Supplementary Materials

Ensemble-based support vector machine classifiers as an efficient tool for quality assessment of beef fillets from electronic nose data

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S1. Naïve Bayes

Let $P(s_j)$ be the probability that classifier D_j predicts sample x to in class $s_j \in \Omega$. . The conditional independence can therefore presented as follows:

$$P(s \mid \omega_k) = P(s_1, s_2, ..., s_T \mid \omega_k) = \prod_{i=1}^T P(s_i \mid \omega_k)$$

The posterior probability can be obtained as follows:

$$P(\omega_k \mid s) = \frac{P(\omega_k)P(s|\omega_k)}{P(s)} = \frac{P(\omega_k)\prod_{i=1}^{T}P(s_i|\omega_k)}{P(s)}$$

Where k = 1, ..., C.

P(s) is constant for each class, and can be therefore ignored. The support for class ω_k can be calculated as follows:

$$\mu_k(x) \propto P(\omega_k) \prod_{i=1}^T P(s_i | \omega_k)$$

For each classifier D_i , a $c \times c$ confusion matrix CM^i is generated based on labeling the training subset. The $(k, s)^{th}$ element of this matrix, $cm_{k,s}^i$ is the number of element classified as ω_s while their true class is ω_k . N_s is the total number of elements of Z from class ω_s . This can be represented as follows:

$$\mu_k(x) \propto \frac{1}{N^T c_k^{-1}} \prod_{i=1}^T c_{k,s_i}^{i}$$

Where $\frac{cm_{k,s_i}^{i}}{N_k}$ is an estimate of the probability $P(\omega_k | s)$, and $\frac{N_k}{N}$ is an estimate of the prior probability for class ω_s .

The previous formula suffers from a drawback, that it when cm_{k,s_i}^i equals zero, it will automatically set $\mu_k(x)$ as zero, regardless to the rest of the estimates. That is why Titterington et al. (Titterington et al., 1981) proposed a modification to the estimate to overcome the null value for $\mu_k(x)$ as follows:

$$P(s|\omega_k) \propto \left\{ \prod_{i=1}^T \frac{cm_{k,s_i}^i + 1/c}{N_k + 1} \right\}^B$$

Where N_k is the number of elements belonging to the class ω_k , and *B* is a constant (Kuncheva, 2004).

S2. Boosting using Adaboost.M1

- Let *S* be the training subset of *N* number of samples *S*: $S = [(x_i, y_i), i = 1, ..., N]$ where x_i is the i^{th} sample, and y_i is the i^{th} label for sample x_i where $y_i \in \Omega, \Omega = \{\omega_1, ..., \omega_C\}$.
- Let *D* be the classifiers ensemble $A = \{h_1, \dots, h_T\}$, Where *T* is the number of classifiers to train (*i.e.* number of iterations). A grid search is performed to identify the best classification parameters using the parameter ranges $C = [1,2,3, \dots, 30]$ and $\gamma = [0.1, 0.2, 0.3, \dots, 5]$. For each cycle within the grid search, a bootstrapped subset of S, S_t is developed using resampling with replacement. S_t is then split into $S_t training_{c,g}$ and $S_t testing_{c,g}$. If $\varepsilon_t > 0.5$, $h_t h_t$, otherwise h_t to the ensemble.
- The classification error for *S* is initialised as follows:

$$D_1(i) = \frac{1}{N} \cdot i = 1, \dots, N_{i}$$

$$\varepsilon_t = \sum_{i:h \in \mathcal{I}} D_t(i)$$

• The error of f h_t is calculated such as $i:h_{t(x_i) \neq y_i}$ The Adaboost Weight for h_t is then calculated as follows

 $\rho = \ln \left(\frac{1 - \varepsilon_t}{\varepsilon_t} \right) \frac{1}{2}$

• The classification error is calculated as follows:

$$D_t: D_{t+1}(i) = D_t(i) * e^{-\rho c}$$

Where: c = 1 if $h_t(x_i) = y_i$; c = -1 if $h_t(x_i) \neq y_i$:

• Test the ensemble classification using weighted majority voting by calculating the total votes received by each class as follows:

$$V_j = \sum_{t:h_t(x) = \omega_j} \rho_t, j = 1, ..., C.$$

• Choose the class that receives the highest total vote as the final classification.

References:

- Kuncheva, Ludmila I. (2004). *Combining pattern classifiers : methods and algorithms*. Hoboken, N.J. ; [Chichester]: John Wiley ;.
- Titterington, D. M., Murray, G. D., Murray, L. S., Spiegelhalter, D. J., Skene, A. M., Habbema, J. D. F., & Gelpke, G. J. (1981). Comparison of Discrimination Techniques Applied to a Complex Data Set of Head Injured Patients. *Journal of the Royal Statistical Society. Series A* (General), 144(2). doi: citeulike-article-id:9414776