



1.9. Naive Bayes

Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the “naive” assumption of independence between every pair of features. Given a class variable y and a dependent feature vector x_1 through x_n , Bayes' theorem states the following relationship:

$$P(y \mid x_1, \dots, x_n) = \frac{P(y)P(x_1, \dots, x_n \mid y)}{P(x_1, \dots, x_n)}$$

Using the naive independence assumption that

$$P(x_i \mid y, x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) = P(x_i \mid y),$$

for all i , this relationship is simplified to

$$P(y \mid x_1, \dots, x_n) = \frac{P(y) \prod_{i=1}^n P(x_i \mid y)}{P(x_1, \dots, x_n)}$$

Since $P(x_1, \dots, x_n)$ is constant given the input, we can use the following classification rule:

$$P(y \mid x_1, \dots, x_n) \propto P(y) \prod_{i=1}^n P(x_i \mid y)$$

$$\Downarrow$$

$$\hat{y} = \arg \max_y P(y) \prod_{i=1}^n P(x_i \mid y),$$

and we can use Maximum A Posteriori (MAP) estimation to estimate $P(y)$ and $P(x_i \mid y)$; the former is then the relative frequency of class y in the training set.

The different naive Bayes classifiers differ mainly by the assumptions they make regarding the distribution of $P(x_i \mid y)$.

In spite of their apparently over-simplified assumptions, naive Bayes classifiers have worked quite well in many real-world situations, famously document classification and spam filtering. They require a small amount of training data to estimate the necessary parameters. (For theoretical reasons why naive Bayes works well, and on which types of data it does, see the references below.)

Naive Bayes learners and classifiers can be extremely fast compared to more sophisticated methods.

The decoupling of the class conditional feature distributions means that each distribution can be independently estimated as a one dimensional distribution. This in turn helps to alleviate problems stemming from the curse of dimensionality.

On the flip side, although naive Bayes is known as a decent classifier, it is known to be a bad estimator, so the probability outputs from `predict_proba` are not to be taken too seriously.

References:

- H. Zhang (2004). [The optimality of Naive Bayes](#). Proc. FLAIRS.

1.9.1. Gaussian Naive Bayes

`GaussianNB` implements the Gaussian Naive Bayes algorithm for classification. The likelihood of the features is assumed to be Gaussian:

$$P(x_i | y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

The parameters σ_y and μ_y are estimated using maximum likelihood.

```
>>> from sklearn import datasets
>>> iris = datasets.load_iris()
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
>>> y_pred = gnb.fit(iris.data, iris.target).predict(iris.data)
>>> print("Number of mislabeled points out of a total %d points : %d"
...       % (iris.data.shape[0], (iris.target != y_pred).sum()))
Number of mislabeled points out of a total 150 points : 6
```

1.9.2. Multinomial Naive Bayes

`MultinomialNB` implements the naive Bayes algorithm for multinomially distributed data, and is one of the two classic naive Bayes variants used in text classification (where the data are typically represented as word vector counts, although tf-idf vectors are also known to work well in practice). The distribution is parametrized by vectors $\theta_y = (\theta_{y1}, \dots, \theta_{yn})$ for each class y , where n is the number of features (in text classification, the size of the vocabulary) and θ_{yi} is the probability $P(x_i | y)$ of feature i appearing in a sample belonging to class y .

The parameters θ_y is estimated by a smoothed version of maximum likelihood, i.e. relative frequency counting:

$$\hat{\theta}_{yi} = \frac{N_{yi} + \alpha}{N_y + \alpha n}$$

where $N_{yi} = \sum_{x \in T} x_i$ is the number of times feature i appears in a sample of class y in the training set T , and $N_y = \sum_{i=1}^{|T|} N_{yi}$ is the total count of all features for class y .

The smoothing priors $\alpha \geq 0$ accounts for features not present in the learning samples and prevents zero probabilities in further computations. Setting $\alpha = 1$ is called Laplace smoothing, while $\alpha < 1$ is called Lidstone smoothing.

1.9.3. Bernoulli Naive Bayes

`BernoulliNB` implements the naive Bayes training and classification algorithms for data that is distributed according to multivariate Bernoulli distributions; i.e., there may be multiple features but each one is assumed to be a binary-valued (Bernoulli, boolean) variable. Therefore, this class requires samples to be represented as binary-valued feature vectors; if handed any other kind of data, a `BernoulliNB` instance may binarize its input (depending on the `binarize` parameter).

The decision rule for Bernoulli naive Bayes is based on

$$P(x_i | y) = P(i | y)x_i + (1 - P(i | y))(1 - x_i)$$

which differs from multinomial NB's rule in that it explicitly penalizes the non-occurrence of a feature i that is an indicator for class y , where the multinomial variant would simply ignore a non-occurring feature.

In the case of text classification, word occurrence vectors (rather than word count vectors) may be used to train and use this classifier. `BernoulliNB` might perform better on some datasets, especially those with shorter documents. It is advisable to evaluate both models, if time permits.

References:

- C.D. Manning, P. Raghavan and H. Schütze (2008). Introduction to Information Retrieval. Cambridge University Press, pp. 234-265.
- A. McCallum and K. Nigam (1998). [A comparison of event models for Naive Bayes text classification](#). Proc. AAAI/ICML-98 Workshop on Learning for Text Categorization, pp. 41-48.
- V. Metsis, I. Androutsopoulos and G. Paliouras (2006). [Spam filtering with Naive Bayes – Which Naive Bayes?](#) 3rd Conf. on Email and Anti-Spam (CEAS).

1.9.4. Out-of-core naive Bayes model fitting

Naive Bayes models can be used to tackle large scale classification problems for which the full training set might not fit in memory. To handle this case, `MultinomialNB`, `BernoulliNB`, and `GaussianNB` expose a `partial_fit` method that can be used incrementally as done with other classifiers as demonstrated in [Out-of-core classification of text documents](#). Both discrete classifiers support sample weighting;

[GaussianNB](#) does not.

Contrary to the `fit` method, the first call to `partial_fit` needs to be passed the list of all the expected class labels.

For an overview of available strategies in scikit-learn, see also the [out-of-core learning](#) documentation.

Note: The `partial_fit` method call of naive Bayes models introduces some computational overhead. It is recommended to use data chunk sizes that are as large as possible, that is as the available RAM allows.