Using NLP transformer models to evaluate the relationship between ethical principles in finance and machine learning

Maryan Rizinski[1,2][0000−0002−9324−0091], Kostadin Mishev[2][0000−0003−3982−3330], Lubomir T. Chitkushev[1][0000−0002−9365−8818], Irena Vodenska[3][0000−0003−1183−7941], and Dimitar Trajanov[1,2][0000−0002−3105−6010]

[1] Department of Computer Science, Metropolitan College, Boston University, Boston, MA 02215, USA
{rizinski,ltc}@bu.edu

[2] Faculty of Computer Science and Engineering, Ss. Cyril and Methodius University, 1000 Skopje, North Macedonia
{kostadin.mishev,dimitar.trajanov}@finki.ukim.mk

[3] Laboratory for Interdisciplinary Finance and Economics (LIFE) Research, Administrative Sciences Department, Metropolitan College, Boston University, Boston, MA 02215, USA
vodenska@bu.edu

Abstract. While the ethical principles of finance are well known in the literature, they are not sufficiently evaluated in the context of machine learning (ML). We use natural language processing (NLP) transformer models to quantitatively evaluate the relationships between the ethical principles of finance and the ethical principles of ML. To the best of our knowledge, such analysis has not been performed in the literature. We assess the performance of more than 80 state-of-the-art (SOTA) transformer models in capturing semantic similarity between the definitions of finance and ML ethics principles. The computational results demonstrate the ability of various transformers to address semantic similarity when comparing the definitions of finance and ML ethics. The results reveal that the NLI-DistilRoBERTa-Base-v2 model has the best performance in this task. The analysis can be beneficial to identify the principles of finance ethics that exhibit the strongest influence on ML ethics and vice-versa.

Keywords: Natural language processing · Machine learning · Transformer models · Ethics · Finance · Fintech.

1 Introduction

Machine learning (ML) has the potential to transform the financial industry and will be the main driver for the development of financial institutions in the future [35, 8, 42]. ML can improve a number of applications in finance, such as risk management, fraud detection, investment management, and trading strategies, among others. Due to the ability to analyze large amounts of data, ML can identify patterns and predict potential risks, which can be used to analyze credit scores, transaction history, and other data to determine the likelihood of default [5, 10]. Analyzing patterns in transaction data using ML can also help identify fraudulent transactions [34, 46]. Fraud poses a tremendous threat to organizations of all types and sizes as it can have negative consequences such as direct and indirect costs, reputational harm, and even loss of business. According to a 2018 report by the Association of Certified Fraud Examiners, the total loss caused by the 2,690 studied cases exceeded USD 7.1 billion, meaning that the global cost of fraud is likely magnitudes higher [3]. Machine learning can be used to analyze market data and other factors for stock market forecasting [31, 23] as well as for optimizing portfolio management and investment opportunities [24, 4]. Recognizing the ML and big data trends, marketplace participants are increasingly adopting quantitative investing strategies, leading to new insights and perspectives offered by machine learning techniques [22].

While the ML benefits from a business perspective are evident and reported in the literature, the financial industry is expected to face a range of ethical challenges in the context of ML-related applications, such as issues with fairness, bias, and discrimination, lack of transparency and accountability, concerns with privacy and security, etc. ML algorithms can perpetuate and amplify biases if the data used to train them is biased, which could lead to discrimination against certain individuals or groups [21, 20, 19]. Due to the complexity and opacity of ML algorithms, it can be difficult for users to understand how they work and make decisions, thereby undermining transparency and trust in ML while also raising questions about accountability. This emphasizes the need for ML model transparency and the development of ML algorithms that are explainable and auditable [30]. As ML-based products and services are predominantly based on information technology, users are more prone to breaches of privacy [49], which necessitates an appropriate approach to study the preservation of privacy in ML systems [26, 2].

