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GOVERNANCE OF TECHNOLOGY

Use and misuse of interpretability in machine learning

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BALANCING
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DEAR READER,

In my new role as CEO of Capco, I am very pleased to welcome you to the latest edition of the Capco Journal, titled **Balancing Innovation and Control**.

The financial services and energy sectors are poised for another transformative year. At Capco, we recognize that this is a new era where innovation, expertise, adaptability, and speed of execution will be valued as never before.

Success will be determined based on exceptional strategic thinking, and the ability to leverage innovative new technology, including GenAI, while balancing a laser focus on risk and resilience. Leaders across the financial services and energy industries recognize the transformative benefits of strong governance while needing to find the optimal balance between innovation and control.

This edition of the Capco Journal thus examines the critical role of balancing innovation and control in technology, with a particular focus on data, AI, and sustainability, with wider corporate governance considerations. As always, our authors include leading academics, senior financial services executives, and Capco's own subject matter experts.

I hope that you will find the articles in this edition truly thought provoking, and that our contributors' insights prove valuable, as you consider your institution's future approach to managing innovation in a controlled environment.

My thanks and appreciation to our contributors and our readers.

Annie Rowland, **Capco CEO**

USE AND MISUSE OF INTERPRETABILITY IN MACHINE LEARNING[1]

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ABSTRACT

Machine learning methods, the foundation of much of artificial intelligence (AI), are now widely used in data analysis and model-building across a variety of disciplines. These techniques have also become the underpinnings of many of the business intelligence (BI) analytics that are being widely deployed across a wide range of industries. In this article, we focus on some elements of inference around analytics possible in machine learning, contrasting them with how applied econometricians traditionally approached inference. We do this in the context of applying both traditional econometric methods and several machine learning methods to the same dataset.

1. INTRODUCTION

Machine learning methods, the foundation of much of artificial intelligence (AI), are now widely used in data analysis and model-building across a variety of disciplines. These techniques have also become the underpinnings of many of the business intelligence (BI) analytics that are being widely deployed across a wide range of industries.[2]

With freely available software such as Keras, Tensorflow from Google, lightGBM from Microsoft, and Torch from Facebook, the techniques have also become widely available. The provision of such open-source software, accompanied by the rise of cloud-based platforms from Amazon, Google, Microsoft, etc., have significantly reduced the need to build out hardware infrastructure. Historically, machine learning has focused much more on prediction than on statistical inference around analytics.

In finance, machine learning (ML) and deep learning (DL) have been applied extensively to credit risk modeling (e.g., default prediction) due to the availability of a large quantity of data. Butaru et al. (2016) have applied machine learning to credit cards. Sadhwani et al. (2021) have applied deep learning to mortgage risk. These have largely been focused on forecasting delinquency or defaults.

Traditionally, econometrics has also analyzed data and built models. In contrast to data scientists, econometricians have traditionally focused significantly on statistical inference. Biddle (2017) provides an overview of how statistical inference has changed over time. His definition of statistical inference – "the process of drawing conclusions from samples of statistical data about things that are not fully described or recorded in those samples" – describes what econometricians do fairly well.

[1] Views and opinions expressed are those of the authors and do not necessarily represent official positions or policy of the Office of the Comptroller of the Currency or the U.S. Department of the Treasury.
[2] Korolov, M., 2018, "New AI tools make BI smarter — and more useful," CIO Magazine, April 18, http://tinyurl.com/yuuszz9k

