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Deep Learning

Deep learning encompasses a variety of architectures, such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and feed-forward artificial neural networks (ANNs). The best architecture for transactional (tabular) data that are not sequential, like the data in this study, is a multi-layer feedforward artificial neural network. Other, more complex designs, such as RNNs, are not always beneficial (Candel & LeDell, 2019). The feed-forward neural network's architectural graph is displayed in Fig. 1. The first column, which shows the input properties, is the input layer. The last single neuron represents the output, to which the final activation function is applied. We call the two intermediary levels "hidden layers. If a neural network contains more than one hidden layer, it is referred regarded as deep. A deep learning model can consist of several hidden layers that are trained via stochastic gradient descent and backpropagation

Data and Processing

The final dataset comes from a retail bank and includes customer information meant for direct marketing campaigns. A total of 45,211 observations were made; 5,289 of these led to a sale, while 39,922 were ineffective. A binary response column indicating whether the person established a bank account subsequent to the direct marketing effort is one of the sixteen characteristics present in every observation.

The experiment required a few adjustments. These datasets exhibit extreme disproportionality. In this study, random under-sampling was used to create a balance between the favourable and unfavourable circumstances. This is also included in Table 1.

To be more precise, the majority of the data in these datasets are of Marketing and Sales are category strings. When required, one-hot encoding was used to convert categorical characteristics into factor variables. For this experimental inquiry, all three datasets are split into an 80:20 ratio training set and test set. To fine-tune the model parameters throughout the classifier generation process, the training set will be further partitioned into distinct training and validation sets using a technique called cross-validation.

Table 4 presents the numerical results for the marketing and sales case scenario. These results may be utilized to accurately predict the number of successful conversions that will arise from direct sales activities. The efficacy of deep learning classifiers using the four-assessment metrics: AUC, Accuracy, F-score, and LogLoss. The exceptional performance has been italicized. The results of each model are categorized based on the assessment measure and presented graphically in Figure 4. The results show that while GBM and RF exceed the two DL models on all performance metrics, logistic regression is the lowest classifier.

A visual representation of each classifier's performance for the marketing and sales case study across the four performance parameters. Gradient Boosting Machine (GBM) wins again; nevertheless, the findings are not as important as they were previously, as Random Forest (RF) achieves fairly similar results.

A reality Check

To further understand Deep Learning's use for business analytics, it was compared to other traditional machine learning models, such as gradient boosting machine, random forest, and GLMs. based on the evaluation parameters for AUC, Accuracy, F-score, and LogLoss.

Based on the case study's actual findings, it doesn't seem that marketing and sales work much better than other approaches when it comes to problems with structured data classification. Instead, the results resoundingly endorse tree-based ensembles such as random forest and gradient boosting. GBM is the most practical model for the types of problems this research looks at.

Higher performance for DL when they benchmarked their suggested embedded DNN model against multiple baseline models. I suggest encouraging the use of DL models in operations research and business analytics. Although it is a very informative and good introduction of DL for Business Analytics, the analysis does not employ GBM as a baseline model for comparison, despite the fact that GBM is a popular model that is well-known for producing accurate and robust predictions on structured datasets.

Does DL perform better than conventional ML models when applied to structured data with fixed-length feature vectors for supervised learning problems?

Ans) The actual results suggest that for classification tasks involving structured datasets and fixed-length feature vectors, deep learning is not more successful than other techniques. The results unequivocally validate tree-based ensembles, such as random forest and gradient boosting. The results of this study support those of other studies (Addo et al., 2018; Hamori et al., 2018; Schmitt, 2022b), which mostly focused on applications of credit risk management. With the addition of use cases from the insurance, marketing, and sales sectors, this study broadened its applicability scope. Several sectors that depend on information management and business analytics for powerful data-driven decision-making might benefit from the fact that GBM outperforms other approaches for structured datasets.

Previous research has identified a number of barriers to the adoption of AI, including computational complexity, a lack of big data infrastructure, a lack of transparency, a shortage of skills, a lack of leadership commitment, and a lack of strategic guidance. The speed at which DL is embraced in particular industries might be impacted by any of those conclusions. Moreover, the results of this research demonstrate that the prediction accuracy of DL is not necessarily superior to other ML models. The results unambiguously suggest that gradient boosting ought to be the go-to method for the vast majority of business analytics problems. For use cases dependent on structured data, it provides the greatest performance currently available.

The main causes of DL's lack of ubiquity in various business activities are often ascribed to its opaque (or "black-box") character, computational difficulty, a lack of big-data infrastructure, and a skills gap. But as this article shown, the fact that DL doesn't outperform traditional analytics in structured data use cases may also account for its lack of popularity in a number of business analytics tasks.

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