With the widespread adoption of AI, there is a growing awareness that AI has the potential to impact society in profound ways. Thus, governance mechanisms are needed to foster trust and to ensure that AI is developed and used in a way that is aligned with human values. Various national, industry, and multi-stakeholder initiatives have been established to address AI-related ethical challenges. National AI strategies include the US National AI Initiative Act (NAIIA), Canada's Pan-Canadian Artificial Intelligence Strategy, European Commission's High-Level Expert Group on Artificial Intelligence, and China's New Generation AI Development Plan. Among the industry initiatives for AI is the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems. There are several multistakeholder initiatives that promote responsible AI governance, such as the World Economic Forum Global AI Council and the Global Partnership on Artificial Intelligence (GPAI). Another prominent organization is the Organisation for Economic Co-operation and Development (OECD) which made a strong contribution to defining public policy for AI.

While ethical principles have been established in the traditional financial services industry [6, 17], these have not been evaluated in the context of ML applications despite multiple initiatives for responsible ML governance that aim to define ML ethics. One step to preventing or minimizing the adverse impact of the above-mentioned ethical challenges in finance is to better understand the relationships between finance ethics and ML ethics. To achieve this, we perform a pair-wise comparison between the principles of finance and ML ethics by using state-of-the-art (SOTA) NLP transformers. Our goal is to get insights into the potential of transformers on this task and find the transformer model that best captures the relationships between finance and ML ethics principles. To the best of our knowledge, such quantitative analysis has not been carried out before in the literature.

This paper focuses on the technical aspects of performing experiments to evaluate transformer models. A larger study related to ethically responsible ML in fintech and explainability techniques was performed in [41], but it did not reveal results about comparing different transformers in their ability to capture the similarity between the ethical principles. As will be shown in subsequent sections of the paper, the comparison is performed between the principles of finance ethics (integrity, objectivity, competence, fairness, confidentiality, professionalism, and diligence) as defined in the literature [38] and the principles of ML ethics adopted by the OECD (inclusive growth, sustainable development, and well-being, human-centered values and fairness, transparency and explainability, robustness, security and safety, and accountability) [33].

The paper is organized as follows. Section 2 presents definitions of ethical principles in finance and machine learning. Section 3 focuses on explaining the methodology for using transformer models to compare the principles of finance and ML ethics. We conduct experiments with more than 80 SOTA transformers with the goal of determining the model that captures most closely the relationship between the principles. The results from the experiments are presented in Section 4. Section 5 concludes the paper.

2 Definitions of Finance and ML Ethics

In this paper, we study the relationships between finance and ML ethics using transformer models. To achieve that, we use the definitions of the ethics principles in finance and ML. We begin by presenting the traditional core principles of ethics in finance. Through the examination of codes of conduct from 11 financial services professional associations, the study in [38] has extracted seven fundamental ethical principles in finance: integrity, objectivity, competence, fairness, confidentiality, professionalism, and diligence. These principles are defined in [38] as follows:

Integrity. Acting with integrity is one of the main principles that underpin the codes of ethics of many organizations in finance. Among the various definitions of integrity, this principle is tied to moral self-governance, autonomy, trustworthiness, and honesty. A person with integrity possesses the ability to

Table 1. A list of ethical principles in finance and their definitions.

Ethical principles in finance	
Principle	***Definition***
Integrity	Moral self-governance, autonomy, trustworthiness, and honesty. Consistent thinking and conduct, good conscience, and responsible acting.
Objectivity	Protecting and advancing the interests of clients. Maintaining trust and accurate perceptions. Avoiding bias and conflict of interests.
Competence	Rendering competent financial services to clients. Maintaining expertise through continuing education and professional experience in the workplace.
Fairness	Treating customers equitably, consistently applying the "Golder Rule", ensuring fair returns to everyone, balancing interests, and avoiding disparate treatment.
Confidentiality	Handling client relationships with confidence, protecting and not divulging sensitive information, and building and maintaining trust through sharing information.
Professionalism	Treating clients with courtesy and respect, establishing confidence, maintaining the reputation and trust with clients and the general public.
Diligence	Providing services promptly and thoroughly, rendering services tailored to the customer needs with attention to detail and persistent focus, and thorough review of support staff.

give honest introspection about their strengths and weaknesses. Integrity means to set consistent thinking and conduct, to have a good conscience, and to adhere to acting responsibly.