Figure 1: Shapley values based on lightGBM

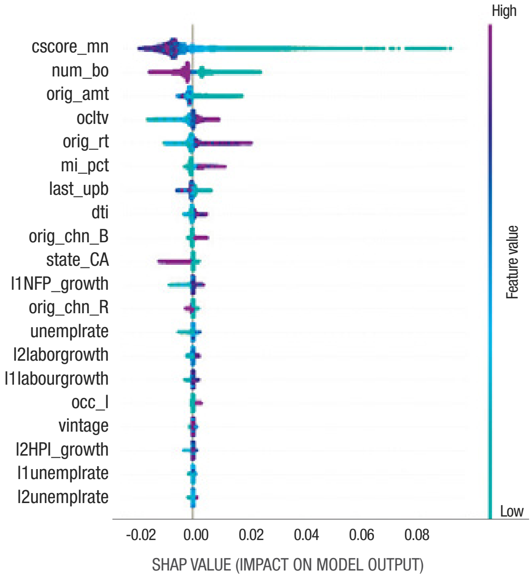


Figure 3: Shapley values based on deep learning/Keras

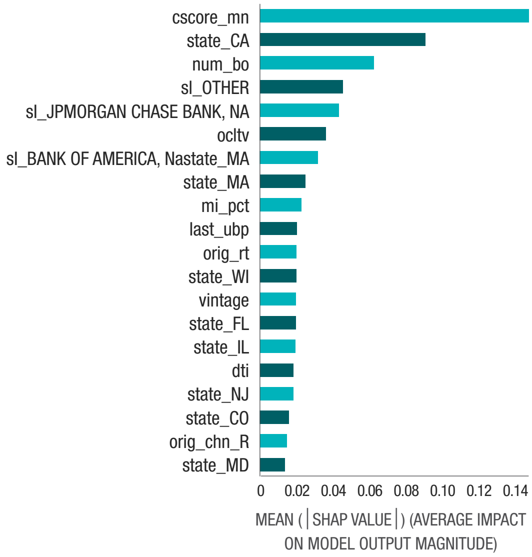
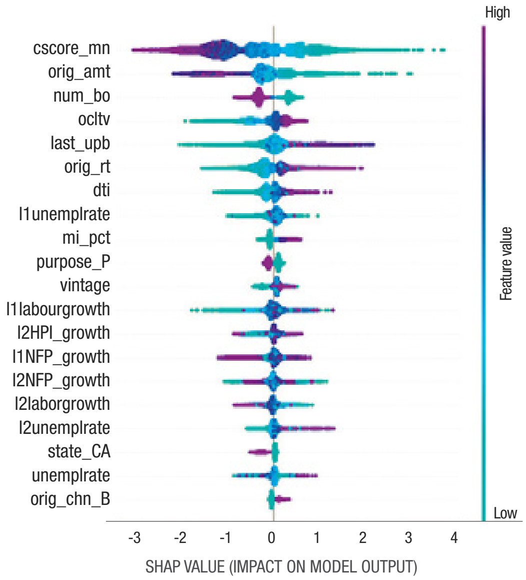


Figure 2: Shapley values based on XGBOOST



Data scientists have frequently come from quite heterogeneous backgrounds and with significant differences from econometricians. Using data from LinkedIn, Stitch Data (2015) summarizes the background of data scientists and finds that computer science is the most common background. Segaran and Hammerbacher (2009) has an interesting article by Jeff Hammerbacher, who supposedly coined the term "data scientist" while leading the data team at Facebook on the eclecticism in the data science backgrounds.

In this article, we focus on some elements of inference around analytics possible in machine learning, contrasting them with how applied econometricians traditionally approached inference. We do this in the context of applying both traditional econometric methods and several machine learning methods to the same data set.

This is the publicly available FNMA 30-year fixed rate mortgages. We then compare and contrast what drivers of risk are identified using some traditional econometric methods as well as different machine learning methods.

Parallels to statistical inference in machine learning/deep learning models are currently focused very heavily on the twin concepts of interpretability/explanability. Most commonly promoted explanability metrics have been Shapley value and feature importance. For example, the AI platforms of both Google and Microsoft provide Shapley values for users to understand what drives the models as well as to identify model bias. Vendors, such as ZestFinance and DataRobot, have also promoted Shapley value as the way to "break open

[3] Merrill, D., 2019, "CEO ZestFinance, Testimony to the House Committee on Financial Services AI Task Force," June 26, http://tinyurl.com/y845wptd

the blackbox."[3] The academic literature on machine learning has also focused on significance tests based on Shapley values and/or feature importances. For example, Horel and Giesecke (2020) develop an asymptotic theory for neural networks using gradients from the fitting algorithms.

Our exploratory analysis in this paper shows that different state-of-the-art machine learning methods can produce models that are similar in their predictive abilities. However, commonly used interpretability metrics can lead to different conclusions about the key risk drivers.

2. DATA

We use the Single-Family Historical Loan Performance Dataset from FNMA. We select the loans originated in the years 2000, 2001, and 2002. The outcome we model is the probability of a loan becoming 90 days past due in the five years after origination. We also combine the national level macroeconomic variables HPI Index, Unemployment Rate, Labor Force, and Non-farm Payroll. These are expressed as growth rates and their first two lags are used. For the categorical variables, we create dummies, or what is referred to in machine learning as one-hot encoding.

3. RESULTS

We first apply two most commonly used machine learning algorithms, XGBOOST and lightGBM, and secondly deep learning with Keras. We optimize the hyper-parameters by grid search. The performance of the three algorithms, as measured by the area under the curve (AUC), is quite similar. We then plot the Shapley values for the features in three figures. These are for lightGBM in Figure 1, XGBOOST in Figure 2, and Keras in Figure 3.

