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REVIEW ARTICLE

A Review of Transformer-Based Financial Sentiment Analysis for Online Investor Conversation

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ABSTRACT: Financial sentiment analysis has become an increasingly important tool for understanding market movement, particularly as online platforms and social media play a growing role. Recent advances in transformer-based language models have significantly improved sentiment modeling in formal financial text. However, their application to informal investor conversation introduces distinct challenges. This review surveys recent transformer-based approaches to financial sentiment analysis with a focus on online investor conversations, where language is highly informal and multimodal. We synthesize prior work across datasets, models, and evaluation settings, highlighting how phenomena such as sarcasm, slang, emojis, mixed-content posts, and domain shift complicate sentiment interpretation. The review contrasts lexicon-based methods, recurrent neural models, and transformer architectures to assess both the strengths and limitations of each. Domain-adaptive, multimodal, and prototype-based modeling techniques are also discussed to determine the future direction of financial sentiment analysis. This paper provides a structured analysis of methodological trends, common failure modes, and open research questions in financial sentiment analysis. By clarifying both the capabilities and limitations of current transformer-based systems, this review aims to inform future research on robust, interpretable, and adaptive sentiment models for online investor conversation.

KEYWORDS: Computer Science and Software Engineering, Finance, Artificial Intelligence, Natural Language Processing, Transformer-Based Model, Financial Sentiment, Social Media.

Introduction

Markets now move at the speed of posts, not headlines. A 2025 study found that social media signals can be used to form a trading strategy that yields 4.6% excess returns, as compared to traditional news sentiment models, using real market data from 2013-2021.[1] Traditional sentiment models focus on structured news reports and company filings. Recently, models have been trained to understand financial sentiment in activity on social media platforms—most commonly Reddit.[2-4] The social media posts being examined contain sarcasm, figurative language, slang, and even images that are used to communicate. The transition towards a new type of financial text data presents both an ability to gain valuable information and a challenge for current Natural Language Processing models (NLPs).

Investor sentiment is defined as either the specific or overall opinion of active investors on a particular sector, index, or security. Investor attention, on the other hand, is the volume at which investors are monitoring said investment opportunity, and it is independent from any opinion. This distinction is significant to understand what moves markets. Cookson's team found that positive sentiment was closely correlated with positive short-term returns, and a positive change in attention signaled a reversal in either direction.[1]

While these two metrics were considered abstract before the internet, now researchers and investors alike have concrete methods to measure both sentiment and attention. Through machine learning and web scraping, data can now be collected on both attention and sentiment on social media platforms, and trends can be more accurately studied.

The evidence that these alternative sources can move markets is strong. During the GameStop and AMC short squeeze events in 2021, Reddit's r/WallStreetBets showed large spikes in post volume with sentiment that closely tracked trading activity and volatility.[3] More recent organized and community research into investor chatter from Reddit, StockTwits, and X concluded that social attention and sentiment can drive same-day market movement. In March of 2025, Cookson and colleagues took it a step further and designed a financial strategy using social media sentiment that significantly outperformed traditional models on historical data. The study importantly concluded that attention and sentiment show greater correlation with market lows than with market highs. This aligns with the idea that investors turn to social media when in a state of panic and not elation.[1] These studies show that online conversations are not just noise but signals that matter.

However, there is a fundamental problem: the language of these platforms looks nothing like the financial news articles on which current models were trained. Reddit posts in finance forums often include slang, humor, emojis, and irony. A post by Reddit user wildcat1055 reads: "AMZN green by open. Also, crayons provide many key nutrients your body needs." While it is clear to people that the second sentence has no significant context, models often hallucinate context instead of classifying the text as insignificant. This is because most financial NLPs are trained on news and reports that contain minimal to no figurative language and humor. The study described in the paper "A Large Self-Annotated Corpus for Sarcasm" has shown that sarcasm is extremely challenging to detect, even with large datasets, and that models trained on structured datasets often

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misinterpret tone when faced with figurative language.[5] Transformer models like BERT and FinBERT (fine-tuned for financial text), which have significantly improved sentiment analysis on structured data, struggle when confronted with Reddit's unconventional writing style.[6,7]

This paper explores how current NLP models extract and interpret sentiment from alternative financial text sources, such as Reddit, with unconventional language. This paper will also determine the key challenges and breakthroughs in this domain. If models can reliably interpret sentiment from social platforms, they can be used to improve trading algorithms, risk models, credit evaluations, and policy decisions. Yet, the field is still in its early stages of fully utilizing alternative text data.

