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| Name Of The Student | Himanshu |
| Internship Project Topic | TCS iON RIO-210: Build a Classification Model for Drug Trials Dataset |
| Name of the Organization | TCS iON |
| Name of the Industry Mentor | Himdweep Walia |
| Name of the Institute | Amity University |

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| Date | Day # | Hours Spent |
| 23-05-2024 | Day-30 | 3.5 Hours |
| **Learn about the accuracy checking of Machine learning models.**  **Creating Classification Report and Confusion Matrix:**  The classification report shows a representation of the main classification metrics on a per-class basis. This gives a deeper intuition of the classifier behavior over global accuracy which can mask functional weaknesses in one class of a multiclass problem. Visual classification reports are used to compare classification models to select models that are “redder”, e.g. have stronger classification metrics or that are more balanced.  The metrics are defined in terms of true and false positives, and true and false negatives. Positive and negative in this case are generic names for the classes of a binary classification problem. In the example above, we would consider true and false occupied and true and false unoccupied. Therefore a true positive is when the actual class is positive as is the estimated class. A false positive is when the actual class is negative but the estimated class is positive. Using this terminology the metrics are defined as follows:  **Precision**  Precision can be seen as a measure of a classifier’s exactness. For each class, it is defined as the ratio of true positives to the sum of true and false positives. Said another way, “for all instances classified positive, what percent was correct?”  **Recall**  Recall is a measure of the classifier’s completeness; the ability of a classifier to correctly find all positive instances. For each class, it is defined as the ratio of true positives to the sum of true positives and false negatives. Said another way, “for all instances that were actually positive, what percent was classified correctly?”  **F1 score**  The F1 score is a weighted harmonic mean of precision and recall such that the best score is 1.0 and the worst is 0.0. Generally speaking, F1 scores are lower than accuracy measures as they embed precision and recall into their computation. As a rule of thumb, the weighted average of F1 should be used to compare classifier models, not global accuracy.  **Support**  Support is the number of actual occurrences of the class in the specified dataset. Imbalanced support in the training data may indicate structural weaknesses in the reported scores of the classifier and could indicate the need for stratified sampling or rebalancing. Support doesn’t change between models but instead diagnoses the evaluation process.  **The parameters of Classification Report:**   * y\_true : In this parameter we have to pass the true target values of the data. * y\_pred : It this parameter we have to pass the predicted output of model. * target\_names : In this parameter we have to pass the names of target.   For Confusion Matrix there are two parameters test and predicted values of the data.   |  | | --- | | print(classification\_report(y\_test, y\_predict, target\_names=class\_names))  print(confusion\_matrix(y\_test, y\_predict)) |     So the output comes as   |  |  |  |  |  | | --- | --- | --- | --- | --- | |  | precision | recall | f1-score | support | | class\_0 | 0.95 | 0.95 | 0.95 | 19 | | class\_1 | 0.95 | 0.95 | 0.95 | 21 | | class\_2 | 0.95 | 0.95 | 0.95 | 19 |  |  |  |  |  |  | | --- | --- | --- | --- | --- | | micro avg | 0.95 | 0.95 | 0.95 | 59 | | macro avg | 0.95 | 0.95 | 0.95 | 59 | | weighted avg | 0.95 | 0.95 | 0.95 | 59 |   [[18 1 0]  [ 0 20 1]  [ 1 0 18]]  Reference:  [https://muthu.co/understanding-the-classification-report-in-sklearn//](https://muthu.co/understanding-the-classification-report-in-sklearn/) | | |