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Summative Assessment (SA) Deep Learning in Business Analytics Case Study

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Abstract

In our fast-paced, internationally competitive digital economy, a stronger focus on data oriented decision that is completely based on AI and ML. While deep learning offers numerous benefits, a number of disadvantages have kept DL from being widely applied in the business. This essay explores the reasons why DL is not taking off in the business analytics industry as rapidly, despite its ubiquitous use. Deep Learning usage is influenced not only by the lack of big data structure, computational complexity, lack of transparency, leadership commitment, and skill shortages, but Deep Learning models do not outperform traditional ML models when used on types of datasets with fixed length feature vectors.

Deep learning is a unique tool to the existing repertoire of machine learning models, not a narrow way solution. The results unambiguously recommend that gradient boosting ought to be regarded as the industry standard approach in business analytics for forecasting structured data. In addition to the empirical examination based on three industrial use cases, the essay offers a extensive analysis of results, a strategy for future R&D, and their practical implications.

Introduction

Over the past 10 years, significant developments in data storing and analytics techniques have had an impact. Globalization and the upgrading shift towards a digital global economy were accelerated by the big data revolution and the period of constant digital infrastructure change that followed. Businesses nowadays face fierce competition from across the world in a market that moves at lightning speed. Information management driven by artificial intelligence is crucial to weathering the digital wave of the twenty-first century.

AI and ML are now widely known as general purpose technology for decision making across a wide range of industries, enterprises, and jobs, including biotech, healthcare, marketing, human resources, insurance, risk management, cybersecurity, and many more.

The discipline of business analytics is known for converting raw datasets from statistics, machine learning, information systems, operations research, and management science. Just a few of the several forms of analytics that comprise business analytics include prescriptive, predictive, and descriptive analytics. Machine learning operates largely in the predictive area of business intelligence; however, it has started to incorporate prescriptive analytics as well.

One of the main technologies advancing the present digital wave is deep learning. It is a branch of machine learning that began with earlier research on neural networks that drew inspiration from the human brain. Complex hierarchical data representations can be learned via deep learning. It was able to surpass traditional usage and possessed prediction skills that, in some situations, were on level with or even superior to human intelligence. Three main areas of progress are responsible for DL's breakthrough.

Methodology

Machine Learning

This section gives a summary of the Machine Learning models used in the experiment as well as predictive analytics. Four machine learning models are used and compared in this experiment: Random Forest, Gradient Boosting Machine, Deep Learning, and Logistic Regression. For a thorough analysis of the underlying theory.

Linear Regression

The logistic regression is a part of the broad family of linear models. A linear model uses a function to connect the input to the output, and its input is a linear combination of features. An exponential probability distribution, such the normal distribution or the binomial distribution, underlies the output of a linear models. For binary classification, the LR is a widely accepted standard method in both academia and business.

Random Forest

The recursive partitioning techniques Random Forest (RF) is a member of the ensemble approach family and works similarly to decision trees with bagging. By using replacement, M randomly selected portions of the training data are bagged and these estimates are averaged. The random forest creates many decision trees and moderate the results in the end to reduce the variance. It's one of the best machine learning algorithms out there for jobs like regression and classification.

Gradient boosting

Boosting is comparable to bagging, except instead of averaging many results, it builds models one after the other. Boosting begins with a weak learner and gradually strengthens it by correcting the errors committed by the last model. This strategy strengthens the performance of the weak result by gradually

increasing accuracy. The most used model for boosting is a decision tree. Gradient Boosting has several implementations available. Gradient boosting is one of the best accessible prediction methods for structured data at the moment.

Deep Learning

Deep learning encompasses a variety of structures, such as recurrent neural networks, convolutional neural networks, and feed-forward artificial neural networks. The best architecture for transactional data that are not sequential, like the data input in this study, is a multi layer feedforward artificial neural network. Other, more advanced designs are not always beneficial. The first column, which shows the input properties, is the input layer. The single neuron showcase the output, to which the final function is applied. We call the two intermediary levels "hidden layers." If a neural network has more than one hidden layer, it is referred as deep. A deep learning model can consist of numerous hidden layers that are trained via stochastic gradient descent and backpropagation

ANN & BNN : Biological neural networks (BNNs) are similar to artificial neural networks in that they employ elements of the organic structure of the brain, such as cell bodies, dendrites, axons, terminal boutons, and many more. Weights serve the same purpose as the ANN's cell body. Both have the same functional topology, and both will have a similar structure when using deep learning as an automation platform to provide a mechanical or biological solution.

Dynamical Systems, Stability of Equilibrium States : In several disciplines, such as fluid dynamics, engineering, biology, and classical mechanics, an understanding of the usage and functionality of dynamical systems is crucial. Stability is the strength of a subset of phase space to extract trajectories from neighboring regions. It's one thing to be in balance inside a system; stability within it is another. like in a stable equilibrium, for example. There are three types of equilibrium: stable, unstable, and neutral.

