Leveraging Deep Learning for Accounting Fraud Detection*

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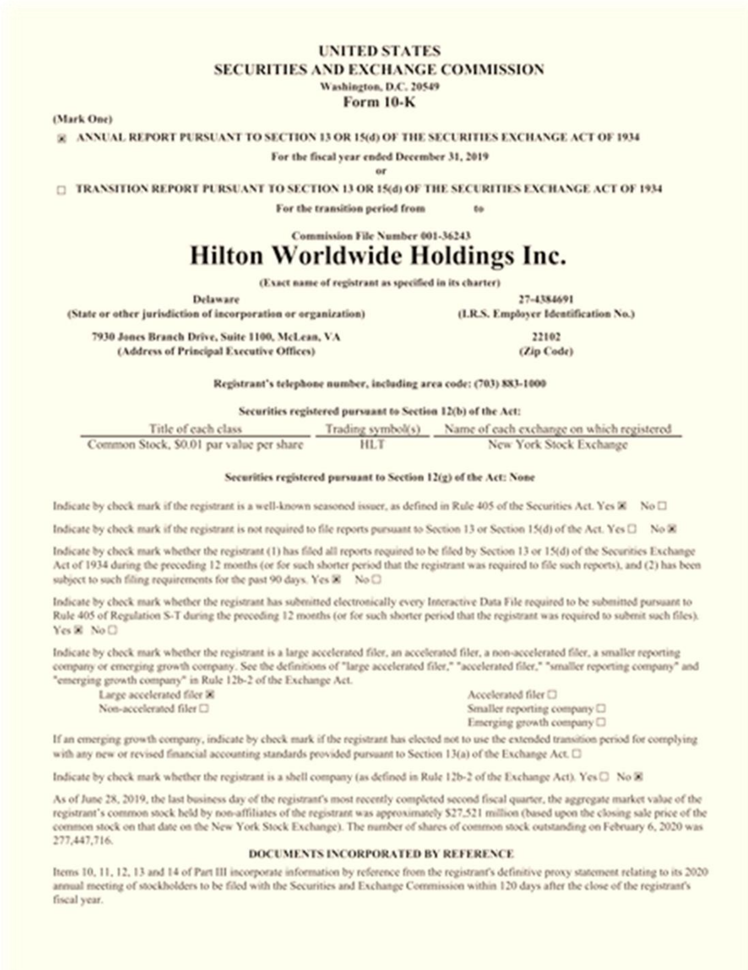
Introduction

- Fraudulent financial reporting encompasses deliberate misstatements or omissions in financial statements, aiming to mislead stakeholders and regulators, resulting in a breach of Generally Accepted Accounting Principles (GAAP).



UNITED STATES
SECURITIES AND EXCHANGE COMMISSION
Washington, D.C. 20549
Form 10-K

(Mark One)

☒ ANNUAL REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934

For the fiscal year ended December 31, 2019

or

☐ TRANSITION REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934

For the transition period from to

Commission File Number 001-36243

Hilton Worldwide Holdings Inc.

(Exact name of registrant as specified in its charter)

Delaware (State or other jurisdiction of incorporation or organization) — 27-4384691 (I.R.S. Employer Identification No.)

7930 Jones Branch Drive, Suite 1100, McLean, VA (Address of Principal Executive Offices) — 22102 (Zip Code)

Registrant's telephone number, including area code: (703) 883-1000

Securities registered pursuant to Section 12(b) of the Act:

Title of each class	Trading symbol(s)	Name of each exchange on which registered
Common Stock, $0.01 par value per share	HLT	New York Stock Exchange

Securities registered pursuant to Section 12(g) of the Act: None

Indicate by check mark if the registrant is a well-known seasoned issuer, as defined in Rule 405 of the Securities Act. Yes ☒ No ☐

Indicate by check mark if the registrant is not required to file reports pursuant to Section 13 or Section 15(d) of the Act. Yes ☐ No ☒

Fig 1. *10-K Annual Filing*

- This research introduces a a Multi-Layer Perceptron (MLP) with Random Under-Sampling (called RUS MLP) for detecting accounting fraud, leveraging publicly available financial data extracted from 10-K filings.

