**I. Pen-and-paper**

Priors : *Class 0*:  *Class 1*:

Y1 distribution:

* *Class 0*:
* *Class 1*: 0.2881

Y2 probability mass function:

* *Class 0*:
* *Class 1*:

Y3 and Y4 distribution:

* *Class 0*:
* *Class 1*:

Assuming naïve Bayes : , where the likelihood of each conditional variable to the class is given by the distributions calculated in question **1)**

Normalization:

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | x1 | | x2 | | x3 | | x4 | | x5 | |
| Class | c = 0 | c = 1 | c = 0 | c = 1 | c = 0 | c = 1 | c = 0 | c = 1 | c = 0 | c = 1 |
| P(class = c) | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.6 |
| P(y1=Y1|class=c) | 0.569 | 0.224 | 1.374 | 1.364 | 1.639 | 1.209 | 1.374 | 1.364 | 1.639 | 0.950 |
| P(y2=Y2|class=c) | 0.5 | 0.1(6) | 0.25 | 0.(3) | 0.5 | 0.1(6) | 0.25 | 0.5 | 0.25 | 0.(3) |
| P(y3=Y3, y4=Y4 | class = c) | 1.207 | 1.210 | 0.460 | 0.955 | 0.707 | 0.610 | 0.512 | 0.203 | 1.174 | 1.206 |
| P(x | class = c) | 0.343 | 0.045 | 0.158 | 0.434 | 0.579 | 0.123 | 0.176 | 0.138 | 0.481 | 0.382 |
| P(class = c | x) | 1.373 | 0.271 | 0.633 | 2.605 | 2.317 | 0.738 | 0.704 | 0.829 | 1.925 | 2.293 |
| Normalization | 0.835 | 0.165 | 0.195 | 0.805 | 0.758 | 0.242 | 0.459 | 0.541 | 0.456 | 0.544 |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | x6 | | x7 | | x8 | | x9 | | x10 | |
| Class | c = 0 | c = 1 | c = 0 | c = 1 | c = 0 | c = 1 | c = 0 | c = 1 | c = 0 | c = 1 |
| P(class = c) | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.6 |
| P(y1=Y1|class=c) | 0.569 | 1.209 | 0.116 | 0.662 | 1.639 | 1.209 | 1.374 | 0.662 | 0.280 | 0.950 |
| P(y2=Y2|class=c) | 0.25 | 0.5 | 0.25 | 0.5 | 0.25 | 0.(3) | 0.5 | 0.1(6) | 0.25 | 0.5 |
| P(y3=Y3, y4=Y4 | class = c) | 0.334 | 0.672 | 0.707 | 0.610 | 1.085 | 0.838 | 0.217 | 0.387 | 1.080 | 1.123 |
| P(x | class = c) | 0.047 | 0.406 | 0.021 | 0.202 | 0.445 | 0.338 | 0.149 | 0.043 | 0.076 | 0.534 |
| P(class = c | x) | 0.190 | 2.437 | 0.082 | 1.212 | 1.778 | 2.027 | 0.598 | 0.256 | 0.303 | 3.202 |
| Normalization | 0.072 | 0.928 | 0.063 | 0.937 | 0.467 | 0.533 | 0.700 | 0.300 | 0.087 | 0.913 |

|  |  |  |  |
| --- | --- | --- | --- |
|  | 0 (predicted) | 1 (predicted) | Sum |
| 0 (true) | 2 | 2 | 4 |
| 1 (true) | 1 | 5 | 6 |
| Sum | 3 | 7 | 10 |

1. Class 0:

Class 1:

1. We used the posteriors as thresholds, because between them, the obtained results from the classifier are the same. So, we can conclude that the best threshold to use is where

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| True | P(class=0|x) | 0.06344 | 0.07224 | 0.08653 | 0.19538 | 0.45643 | 0.45923 | 0.46736 | 0.70014 | 0.75846 | 0.83522 |
| 0 | 0.835224838 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 0 | 0.195377549 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0 | 0.758462001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| 0 | 0.459234927 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0.456434993 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0.072240527 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0.063438589 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0.467357063 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 1 | 0.700142029 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| 1 | 0.086525992 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| accuracy | | 0.5 | 0.6 | 0.7 | 0.6 | 0.7 | 0.6 | 0.7 | 0.8 | 0.7 | 0.6 |

**II. Programming and critical analysis**

1. Answer 5
2. Answer 6
3. Answer 7
4. Answer 8

**III. APPENDIX**

Paste your programming code here using Consolas 9pt or 10pt.

Use **highlighting** or colored text to facilitate the analysis by your faculty hosts.

**END**