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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **XGBoost** | | | **LightGBM** | | | | **CATBoost** | | | |
| **Datasets** | Accuracy | Training Time (sec) | Testing Time (sec) | Accuracy | Training Time (sec) | Testing Time (sec) | Accuracy | | Training Time (sec) | Testing Time (sec) |
| **Original** | 0.8985 | 231.01 | 0.089 | 0.8940 | 80.04 | 0.179 | 0.8926 | | 2129.96 | 0.055 |
| **SOM** | 0.6205 | 2.578 | 0.075 | 0.6205 | 1.745 | 0.147 | 0.6205 | | 22.043 | 0.024 |
| **RBM** | 0.1906 | 4.118 | 0.032 | 0.1907 | 3.57 | 0.14 | 0.1908 | | 123.37 | 0.019 |
| **VAE** | 0.6698 | 3.04 | 0.043 | 0.67 | 1.55 | 0.127 | 0.6699 | | 27.61 | 0.023 |

# Analysis:

For the same dataset, XGBoost, LightGBM and CATBoost all have same accuracy. As we have seen in HW3, the LightGBM tends to be the fastest and CATBoost the slowest.

As different methods are applied to the dataset, we can see that SOM and VAE shares the similar accuracy result, with VAE slightly in the lead, although both are lower than the original dataset. With RBM, the accuracy is significantly lower at 19%. It is expected that with dimension reduction methods, due the loss of information during the dimension reduction process.

With the loss of accuracy, however, we gain significant improvements in training time and moderate improvements testing time. CATBoost shows the highest decrease in training time from over 35mins (2129.96 seconds) to only 27.61 seconds with VAE. Between SOM, RBM and VAE, SOM and VAE has relatively same training time, while RBM trains slightly slower. Similar story can be told with testing time, with SOM in general faster than VAE, and VAE faster than RBM.