Summary

1. This matter arises from Hilton Worldwide Holdings Inc.'s failure to disclose in its definitive proxy statements approximately $1.7 million worth of certain travel-related perquisites and personal benefits it paid to, or on behalf of, its Chief Executive Officer, President, and member of its board of directors (the "CEO") and certain other executives who were eligible for travel-related benefits (together with the CEO, the "Named Executive Officers"), from 2015 through 2018. The Board-authorized perquisites included, among other things, expenses associated with the CEO's personal use of Hilton's corporate aircraft and the Named Executive Officers' hotel stays. In connection with this conduct, Hilton violated Sections 13(a) and 14(a) of the Exchange Act and Rules 12b-20, 13a-1, and 14a-3 thereunder.

Fig 2. *Accounting and Auditing Enforcement Releases*

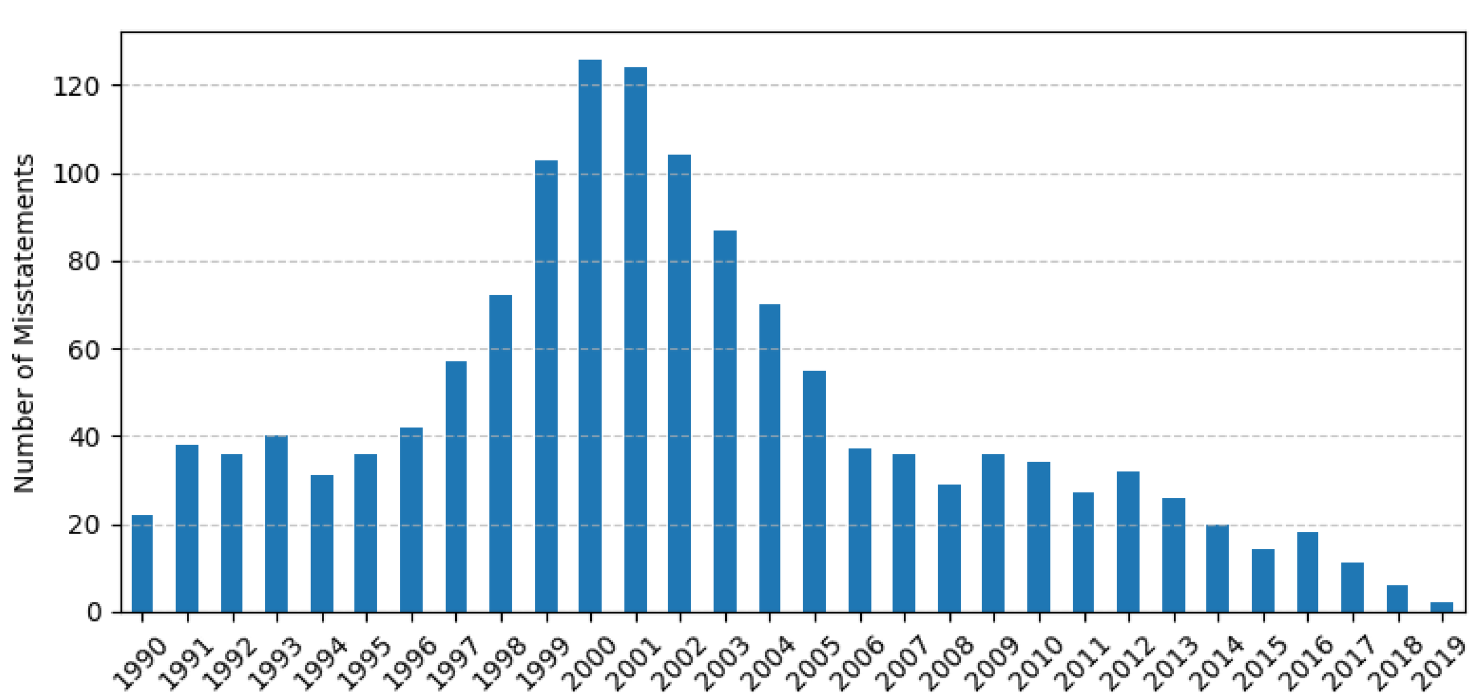


Fig 3. *Misstatements distributions by year*

Multilayer Perceptron (RUS MLP)

- MLP - a feed-forward artificial neural network.
- Comprises of fully connected neurons with nonlinear activation functions like logistic, tanh, or ReLU.
- Structured into three layers: the input, hidden layers and output layer