Hopefield Model : Dr. John J. Hopfield developed the Hopfield Neural Networks, which consist of one layer of "n" totally coupled recurrent neurons. It is typically used for optimization and auto-association tasks. It is generated using a converging interactive process and yields a different response in comparison to our normal neural networks. When optimization is needed for automation, the current degree of engagement must be sufficient to meet the demand.

Backward & Forward Propagation : When training artificial neural networks (ANNs), backward propagation is a helpful method that lowers costs by determining which biases and weights should be modified or avoided. Furthermore, a related procedure called "forward propagation" uses a hidden layer and operates somewhat in the opposite manner from "backward." The organization's wish list and demand are taken into account when applying automation to deep learning.

Correlation Learning Model : Following a similar idea to the Hebbian rule, the correction rule also adjusts the weights based on the phases of the two neurons. If the neurons are in the same phase as each other, the weight should be towards the positive side; if they are in the opposite phase, the weight should be towards the negative side. The only thing that separates this rule from the Hebbian learning rule is that it is supervised. When industrial work is done by machines and robots, the weights are at the positive side of the working phase, therefore the applied neurons to operation in automation will be at the opposite side of the phase.

Data and Processing

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

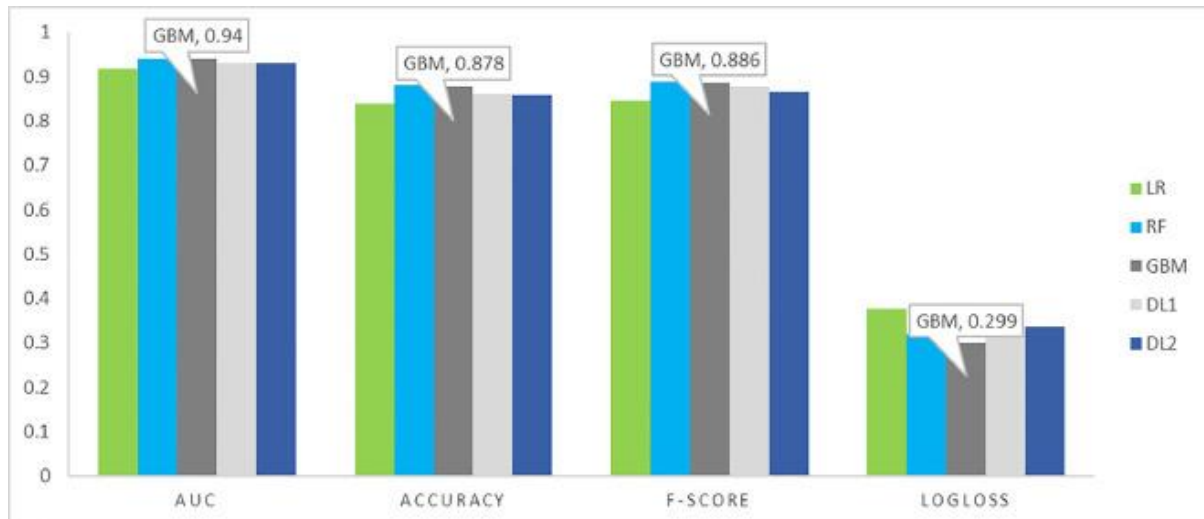
The experiment required a few adjustments. These datasets exhibit extreme disproportionality. In this research, random under sampling was used to create a balance between the favourable and unfavourable circumstances. This is also included in Table 1.

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 dataset and testing dataset. To fine tune the model functionality throughout the classifier generation process, the training dataset will be partitioned into distinct training and validation datasets using a technique called cross validation.

Method	Out-of-Sample Performance			
	AUC	Accuracy	F-score	Logloss
Logistic Regression	0.918	0.839	0.845	0.377
Random Forest	0.940	0.879	0.888	0.320
Gradient Boosting Machine	0.940	0.878	0.886	0.299
Deep Learning+ReLU	0.930	0.861	0.877	0.328
Deep Learning+Maxout	0.930	0.857	0.865	0.336

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 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 research, 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 the problems arise with structured dataset classification. Instead, the results resoundingly endorse tree-based gathers 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 to recommend the extensive usage of DL models in operations research and business analytics. Although it is a very informative and good introduction of Deep Learning for Business Analytics, the research does not employ GBM as a main model for comparison, despite the fact that GBM is a popular model that is well-known for producing accurate aims 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, like random forest and gradient boosting. The outcome of this study support those of other studies, 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 research for powerful data driven oriented 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 difficulties, a shortage of big data infrastructure, a lack of transparency, a shortage of skills, and less of commitment in leadership, 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 aim of DL is not necessarily superior to other ML models. The results unambiguously point that gradient boosting ought to be the main method for the vast majority of business analytics problems. For used database dependent on structured data, it provides the greatest performance right now 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.