Objectivity. Objectivity is grounded in the subordination of the interests of the financial professionals to the needs and interests of the clients. Two elements that represent threats to objectivity are perpetual bias and conflict of interest. Bias reduces the ability to have accurate perceptions about the surrounding world and leads to faulty beliefs. Conflict of interest appears in situations governed by compensations when professionals advance their personal or institutional gains contrary to the position of trust and related duties that clients expect from professionals. Both factors adversely affect the objectivity, integrity, and public trust in the financial industry.

Competence. Professionals have an obligation to maintain their competence through continued education and experience to service clients and protect their interests competently. Financial products are so increasingly complex that clients lack the information necessary to assess the expertise of professionals and whether they are acting in their interests. The inherent information asymmetry may lead to a conflict of interest such that professionals exploit their expertise to gain an advantage at the expense of clients. Another issue may occur if professionals attempt to handle activities beyond their scope of expertise, which may also be related to a conflict of interest in relation to monetary compensation.

Professionals are obligated to refrain from giving advice beyond their expertise and defer these services to outside experts.

Fairness. The principle of fairness is an integral part of the codes of ethics in the financial industry. Fairness is broadly defined through three concepts: treating customers equitably, offering financial advice that professionals would be comfortable applying to their own portfolios (Golden Rule), and allocating fair returns to everyone. With regard to the concept of equality, any disparate treatment requires an explanation and justification to the affected parties. The Golden Rule assists professionals with clarifying their actions based on the best understanding of their own interests. The third concept is related to the obligation to properly balance the valid interests of all parties affected by certain decisions.

Confidentiality. Confidentiality is the obligation to hold client information in confidence. When seeking financial advice, clients may share sensitive information about their finances and financial goals, such as family dynamics. As this information is sensitive, financial services professionals should not divulge personal information because otherwise, it can break the trusting relationship. There are four reasons that show the need for confidentiality: personal autonomy, respect for relationship obligations, client vulnerability, and serving the common good. While personal autonomy acknowledges that clients have jurisdiction over their own personal information, it is also important to respect the obligations entailed in relationships. Relationship obligations are important as trust and intimacy are built through sharing of personal information. Confidentiality is also needed as clients become vulnerable by sharing personal information, which is inevitable to receive the service. It thus obliges professionals to act in the best interests of their clients. Finally, a system that respects confidentiality will work for the public interest better than one that does not.

Professionalism. The principle of professionalism has three requirements: treatment based on respect and consideration, the duty of professionals to maintain their reputation, and improving the quality of service provided to the public. Regarding the first requirement, professionals should not treat clients as mere means to achieve their own goals as such treatment hampers clients' autonomy. Treating clients with courtesy and respect is the basis for protecting the interests of clients and also for establishing trust. The second requirement is needed because the success of the financial services industry is grounded in public trust. Without trust, it is much more difficult to establish confidence between professionals and clients. Finally, assisting clients with making better financial decisions contributes not only to their financial security but also to societal well-being. The reputation of the financial industry improves when its practitioners work toward a common goal rather than focusing on personal success.

Diligence. The ethical principle of diligence can be interpreted in three different ways. One way to interpret it is through providing services promptly and thoroughly. Clients have expectations about when work should be completed, and it is the responsibility of the professional to meet those expectations. Failure to do so undermines the trust between the client and the professional. Secondly,

Table 2. OECD principles of artificial intelligence.

OECD AI Principles	
Principle	***Definition***
Inclusive growth, sustainable development, and well-being	Trustworthy AI should contribute to overall growth and prosperity for all – individuals, society, and the planet – and advance global development objectives.
Human-centered values and fairness	AI systems should be designed in a way that respects the rule of law, human rights, democratic values, and diversity. They should include appropriate safeguards to ensure a fair and just society.
Transparency and explainability	Transparent and responsible disclosure around AI systems to ensure that people understand when they are engaging with them and can challenge outcomes.
Robustness, security, and safety	AI systems must function in a robust, secure, and safe way throughout their lifetimes, and potential risks should be continually assessed and managed.
Accountability	Organisations and individuals developing, deploying, or operating AI systems should be held accountable for their proper functioning in line with the OECD's values-based principles for AI.

professionals are required to render services with due care, which means acting with attention to detail and persistent focus throughout the process of working with a client. For financial services professionals, this means carefully understanding the needs of each individual client and giving financial advice tailored to the circumstances of that client. Lastly, due diligence extends the obligation for a thorough review of support staff.