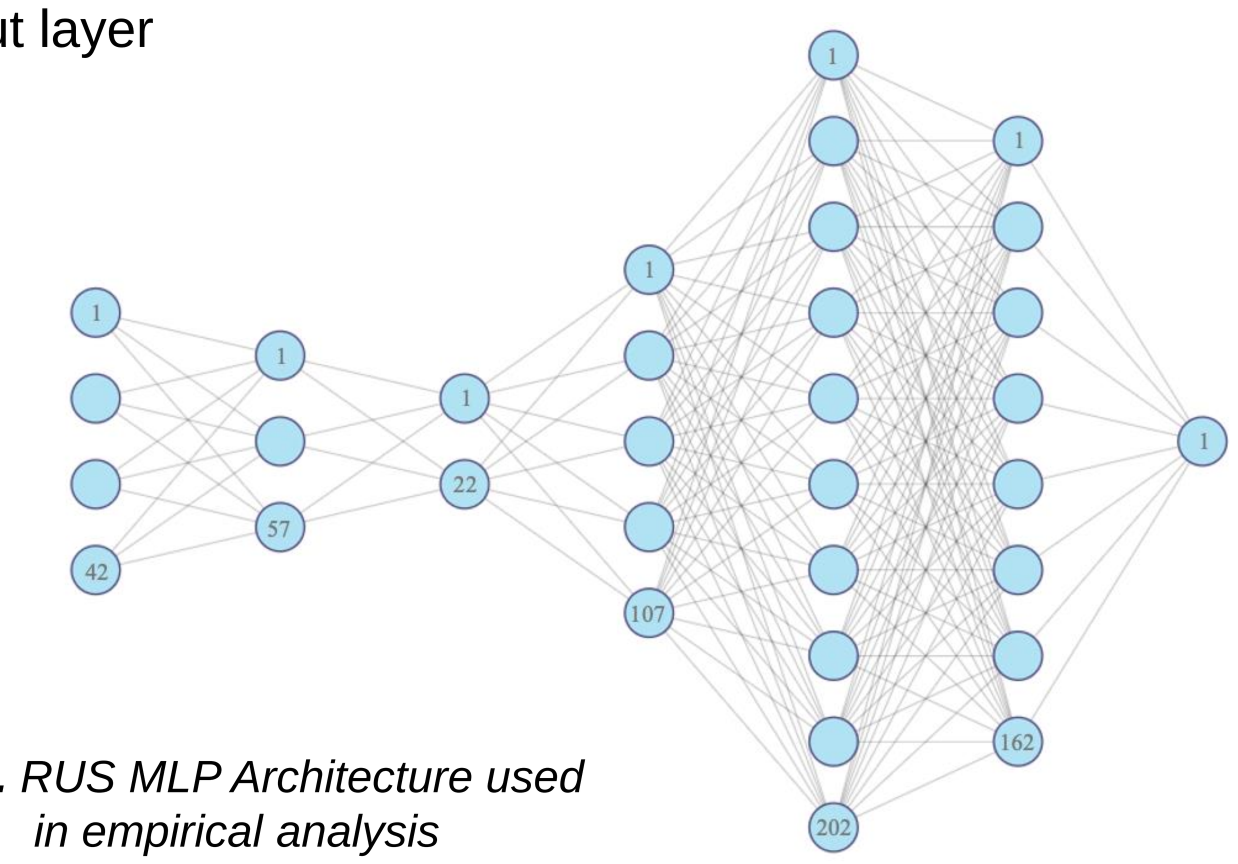


Fig 4. *RUS MLP Architecture used in empirical analysis*

Optimization

The Optuna** framework was used for hyperparameter tuning. Three parameters were optimized (# of layers, # of neurons in each layer, and activation functions. The number of neurons of the 1st layer was most relevant for higher performance.

