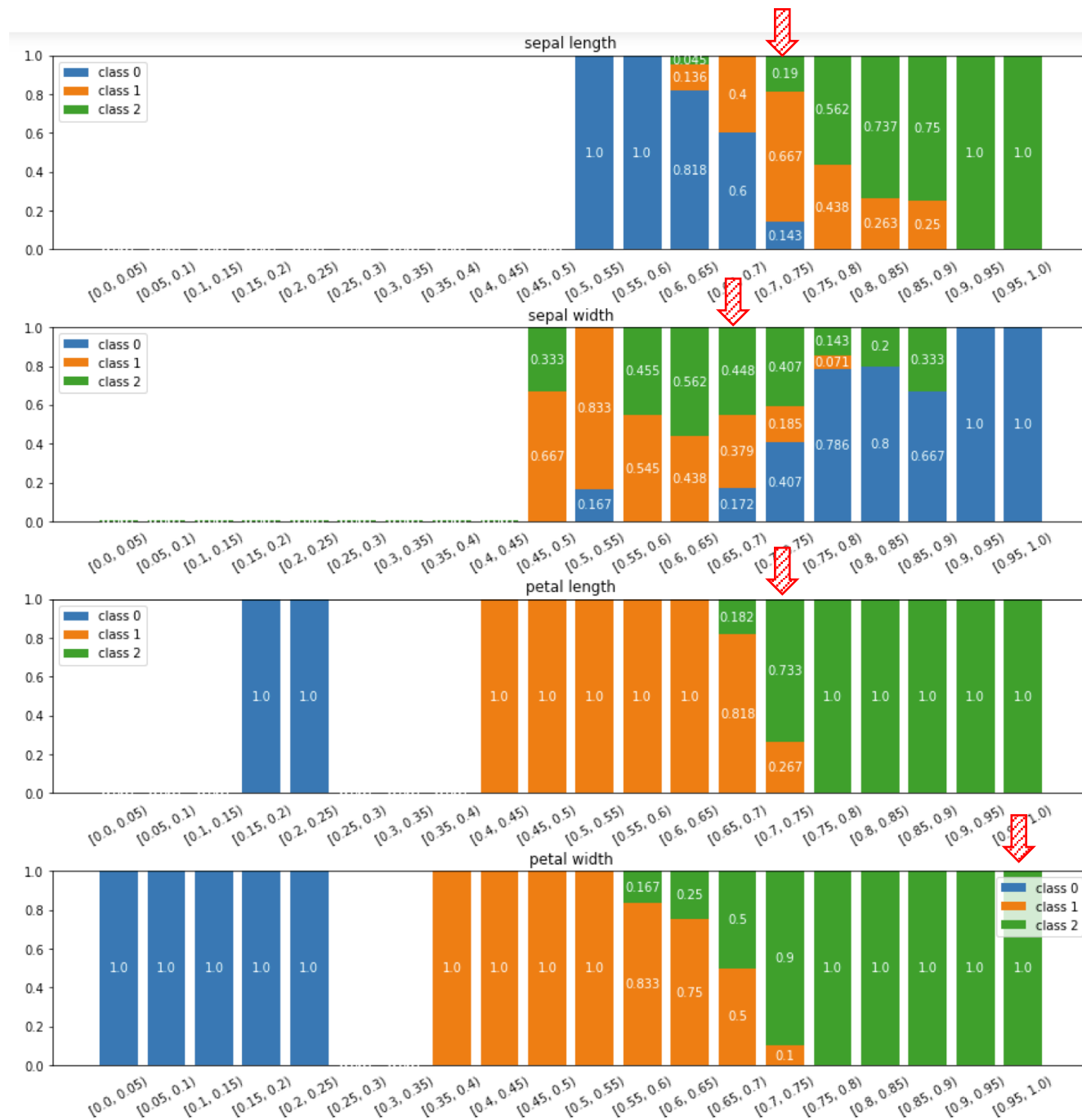
```
iris_bc.normalize(iris_bc.X_test[0])
array([0.73417722, 0.68292683, 0.73913043, 0.96      ])
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[(0.7, 0.75), (0.65, 0.7), (0.7, 0.75), (0.95, 1.0)]
```

| | Class 0 | Class 1 | Class 2 |
|----|--------------|------------|-------------|
| F1 | [[0.14285714 | 0.66666667 | 0.19047619] |
| F2 | [0.001 | 0.4375 | 0.5625] |
| F3 | [0.001 | 0.26666667 | 0.73333333] |
| F4 | [0.001 | 0.001 | 1.]] |

Predicted class: 2, Original class: 2

[1.42857143e-10, 7.77777778e-05, 7.85714286e-02]



Let's go to the code...