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Naïve Bayes Classifier 14 Exampl...

Naïve bayes classifier 14 example consider the data

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Naïve Bayes Classifier

- Example:
Consider the data about car theft given in the table below

Example No.	Color	Type	Origin	Stolen
1	Red	Sports	Domestic	Yes
2	Red	Sports	Domestic	No
3	Red	Sports	Domestic	Yes
4	Black	Sports	Domestic	No
5	Black	Sports	Imported	Yes
6	Black	SUV	Imported	No
7	Black	SUV	Imported	Yes
8	Black	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	Sports	Imported	Yes



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- **Solution:**

Since the goal is to classify a Red Domestic SUV as stolen or not, we first define two classes C_1 and C_2 , corresponding to Stolen = Yes and Stolen = No, respectively.

To classify the given car with attributes x , we need to compute $p(\text{Stolen} = \text{Yes} \mid \text{Color} = \text{Red}, \text{Type} = \text{SUV}, \text{Origin} = \text{Domestic})$

and $p(C_2 \mid x)$:

$p(\text{Stolen} = \text{No} \mid \text{Color} = \text{Red}, \text{Type} = \text{SUV}, \text{Origin} = \text{Domestic})$

and find which conditional probability is larger. If the first one is larger, then our prediction is Stolen = Yes. If the second one is larger, the prediction is Stolen = No. Note that x here is 3 dimensional corresponding to Color, Type and Origin.

Naïve Bayes Classifier

Since
$$p(C_1 \mid x) = \frac{p(x \mid C_1) p(C_1)}{p(x)}$$

We need to compute $p(x \mid C_1) = p(\text{Color} = \text{Red}, \text{Type} = \text{SUV}, \text{Origin} = \text{Domestic} \mid \text{Stolen} = \text{Yes})$.

Using the Naïve Bayes assumption which assumes that the dimensions of the input data (the attributes of the car) are independent, we can compute $p(x \mid C_1)$ as

$$p(x \mid C_1) = \prod_{i=1}^D p(x_i \mid C_1)$$

$= p(\text{Color} = \text{Red} \mid \text{Stolen} = \text{Yes}) p(\text{Type} = \text{SUV} \mid \text{Stolen} = \text{Yes}) p(\text{Origin} = \text{Domestic} \mid \text{Stolen} = \text{Yes})$



Similarly, $p(x|C_2)$ can be re-written as $\prod_{i=1}^n p(x_i|C_2)$

Naive Bayes Classifier

$= p(\text{Color} = \text{Red} \mid \text{Stolen} = \text{No}) p(\text{Type} = \text{SUV} \mid \text{Stolen} = \text{No}) p(\text{Color} = \text{Red} \mid \text{Type} = \text{SUV})$

$p(\text{Domestic} \mid \text{Stolen} = \text{No})$



Naïve Bayes Classifier

- From the available data in the table and using frequentist statistics:
 $p(\text{Color} = \text{Red} \mid \text{Stolen} = \text{Yes}) = 3/5$ (out of the 5 stolen cars, 3 were red)
 $p(\text{Color} = \text{Red} \mid \text{Stolen} = \text{No}) = 2/5$ (out of the 5 non-stolen cars, 2 were red)
 $p(\text{Type} = \text{SUV} \mid \text{Stolen} = \text{Yes}) = 1/5$ (out of the 5 stolen cars, 1 was SUV)
 $p(\text{Type} = \text{SUV} \mid \text{Stolen} = \text{No}) = 3/5$
 $p(\text{Origin} = \text{Domestic} \mid \text{Stolen} = \text{Yes}) = 2/5$
 $p(\text{Origin} = \text{Domestic} \mid \text{Stolen} = \text{No}) = 3/5$

Therefore,

$$p(\text{Color} = \text{Red} \mid \text{Stolen} = \text{Yes}) p(\text{Type} = \text{SUV} \mid \text{Stolen} = \text{Yes}) p(\text{Origin} = \text{Domestic} \mid \text{Stolen} = \text{Yes}) = (3/5) \times (1/5) \times (2/5) = 0.24$$

And

$$p(\text{Color} = \text{Red} \mid \text{Stolen} = \text{No}) p(\text{Type} = \text{SUV} \mid \text{Stolen} = \text{No}) p(\text{Origin} = \text{Domestic} \mid \text{Stolen} = \text{No}) = (2/5) \times (3/5) \times (3/5) = 0.36$$

$$\text{Also } p(\text{Stolen} = \text{Yes}) = 5/10 \text{ and } p(\text{Stolen} = \text{No}) = 5/10$$

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Naïve Bayes Classifier

To classify the given car, we need to compare $p(C_1|x)$ to $p(C_2|x)$

If _____ then _____, otherwise _____

Therefore, for the this problem

Therefore, our prediction is C_2 which is that the car is not stolen



Naïve Bayes Classifier

$$\frac{P(C_1)}{P(C_2)} = \frac{P(X_1|C_1)}{P(X_1|C_2)} \cdot \frac{P(X_2|C_1)}{P(X_2|C_2)} \cdot \frac{P(X_3|C_1)}{P(X_3|C_2)}$$

$$\frac{P(C_1)}{P(C_2)} = \frac{P(X_1|C_1)}{P(X_1|C_2)} \cdot \frac{P(X_2|C_1)}{P(X_2|C_2)} \cdot \frac{P(X_3|C_1)}{P(X_3|C_2)}$$

$$\frac{P(C_1)}{P(C_2)} = \frac{P(X_1|C_1)}{P(X_1|C_2)} \cdot \frac{P(X_2|C_1)}{P(X_2|C_2)} \cdot \frac{P(X_3|C_1)}{P(X_3|C_2)} = \frac{0.0001 \cdot 0.5}{0.0001 \cdot 0.5} = 1$$

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Linear Probabilistic Models for Classification

$$p(C_i|\mathbf{x}) = \frac{p(\mathbf{x}|C_i)p(C_i)}{p(\mathbf{x})}$$

- Inference Stage: Find $p(C_i|\mathbf{x})$
- Decision Stage: $k^* = \arg \max_i p(C_i|\mathbf{x})$

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- Probabilistic Discriminative Model: Learns $p(C_i|\mathbf{x})$ directly

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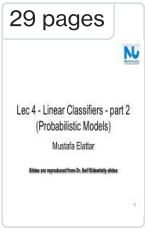
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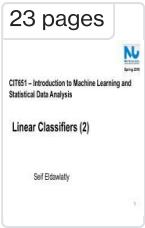
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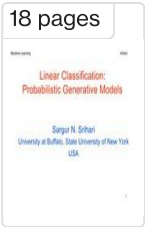
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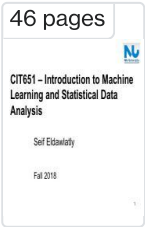
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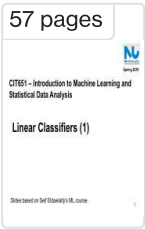
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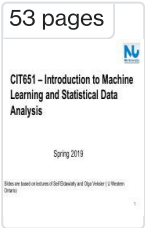
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