It was deduced that while sentiment-based financial strategies have taken a major step forward by using alternative text data from social media, the models used to interpret sentiment in said data still have challenges to overcome before financial sentiment analysis is consistent. Recent research points to possible solutions. Prototype-based models, which classify sarcasm and sentiment into distinct archetypes, can improve performance on noisy social media data.[8] Another solution is multimodal modeling, which combines images and audio with text data to fully capture the message of every user. Finally, domain adaptation methods allow models to adapt to unlabeled Reddit data, which is abundant but difficult to label.[7]

This paper will first discuss the evolution of financial sentiment models from clean, structured datasets. Then, the unique linguistic challenges posed by alternative text data will be examined, along with highlighting recent innovations in NLP that address these issues. Finally, we will look to the future, identifying directions for financial sentiment analysis that can keep pace with ever-changing markets.

Discussion

Evolution of Financial Sentiment Models:

The first models to analyze financial sentiment worked primarily with structured text. These included earnings reports, SEC filings, news articles, and analyst briefings. A common characteristic between these is straightforward language, free from slang and ambiguity. Because of this, early models used rule-based methods and financial dictionaries to classify sentiment. Lexicon-based tools such as the Harvard IV dictionary and Loughran-McDonald sentiment word list were widely used in order to assign "positive" and "negative" labels to words or sentences appearing in financial media.[9] While these tools laid the foundation, they struggled with more nuanced language. For instance, the phrase "performance remained in line with expectations" is technically neutral in the eyes of a sentiment model. However, the statement could signal either confidence or disappointment based on the context from which it was taken.

As researchers began to look into these models, the limitations became clear. Lexicon-based approaches lacked the ability to understand negation, word order, or sentence structure. A phrase such as "not a good outlook" may be interpreted as positive signaling to the model because it identifies the word "good." In a 2019 review, it was concluded that these rule-based methods could not reliably predict market reaction based on textual sentiment alone.[10] Similarly, it was found that dictionary-driven models were consistently outperformed by modern machine-learning methods.[6]

The next major leap in this technology came from the rise of transformer-based models. In 2018, Google released BERT, a pre-trained language model capable of understanding contextual relationships between words.[11] Not long after, FinBERT was introduced, a version of BERT fine-tuned specifically for data such as analyst reports and earnings calls. Unlike the previously used lexicon-based models, FinBERT uses a transformer architecture to create contextual embeddings. These are dynamic mathematical representations of words that depend on the surrounding context.[12]

FinBERT achieved high accuracy and precision on standard financial sentiment benchmarks, such as FiQA and Financial PhraseBank.[12] It was also shown that combining FinBERT with a long short-term memory (LSTM) network improved the prediction of stock price direction in response to sentiment shifts.[13] In 2024, FinBERT performed on par with GPT-4o when dealing with formal financial text.[14]

Yet, these models were never designed to handle user-generated content in blogs and other social media. Transformer-based systems like FinBERT were trained on formal documents, not social media posts full of emojis, slang, and sarcasm. Applying them to Reddit or StockTwits in their current form would not be effective. This is largely due to the problem of domain shift, which is especially common in NLP tasks involving informal versus formal text.[7]

It has been proven that the issue of domain adaptation limits NLP models from analyzing financial sentiment. The ability of large language models (LLMs) to perform sentiment classification on Reddit posts was studied, and it was found that even advanced models struggled without additional fine-tuning or weak supervision.[15] The models, although powerful when it comes to traditional financial text, failed to analyze financial sentiment from social media activity with precision.

In conclusion, financial sentiment models built on structured text, starting with lexicon-based models and now transformer-based models such as FinBERT, are strong when it comes to analyzing the data they are trained on. These models can accurately identify sentiment in financial news and reports, signaling market movement. However, they are not equipped to handle the messy, unpredictable language of online investor communities. As the next section will show, social media platforms like Reddit present challenges that demand a new generation of adaptable NLP models.