For the purposes of the NLP experiments, we consider both the long and short definitions of the ethics principles. The experimental methodology is detailed in Section 3. The long definitions of finance ethics are given in the respective paragraphs above, whereas the long definitions of ML ethics are defined as per the OECD principles [33, 32]. The short definitions are obtained as summaries of the long definitions and can be found in Tables 1-2.

3 Methodology

We compare the principles of finance and ML ethics by applying cosine similarity to pairs of ethical principles using transformers. Transformers represent a new paradigm in NLP architecture for sentence encoding, utilizing attention mechanisms to address long-range dependencies in textual data, a task previously unattainable with older models such as RNNs [11, 39, 45]. As a result, transformers have recently revolutionized the field of NLP by delivering exceptional performance in a variety of tasks, including machine translation [47, 28, 40], question answering [7, 1, 37, 48], sentiment analysis [9, 27, 43, 29], named entity recognition [25, 36, 15, 18], and both extractive and abstractive document summarization [12–14, 44], among others.

Transformers have the ability to convert any text into a vector representation, which can then be utilized for further analysis by a machine learning model. One practical use of this capability is to evaluate the semantic similarity between two pieces of text, such as two sentences or two paragraphs. The similarity is measured by cosine similarity, which is a normalized dot product and is suitable for computing the semantic similarity of vector-encoded texts. Because NLP transformers are pre-trained models that are often used for zero-shot learning, the use of cosine similarity is feasible without the need to divide the dataset into a training and validation set. This is adequately suited for our comparison, which aims to assess the semantic similarity between definitions of ethical principles.

We use P_f to denote a definition of an ethical principle in finance. Similarly, we use P_{ML} to denote a definition of an ethical principle in ML. The comparison between the finance and ML ethical principles consists of two steps. In the first step, we evaluate how strong the mapping is between P_f and P_{ML}. For a given pair (P_f, P_{ML}), the mapping can reveal weak, moderate, or strong relationships depending on how much the principles are related to one another semantically. This defines the strength of the link for that pair. For determining the strength of the links, we calculate the 33.33% and 66.66% percentiles obtained from the set of cosine similarities for all pairs of principles for each transformer. If the cosine similarity for a given pair (P_f, P_{ML}) is less than the 33.33% percentile, less than 66.66% percentile, or higher than the 66.66% percentile, the link for that pair is labeled as weak, moderate or strong, respectively.

We perform this first step using both the long and short definitions of ethical principles. This means that the dataset of all pairs (P_f, P_{ML}) consists of two parts: (P_f^l, P_{ML}^l) for the long definitions, and $(P_f^s, P_M L^s)$ for the short definitions [4]. Each part consists of 35 pairs of definitions since P_f^l (P_f^s) and P_{ML}^l (P_{ML}^s) have 7 and 5 definitions accordingly.

In the second step, we use more than 80 SOTA transformer models to calculate the cosine similarity across all pairs of principles. The performance of a model is measured by the number of overlaps between the principles of finance and ML ethics as evaluated using both the long and short definitions of the principles. For a given transformer, we calculate how many times its link labels for the long definitions (P_f^l, P_{ML}^l) coincide with the link labels for the short definitions (P_f^s, P_{ML}^s). In other words, we consider that there is an overlap if the link between the definitions is labeled in the same way for both the long and short definitions (i.e., "strong").

4 Results and Discussion

The results reveal that the NLI-DistilRoBERTa-Base-v2 model from HuggingFace [16] achieves the highest number of overlaps on the dataset (P_f, P_{ML}) with

[4] The code and dataset for the experiments can be found at a GitHub link will be provided here.

