# Naive Bayes Classifier 

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A naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions. It assumes the conditional idependence of attribute values given the class:

$$
P\left(v_{1}, v_{2}, \ldots, v_{n} \mid c_{i}\right)=\prod_{i=1}^{n} P\left(v_{i} \mid c_{i}\right)
$$

## Naive Bayes formula

$$
P\left(c_{i} \mid v_{1}, v_{2}, \ldots, v_{n}\right) \propto P\left(c_{i}\right) \prod_{j=1}^{n} P\left(v_{j} \mid c_{i}\right)
$$

Legend:

$$
\begin{array}{ll}
c_{1}, c_{2}, \ldots, c_{k} & \text { classes } \\
P\left(c_{1}\right), P\left(c_{2}\right), \ldots, P\left(c_{k}\right) & \text { prior probabilities of classes } \\
v_{1}, v_{1}, \ldots, v_{n} & \text { attribute values } \\
\propto & \text { is proportional to } \\
\prod & \text { product }
\end{array}
$$

## Classifying a new instance $\left(v_{1}, v_{2}, \ldots, v_{n}\right)$

Let's say that our dataset has $k$ classes $\left(c_{1}, c_{2}, \ldots, c_{k}\right)$ (target variable with $k$ values). The Naive Bayes classifier calculates for each class $c_{i}$ the conditional probability ${ }^{1}$ of class $c_{i}$ given evidence $\left(v_{1}, v_{2}, \ldots, v_{n}\right)$

$$
P\left(c_{i} \mid v_{1}, v_{2}, \ldots, v_{n}\right)
$$

according to the naive Bayes formula. It classifies the example into the class with the highest value:

$$
\text { classification }=\operatorname{argmax}_{c_{i}} P\left(c_{i}\right) \prod_{j=1}^{n} P\left(v_{j} \mid c_{i}\right)
$$

[^0]
## Example

Will the spider catch an ant?
Past experiences of the spider catching ants:

| Color | Size | Time | Caught |
| :---: | :---: | :---: | :---: |
| black | large | day | YES |
| white | small | night | YES |
| black | small | day | YES |
| red | large | night | NO |
| black | large | night | NO |
| white | large | night | NO |

## Ant 1: Color $=$ white, Time $=$ night

$$
\begin{gathered}
v_{1}=" \text { Color }=\text { white } "=" C=w^{\prime} \\
v_{2}=" \text { Time }=\text { night } "=" T=n^{\prime \prime} \\
c_{1}=Y E S \\
c_{2}=N O
\end{gathered}
$$

$$
\begin{aligned}
P\left(C_{1} \mid v_{1}, v_{2}\right) & = \\
& =P(\mathrm{YES} \mid C=w, T=n) \\
& =P(\mathrm{YES}) \cdot P(C=w \mid \mathrm{YES}) \cdot P(T=n \mid \mathrm{YES}) \\
& =\frac{1}{2} \cdot \frac{1}{3} \cdot \frac{1}{3} \\
& =\frac{1}{18}
\end{aligned}
$$

$$
\begin{aligned}
P\left(C_{2} \mid v_{1}, v_{2}\right) & = \\
& =P(\mathrm{NO} \mid C=w, T=n) \\
& =P(\mathrm{NO}) \cdot P(C=w \mid \mathrm{NO}) \cdot P(T=n \mid \mathrm{NO}) \\
& =\frac{1}{2} \cdot \frac{1}{3} \cdot 1 \\
& =\frac{1}{6}
\end{aligned}
$$

The spider will not catch the white ant at night because $\mathrm{P}(\mathrm{NO} \mid$ Color $=$ white, Time $=$ night $)>\mathrm{P}($ YES $\mid$ Color $=$ white, Time $=$ night $)$.

Ant 2: Color $=$ black, Size $=$ large, Time $=$ day

$$
\begin{gathered}
v_{1}=" \text { Color }=\text { black" }=" C=b " \\
v_{2}=" \text { Size }=\text { large" }=" S=l " \\
v_{3}=" \text { Time }=\text { day" }=" T=d " \\
c_{1}=Y E S \\
c_{2}=N O
\end{gathered}
$$

$$
\begin{aligned}
P\left(C_{1} \mid v_{1}, v_{2}, v_{3}\right) & = \\
& =P(\mathrm{YES} \mid C=b, S=l, T=d) \\
& =P(\mathrm{YES}) \cdot P(C=b \mid \mathrm{YES}) \cdot P(S=l \mid \mathrm{YES}) \cdot P(T=d \mid \mathrm{YES}) \\
& =\frac{1}{2} \cdot \frac{2}{3} \cdot \frac{1}{3} \cdot \frac{2}{3} \\
& =\frac{4}{54}=\frac{2}{27} \\
P\left(C_{2} \mid v_{1}, v_{2}, v_{3}\right) & = \\
& =P(\mathrm{NO} \mid C=b, S=l, T=d) \\
& =P(\mathrm{NO}) \cdot P(C=b \mid \mathrm{NO}) \cdot P(S=l \mid \mathrm{NO}) \cdot P(T=d \mid \mathrm{NO}) \\
& =\frac{1}{2} \cdot \frac{1}{3} \cdot \frac{3}{3} \cdot 0 \\
& =0
\end{aligned}
$$

The spider will catch the large black ant at night because p (Caught $=$ YES $\mid$ Color $=$ black, Size $=$ large, Time $=$ day $)>p($ Caught $=\mathrm{NO} \mid$ Color $=$ black, Size $=$ large, Time $=$ day .

## Probability estimates

The simplest way of estimating the probability of an event $e$ from data is to count the number of times an event occurred $(|e|)$ and divide by the total number of trials $n$. This is referred to as the relative frequency of the event.

$$
\text { relative frequency }=\frac{|e|}{n}
$$

Such estimates are unreliable when estimated on small samples. For example, in our spider case, $P($ Time $=$ day $\mid$ Class $=\mathrm{NO})=0 / 3=0$. Is it really impossible that a spider catches an ant during the day? Or is just that the sample to small? In our the Naive Bayes case, even if all other evidence was in favor of catching the ant, if it was during the day, the classifier would consider this impossible.

We can overcome this by using the Laplace probability estimate. Laplace estimate assumes equal prior probability of events if no evidence is given. The more evidence it has, the more it is close to relative frequency.

$$
\text { Laplace estimate }=\frac{|e|+1}{n+k}
$$

, where $k$ is the number of all possible outcomes.
In our spider example $P($ Time $=$ day $\mid$ Class $=\mathrm{NO})$, there are three trials with Class $=$ NO $(n=3)$, there are 0 cases where Time $=$ day and Class $=$ NO $(|e|=0)$ and there are two possible values of the attribute Time: day and night $(k=2)$.

$$
P(\text { Time }=\text { day } \mid \text { Class }=\mathrm{NO})=\frac{0+1}{3+2}=\frac{1}{5}
$$

If there were 300 cases when the spider didnt catch ants at night:

$$
P(\text { Time }=\text { day } \mid \text { Class }=\text { NO })=(0+1) /(300+2)=1 / 302=0.003
$$

With Laplace estimate, probabilities can never be 0 .


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    ${ }^{1}$ a value proportional to the conditional probability