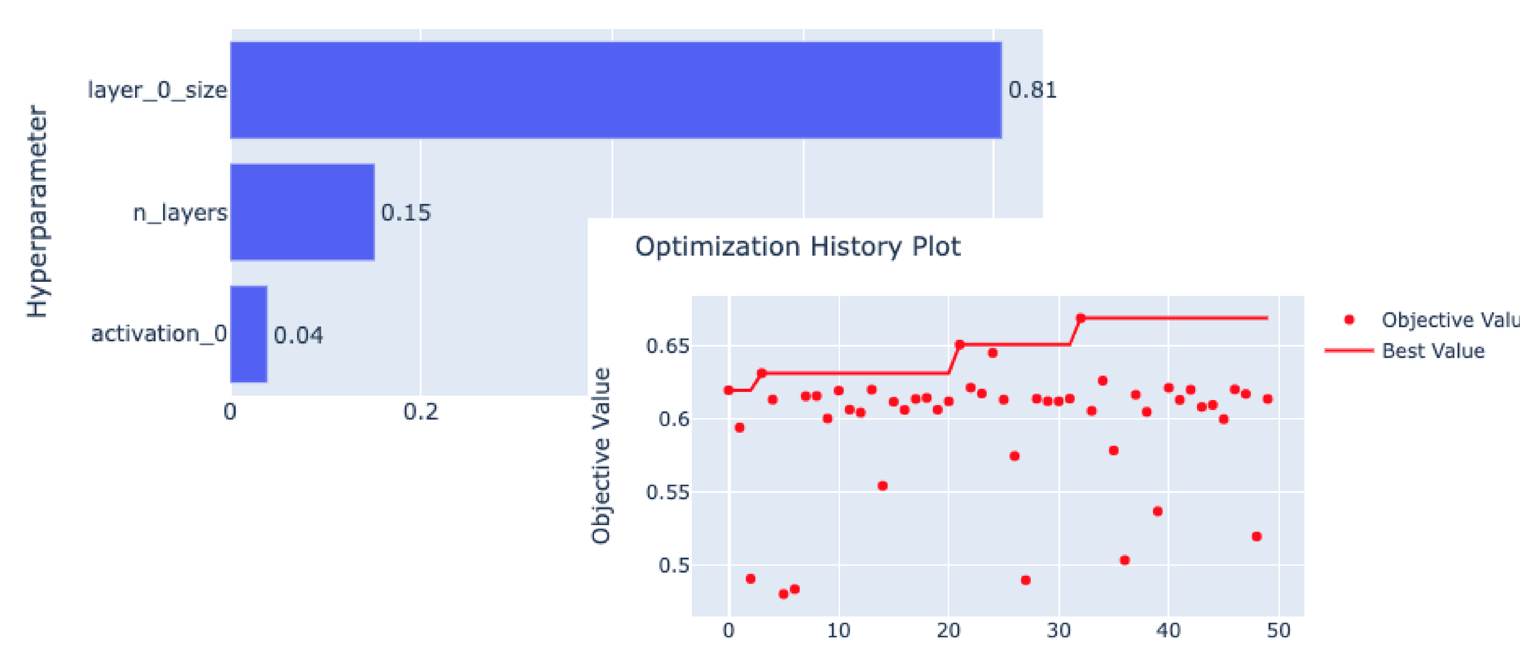


Fig 5. *Hyperparameter importance and AUC evolution over different trials.*

** Optuna: A Next-generation Hyperparameter Optimization Framework, Akiba et al. 2019.

Results

- MLP model outperforms Logit and Probit models in terms of AUC scores across 10 randomized training trials.
- Three under-sampling ratios (minority vs majority class) were tested: 1:1, 1:2, and 1:3.

Features	RUS MLP	Logit	Probit
28 Raw Items + 14 Ratios	**0.62** $\pm$ 0.01	0.57 $\pm$ 0.05	0.61 $\pm$ 0.0
14 Ratios	**0.63** $\pm$ 0.02	0.57 $\pm$ 0.05	0.61 $\pm$ 0.0
28 Raw Items	0.55 $\pm$ 0.06	0.52 $\pm$ 0.07	**0.57** $\pm$ 0.0

Table 1. *AUC results with RUS ratio 1:1*

Features	RUS MLP	Logit	Probit
28 Raw Items + 14 Ratios	**0.61** $\pm$ 0.01	0.55 $\pm$ 0.05	0.53 $\pm$ 0.0
14 Ratios	**0.62** $\pm$ 0.01	0.54 $\pm$ 0.07	0.51 $\pm$ 0.0
28 Raw Items	0.51 $\pm$ 0.07	**0.55** $\pm$ 0.07	0.52$\pm$0.0

Table 2. *AUC results with RUS ratio 1:2*

Features	RUS MLP	Logit	Probit
28 Raw Items + 14 Ratios	**0.60** $\pm$ 0.04	0.54 $\pm$ 0.05	0.53 $\pm$ 0.0
14 Ratios	**0.58** $\pm$ 0.05	0.56 $\pm$ 0.06	0.50 $\pm$ 0.0
28 Raw Items	0.51 $\pm$ 0.06	0.47 $\pm$ 0.07	**0.53** $\pm$ 0.0

Table 3. *AUC results with RUS ratio 1:3*

Conclusion

- This study investigates the implementation of a RUS MLP for detecting accounting fraud in out-of-sample financial data.
- Employing Optuna, we optimized the MLP architecture, identifying the best hyperparameters for the model.
- Our analysis reveals that deep neural network models have the potential to surpass the AUC of traditional linear models.

* This work has been accepted for presentation at the International Conference on Business Analytics at SUNY Fredonia.

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