23 overlaps out of 35 pairs of definitions in total. Table 3 shows a list of transformer models that achieve the highest number of overlaps between the principles of finance and ML ethics. The list is given in descending order based on the number of overlaps and shows the first 10 transformers with the highest number of overlaps. As can be seen, there are two other RoBERTa models, namely nli-roberta-large and stsb-roberta-base-v2, that are among the top-performing models, each resulting in 21 overlaps. This is in line with prior research, which confirmed that RoBERTa achieves superior performance on sentiment tasks in finance when compared to other transformers [29]. Cosine similarity between selected pairs of short definitions for the NLI-DistilRoBERTa-Base-v2 model is given in Table 4. The cosine similarity for all pairs of principles (for both the long and short definitions) is calculated across all transformers. Due to the page constraints, Table 4 shows only an illustrative example for selected pairs of ethics principles based on the short definitions. In particular, Table 4 fixes one finance ethics principle and calculates the cosine similarity of NLI-DistilRoBERTa-Base-v2 across all OECD AI principles of ML.

Table 3. List of transformer models that achieve the highest number of overlaps between the principles of finance and ML ethics. The list is in descending order based on the number of overlaps and shows only the first 10 transformers out of the transformer models that were evaluated in the experiments.

Model	Number of overlaps
nli-distilroberta-base-v2	23
nli-roberta-large	21
stsb-roberta-base-v2	21
LaBSE	21
nli-bert-large	20
bert-large-nli-mean-tokens	20
stsb-roberta-base	19
distilroberta-base-msmarco-v1	19
paraphrase-distilroberta-base-v1	18
xlm-r-distilroberta-base-paraphrase-v1	18

5 Conclusion

Our study evaluates the relationship between the ethical principles of finance and machine learning using natural language processing transformer models. We aim to address a gap in the literature by providing a quantitative analysis of this relationship. We evaluate the performance of over 80 state-of-the-art transformer models in capturing the semantic similarity between the definitions of finance and ML ethics principles. To our knowledge, such an analysis has not been performed before in the literature. Our findings indicate that the NLI-DistilRoBERTa-Base-v2 transformer model outperforms the other studied mod-

Table 4. Cosine similarity using the NLI-DistilRoBERTa-Base-v2 model for selected definitions of finance and ML ethics principles. The comparison is between the finance principle of integrity and all ML ethics principles as defined by OECD.

Finance ethics principle	ML ethics principle	Cosine similarity with nli-distilroberta-base-v2
Moral self-governance autonomy, trustworthiness and honesty. Consistent thinking and conduct, good conscience and responsible acting.	Trustworthy AI should contribute to overall growth and prosperity for all – individuals, society, and planet – and advance global development objectives.	0.314517
Moral self-governance autonomy, trustworthiness and honesty. Consistent thinking and conduct, good conscience and responsible acting.	AI systems should be designed in a way that respects the rule of law, human rights, democratic values and diversity, and should include appropriate safeguards to ensure a fair and just society.	0.373912
Moral self-governance autonomy, trustworthiness and honesty. Consistent thinking and conduct, good conscience and responsible acting.	Transparent and responsible disclosure around AI systems to ensure that people understand when they are engaging with them and can challenge outcomes.	0.407513
Moral self-governance autonomy, trustworthiness and honesty. Consistent thinking and conduct, good conscience and responsible acting.	AI systems must function in a robust, secure and safe way throughout their lifetimes, and potential risks should be continually assessed and managed.	0.321908
Moral self-governance autonomy, trustworthiness and honesty. Consistent thinking and conduct, good conscience and responsible acting.	Organisations and individuals developing, deploying or operating AI systems should be held accountable for their proper functioning in line with the OECD's values-based principles for AI.	0.429124

els, confirming prior research on the general ability of RoBERTa to address sentiment classification tasks in finance-related contexts. The analysis can help reveal the most influential ethical principles of finance and machine learning on each other, which could guide financial institutions and fintech companies in developing ML-driven products and services while taking into account ethical considerations. Our study contributes to the literature by presenting a novel approach using transformers to evaluate the relationship between finance and machine learning ethics principles. It lays a foundation for future research in this field.

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