

OBJECTIVE: COMPUTE OBJECT STABILITY VALUES FOR THE TRAINING SAMPLE

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Stability, also known as algorithmic stability, is the concept in computational learning theory of how a machine learning algorithm is disturbed by small changes in its input.

The stability of a feature selection algorithm is that it produces a consistent set of features when new training samples are added or removed (A feature selection algorithm is only stable if it produces similar features under changing training data. Feature Selection neglecting the issue of stability of the algorithm may lead to false conclusions. Among the highly correlated features, discarding features that are related to the selected features but not related to the response variable is one of the main causes of instability. (Kamkar et al., 2015). If a small change in the input leads to a large change in the output, the problem is called ill-posed (Cui et al., 2019). relative instability produces different results and makes the solution unreliable. The idea of regularization transforms an ill-posed problem into a stable form. Regularization mnormalization modifies the learning algorithm in such a way that it reduces the generalization error but not the training error.

The robustness motivation arises from increasing the domain expert's confidence in analyzing the output and selecting features that are robust to input perturbations (Kalousis et al., 2007). Stability provides the best objective criteria, so we can choose a feature selection algorithm that provides a high-quality feature set and also provides high confidence in better classification performance. Augmenting the feature selection method with parallel stability analysis develops a high-quality feature set (Goh and Wong, 2016). In knowledge discovery, consistency plays an important role in feature selection to identify important features (George and Cyril Raj, 2015). The feature selection algorithm selects different subsets under the perturbation of the input data, but most of these subsets are equivalent in terms of classification performance (Li et al., 2015). Such instability reduces the confidence of experts in confirming the selected characteristics. Therefore, it is important to develop a robust method for selecting important features that is robust against selection bias (Ambroise and McLachlan, 2002).

Let's consider a program that calculates the values of object stability according to the learning sample $E_0 = \{S_1, \dots, S_2\}$ divided into l non-intersecting classes K_1, K_2, \dots, K_i . Let each S sample (belonging to the set E_0) object be characterized by n quantitative features, and the Chebyshev metric be used to find the distance. Stability of object S_i in class K_j is found by the following formula.

$$\lambda'_i = \frac{d'_i}{2 \min_{1 \leq j \leq l} |K_j| - 3}$$

The result is as follows:

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C:\Users\Admin\.jdk\openjdk-17.0.1\bin\java.exe "-javaagent:C:\Program Files\JetBrains\IntelliJ IDEA 2021.3.2\lib\idea_rt.jar=62172:C:\Program Files\JetBrains\IntelliJ IDEA 2021.3.2\bin" -Dfile.encoding=UTF-8 -classpath "D:\spring boot project\chebishovTurg'unlik\out\production\chebishovTurg'unlik" Main

Your selection: Sepal_length  Sepal_width  Petal_length  Petal_width  Group
Result: 0.5154639175257731  5.1        3.5         1.4         0.2         1.0
Result: 0.5154639175257731  4.9        3.0         1.4         0.2         1.0
Result: 0.5154639175257731  4.7        3.2         1.3         0.2         1.0
Result: 0.5154639175257731  4.6        3.1         1.5         0.2         1.0
Result: 0.5154639175257731  5.0        3.6         1.4         0.2         1.0
Result: 0.5154639175257731  5.4        3.9         1.7         0.4         1.0
Result: 0.5051546391752577  4.6        3.4         1.4         0.3         1.0

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The Chebyshev distance between two vectors or points x and y , with standard coordinates x and y , respectively, is

$$D_{\text{Chebyshev}}(x, y) := \max_i (|x_i - y_i|).$$

This equals the limit of the L_p metrics:

$$\lim_{p \rightarrow \infty} \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{1/p},$$

hence it is also known as the L_∞ metric.

Mathematically, the Chebyshev distance is a [metric](#) induced by the [supremum norm](#) or [uniform norm](#). It is an example of an [injective metric](#).

In two dimensions, i.e. [plane geometry](#), if the points p and q have [Cartesian coordinates](#) (x_1, y_1) and (x_2, y_2) , their Chebyshev distance is

$$D_{\text{Chebyshev}} = \max(|x_2 - x_1|, |y_2 - y_1|).$$

Under this metric, a [circle](#) of [radius](#) r , which is the set of points with Chebyshev distance r from a center point, is a square whose sides have the length $2r$ and are parallel to the coordinate axes.

On a chess board, where one is using a *discrete* Chebyshev distance, rather than a continuous one, the circle of radius r is a square of side lengths $2r$, measuring from the centers of squares, and thus each side contains $2r+1$ squares; for example, the circle of radius 1 on a chess board is a 3×3 square.

References:

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2. Игнатьев Н.А “Обобщенные оценки и локальные метрики объектов в интеллектуальном анализе данных”, “Университет” 2015.

