Naïve bayes classifier 14 example consider the data

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

- Solution:

  Since the goal is to classify a Red Domestic SUV as stolen o
  first define two classes C_1 and C_2, corresponding to Stolen =
  Stolen = No, respectively.

  To classify the given car with attributes x, we need to compu
  p(Stolen = Yes | Color = Red, Type = SUV, Origin = Domesti

  and $p(C_2|x)$:
  p(Stolen = No | Color = Red, Type = SUV, Origin = Domestic

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

Naïve Bayes Classifier

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

We need to compute $p(x|C_1)$ = p(Color = Red, Type = SUV, Orig
Domestic | Stolen = Yes).

Using the Naïve Bayes assumption which assumes that the dim
the input data (the attributes of the car) are independent, we ca
$p(x|C_1)$ as

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

= p(Color = Red | Stolen = Yes) p(Type = SUV | Stolen = Yes) p
Domestic | Stolen = Yes)

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

Naive Bayes Classifier

= *p*(Color = Red | Stolen = No) *p*(Type = SUV | Stolen = No) *p*(

Domestic | Stolen = No)

Naïve Bayes Classifier

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

Linear Probabilistic Models for Classification

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

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

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

Term	Professor	Tags
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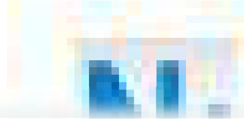

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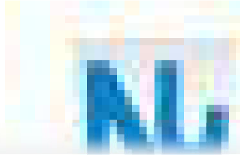

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