

PyCM: Multiclass confusion matrix library in Python

Sepand Haghighi¹, Masoomeh Jasemi¹, Shaahin Hessabi¹, and Alireza Zolanvari²

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1 Sharif University of Technology 2 Amirkabir University of Technology

Software

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Summary

In the field of machine learning and specifically for statistical classification a confusion matrix - also known as error matrix - is a specific table layout that allows visualization of the algorithm performance, and is mostly used in supervised learning. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predict class (or vice versa) (Powers 2011; Sammut and Webb 2010; Shepperd, Bowes, and Hall 2014; X. Deng et al. 2016).

PyCM is a multi-class confusion matrix library written in Python that supports both input data vectors and direct matrix, and a proper tool for post-classification model evaluation that supports most classes and overall statistics parameters (Landis and Koch 1977; Fleiss 1971; Altman 1990; Gwet 2008; Scott 1955; Bennett, Alpert, and Goldstein 1954; Cicchetti 1994; Davies 1980; Kullback and Leibler 1951; Goodman and Kruskal 1972, 1963; Byrt, Bishop, and Carlin 1993).

We can categorize these statistics in 3 sections:

1. Basic
2. Class Statistics
3. Overall Statistics

PyCM is also capable of generating report in HTML, CSV and .pymc formats.

To sum it up, PyCM is the swiss-army knife of confusion matrices, targeted mainly at data scientists that need a broad array of metrics for predictive models and an accurate evaluation of large variety of classifiers (Haghighi, Jasemi, and Hessabi 2018).

Website : <http://pymc.shaghighi.ir>

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