As can be seen in these figures, there are very significant overlaps between the three methods. However, there are also important differences. The two methods, lightGBM and XGBOOST, broadly select the same set of borrower characteristics in the top five. However, XGBOOST selects lagged unemployment rate as the eighth most significant driver. In contrast, lightGBM does not have any macroeconomic variables in the top ten drivers. Deep learning via Keras has a very different set of features selected as the most important ones based on Shapley values.

We then use econometric methods to identify what drives default. We choose the Elasticnet method, which was proposed by Zou and Hastie (2005) and has been used in more than 20,000 studies. The Elasticnet method bridges the "least absolute shrinkage and selection operator" LASSO method and ridge regression.

$$\min \|y - X\beta\|^2 \text{ subject to } \sum_{j=1}^{m} |\beta_j| \leq t_1,\ \sum_{j=1}^{m} \beta_j^2 < t_2$$

Elasticnet ends up with 16 variables or features. We then run a logistic regression with the selected features. The results are presented in Table 1. These results show that Elasticnet finds significantly greater importance for the macroeconomic variables. Lagged Nonfarm Payroll growth and unemployment rate show up as the third and fourth most important variables.

4. CONCLUSION

Using single family mortgage data, we find that different machine learning algorithms can produce rather different rankings of the variables that drive the outcome of interest. This suggests that one needs to exercise caution in relying on these methods in terms of identifying the drivers of risk.

Table 1: Results from estimating logistic regressions for mortgage delinquency

VARIABLE	PARAMETER	STD. ERROR.	WALD χ^2
Intercept	4.860	0.176	759.02
cscore_mn	-0.016	0.000	16070.73
l1NF growth	5.541	0.600	85.42
l2unemplrate	0.028	0.005	36.02
mi pct	0.013	0.001	251.29
numbo	-0.791	0.015	2740.16
ocltv	0.018	0.001	433.90
orig amt	0.000	0.000	975.22
orig chn B	0.208	0.019	117.21
orig chn R	-0.066	0.018	13.69
orig rt	0.383	0.015	634.05
prop typ CO	-0.376	0.046	66.71
prop typ CP	-0.605	0.128	22.46
prop typ MH	0.813	0.057	201.27
prop typ SF	0.101	0.032	10.06
purpose P	-0.591	0.022	700.70
purpose R	-0.028	0.024	1.35

This table reports the parameter estimates from a logistic regression of key drivers of mortgage delinquency that had been identified via an Elasticnet regression. The sample had been divided into 80% training and 20% validation subsamples. The variables are first selected via an Elasticnet method. A logistic regression is run with the top 21 selected variables and the results are presented below. The out of sample AUC is 0.852.

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APPENDIX

Table A1: This table lists the features (i.e., variables) from the FNMA data

FEATURE	DESCRIPTION
cscore_mn	Borrower credit score; FICO score.
last_upb	The current actual outstanding unpaid principal balance of a mortgage loan, reflective of payments actually received from the related borrower.
mi_pct	The original percentage of mortgage insurance coverage obtained for an insured conventional mortgage loan and used following the occurrence of an event of default to calculate the insurance benefit.
mi_type	"The entity that is responsible for the Mortgage Insurance premium payment. 1 = borrower paid; 2 = lender paid; 3 = enterprise paid; * Null = No MI"
num_bo	The number of individuals obligated to repay the mortgage loan.
num_unit	The number of units comprising the related mortgaged property (one, two, three, or four).
occ_stat	The classification describing the property occupancy status at the time the loan was originated. Principal = P; second = S; investor = I; unknown = U
ocltv	The ratio, expressed as a percentage, obtained by dividing the amount of all known outstanding loans at origination by the value of the property.
orig_amt	Origination amount
orig_chn	Origination channel: retail = R; correspondent = C; broker = B
orig_rt	The original interest rate on a mortgage loan as identified in the original mortgage note.
orig_trm	Original term
prop_typ	"Property type: CO = condominium CP = co-operative PU = Planned Urban Development MH = manufactured home SF = single-family home"
purpose	"An indicator that denotes whether the mortgage loan is either a refinance mortgage or a purchase money mortgage. Cash-Out Refinance = C Refinance = R Purchase = P Refinance-Not Specified = U"
dti	The ratio obtained by dividing the total monthly debt expense by the total monthly income of the borrower at the time the loan was originated.

ABOUT CAPCO

Capco, a Wipro company, is a global technology and management consultancy focused in the financial services industry. Capco operates at the intersection of business and technology by combining innovative thinking with unrivalled industry knowledge to fast-track digital initiatives for banking and payments, capital markets, wealth and asset management, insurance, and the energy sector. Capco's cutting-edge ingenuity is brought to life through its award-winning Be Yourself At Work culture and diverse talent.

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