**Peer response: Focusing on Automating Accounting with Learning Algorithms**

Andrei discussed applications of machine learning (ML) approaches in accounting, namely by automating some tasks and allowing professionals to focus on strategic analysis. He provides particularly good insight into how AI can empower individuals working in data-heavy environments, rather than simply replacing them, while also stressing the ongoing importance of adequate human supervision in developing and interpreting AI models.

The first example provided is the application of supervised learning algorithms to automate invoice processing within accounts payable processes. Besides reducing workload, Andrei also highlights the potential to reduce human error. While he does not provide an example of a potential ML algorithm, Georgios then suggest that decision trees (DTs) may perform well in reconciling data from multiple entities. Importantly, the explainability of DTs makes them particularly suited for sectors where auditing and traceability is of paramount importance, such as accounting. Other potential approaches include random forests, AdaBoost, and artificial neural networks (Bardelli, Rondinelli, Vecchio and Figini, 2020), which may all be better suited for cases which require predicting a large number of distinct classes, but are more demanding computationally and harder to interpret.

Andrei then describes how unsupervised learning approaches can help identify potentially fraudulent activities by highlighting transactions whose nature is significantly different from most others (as also alluded to by Natali in a separate post). Importantly, unsupervised learning allows detection of anomalies based on statistical patterns which are not specified a priori by a human operator, making it a particularly helpful tool to contest ever-evolving and creative fraudulent agents. While Andrei does not refer any specific algorithm solutions, such problems could be addressed using k-means clustering (Sahoo and Sahoo, 2021)or one-class support vector machines (Hejazi and Singh, 2013).

Georgios suggested that ML algorithms could also help match and reconcile disparate sources of financial information. Although he does not specify how (and the reference provided does not seem to refer to ML), once might assume he refers to unsupervised learning models (such as the aforementioned two). Such models may for example aggregate transactions related to the same customer, or identify potentially erroneous records as outliers. Alternatively, other AI applications such as computer vision, natural-language processing, and large language models may also be employed to help process large volumes of structured or unstructured financial data.

**References:**

Bardelli, C., Rondinelli, A., Vecchio, R. and Figini, S. (2020) ‘Automatic Electronic Invoice Classification Using Machine Learning Models’, *Machine Learning and Knowledge Extraction*, 2(4), pp. 617–629. Available from: https://doi.org/10.3390/make2040033.

Hejazi, M. and Singh, Y.P. (2013) ‘One-class support vector machines approach to anomaly detection’, *Applied Artificial Intelligence*, 27(5), pp. 351–366. Available from: https://doi.org/10.1080/08839514.2013.785791.

Sahoo, G. and Sahoo, S.S. (2021) ‘Accounting Fraud Detection Using K-Means Clustering Technique’, in D. Swain, P.K. Pattnaik, and T. Athawale (eds) *Machine Learning and Information Processing*. Singapore: Springer Singapore (Advances in Intelligent Systems and Computing), pp. 171–180. Available from: https://doi.org/10.1007/978-981-33-4859-2\_17.