Future

More study in the following four important areas could be necessary to upscale the usage and, in turn, the acceptability of Deep Learning in business analytics.

- Research on business analytics in the future may focus on identifying applications that enhance DL's capabilities but aren't already in use. Because of its uniqueness to manage huge amounts of unstructured data, DL is more interesting than traditional analytics in terms of possible future applications and use cases. DL have the ability to create completely unique value generating methodologies and commercial strategies.
- Enhancing DL's prediction accuracy for structured data would be transformative for neural networks. Even while deep learning has many advantages over traditional methods, it still can't match tree-based ensembles like Random Forest and GBM in terms of performance and accuracy when it comes to structured data prediction. Therefore, a simple substitution is not very sensible until more research in this area leads to better performance for DL on structured classification problems.
- Another issue is that, given the lack of expertise, hyperparameter tuning might be a highly challenging process requiring the necessary ability. AutoML, or automated machine learning, is a relatively recent finding that is starting to gain popularity. It is a fascinating area of research with the potential to further make accessible the use of deep learning models. AI may be made more palatable for users by simplifying its design and better tailoring it to their needs in order to increase job fit. AI has to become human-adapted in order to enable a fully augmented workforce

Conclusion

Everywhere we turn, there are innumerable new real-world uses for DL, proving the technology's undeniable advances and developments. In spite of this, the adoption rate and therefore the spread of business analytics services have lagged. This study provides some insight into why DL adoption in business analytics operations is still lacking. The literature research identifies five primary reasons computational difficulties, lack of big-data structure, lack of transparency or black-box nature, lack of expertise, and lack of leadership commitment—for why DL isn't being embraced across business units. Yet, the important analysis based on various case studies shown that, in contrast to what is commonly believed, DL does not improve performance when it comes to predictions made using structured data sets.

This answers the question of why analytics departments don't always utilize these models and is something that has to be measured when applying deep learning to data driven decisions in the similarity of business analytics. All things considered, business research and user information management will continue to be impacted by machine learning, a popular purpose technology for data oriented prediction. Deep learning has strengthened our ability to extract information from unstructured data, which has helped the ML ecosystem. It is difficult to replace the other models, though. Tree-based classifiers such as random forest and gradient boosting work incredibly well with structured datasets. Rather of trying to impose new use cases that capitalize on DL's benefits, creators should focus on creating models that can replace the conventional ones.

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Abstract

In our fast-paced, internationally competitive digital economy, a stronger focus on data-driven decision-making based on artificial intelligence (AI) and machine learning (ML) is required. While deep learning (DL) offers numerous benefits, a number of disadvantages have kept DL from being widely applied in the business. This essay explores the reasons why DL is not taking off in the business analytics industry as rapidly, despite its ubiquitous use. It is shown that the adoption of deep learning is influenced not only by the lack of big data architecture, computational complexity, lack of transparency (black-box), leadership commitment, and skill shortages, but also by the fact that DL models do not outperform traditional ML models when used on structured datasets with fixed-length feature

Deep learning is a powerful addition to the existing repertoire of machine learning models, not a "one size fits all" solution. The results unambiguously suggest that gradient boosting ought to be regarded as the industry standard approach in business analytics for forecasting structured data. In addition to the empirical examination based on three industrial use cases, the essay offers a comprehensive analysis of those results, a strategy for future research, and their practical implications.

Introduction

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Future

More study in the following four important areas could be necessary to increase the utility and, in turn, the acceptability of DL in business analytics.

Research on business analytics in the future may focus on identifying applications that enhance DL's capabilities but aren't already in use. Because of its ability to manage enormous amounts of unstructured data, DL is more interesting than traditional analytics in terms of possible future applications and use cases. DL have the ability to create completely unique value generating methodologies and commercial strategies. Enhancing DL's prediction accuracy for structured data would be transformative for neural networks. Even while deep learning (DL) has many advantages over traditional methods, it still can't match tree-based ensembles like Random Forest and GBM in terms of performance and accuracy when it comes to structured data prediction. Therefore, a simple substitution is not very sensible until more research in this area leads to better performance for DL on structured classification problems.

Another issue is that, given the lack of expertise, hyperparameter tuning might be a highly challenging process requiring the necessary ability. AutoML, or automated machine learning, is a relatively recent finding that is starting to gain traction. It is a fascinating field of research with the potential to further democratize the use of deep learning models. AI may be made more palatable for users by simplifying its design and better tailoring it to their needs in order to increase job fit. AI has to become human-adapted in order to enable a fully augmented workforce.

Conclusion



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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.

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