Model Development:

Most sentiment analysis tools employ machine learning (ML). Instead of following hard-coded rules, ML models identify and use statistical patterns in data. In supervised learning, the model is trained using labeled examples. In the case of sentiment analysis, the data would consist of words and phrases, labeled with the sentiment, commonly positive, negative, or neutral. Once trained, it can classify new text. Traditional ML methods like logistic regression and support vector machines

(SVMs) worked for simple sentiment tasks, but struggled with the complexity of financial language. Training these models was time-consuming for the performance achieved.[16]

Transformer-based models solved this issue by being able to process all tokens in the data simultaneously, known as parallelization. They are an improvement on recurrent neural networks (RNNs), which process sequences one token at a time. This makes it difficult for RNNs to retain information over larger stretches of data (the vanishing gradient problem). Long Short-Term Memory networks (LSTMs) partially remedy this by selectively forgetting and remembering key tokens using logic gates, but the underlying language processing remains the same.[17] Transformers use self-attention, assigning weight to tokens using pattern recognition instead of a predefined algorithm. This creates relationships between words in a way that RNNs are incapable of doing, dealing with negation and context at a much higher level. For instance, a transformer has the ability to interpret that "good" is negated in "not a good outlook" with greater consistency. In the case of a longer post or tweet on social media, a transformer-based model will more accurately be able to interpret modifiers and key phrases that indicate sarcasm and negation. Transformers perform up to 18% more accurately and consistently faster than RNNs when translating text between etymologically related languages (Lakew). This gap further increases when dealing with more complex language. Self-attention and parallelization make transformers able to be trained and do NLP efficiently and accurately.[18]

FinBERT is a transformer-based LLM that can handle financial language with greater accuracy than its base model BERT. This is because FinBERT was fine-tuned on financial text in addition to common language. Terms such as "bear" and "bull" are understood differently by FinBERT and BERT. The pre-training step involves training the model on broad language knowledge with massive datasets. BERT was trained using a technique known as masked word prediction, where the model evaluates its own prediction of words in a sequence in comparison to the original texts in the dataset.[11] FinBERT was fully fine-tuned using financial reports by updating all parameters on the labeled task data, completely redefining interpretations of certain words and phrases. Now, researchers use a method known as parameter-efficient fine-tuning (PEFT), which updates a smaller fraction of trainable parameters to save resources and time.[19] The process of conducting a literature review and writing a review article can also be a great way to help you get up to speed on a topic you're not so familiar with.

Linguistic and Data Challenges:

Understanding online investor-to-investor interaction is the next step in algorithmic trading strategies, but classifying sentiment in millions of social media posts daily is a difficult task. Wen and Rezapour note that "sarcasm detection has unique challenges for sentiment analysis because of figurative language and contradiction between literal and intended meaning".[8] At the same time, informal tokens (emoticons, hashtags, emojis) can carry sentiment information: one study finds that simply including emoji descriptors slightly improves classifier accuracy on social text.[20]

Another challenge is domain shift. Most sentiment models (like FinBERT) are trained on formal financial news and SEC filings, not Reddit or Twitter chatter. Domain adaptation is required in this instance because the test data differs from the training data. In the financial case, vocabulary and style diverge sharply: Reddit traders routinely use novel terms (e.g., meme-stock nicknames, gaming metaphors) not seen in corpora like 10-K filings. Examples of these tokens are seen in Table 1, as well as their impact on transformer models attempting to interpret them. This mismatch means applying a model trained on news to social posts can fail. Recent work, therefore, emphasizes domain-aware training: for instance, Delgadillo and team pre-train a financial LLM on news and then fine-tune on social-finance text to bridge that gap. However, the scarcity of high-quality labeled social-finance data remains an issue. New data and trends are emerging, but annotation is expensive. In sum, the linguistic creativity and dynamic jargon of social forums make sentiment extraction "difficult", and one must carefully adapt models to these domain specifics.[21]

Table 1: Challenging language for transformer-based models, with examples and specific impact on the interpretation.

Challenge	Description	Impact on Transformer Models	Example
Sarcasm & Irony	Sentiment is expressed indirectly and often opposite to literal meaning	Literal token interpretation leads to polarity reversal	"Great, another earnings miss 🙄"
Slang & Informal Language	Use of community-specific jargon and memes	Out-of-vocabulary terms weaken interpretations	"This stock is giga-busted"
Emojis & Emoticons	Emojis convey or modify sentiment	Emoji meaning is misrepresented	"Loading calls 🚀 (or not 🤡)"
Mixed-Content Posts	Serious analysis mixed with jokes or irrelevant text	Noise dilutes true sentiment signal	"AMZN green by open. Crayons are nutritious."
Domain Shift	Language differs from formal financial news or reports	Models pretrained on formal text generalize poorly	"YOLO'd into puts before CPI"
Implicit Targets	Companies are implied rather than explicitly named	Difficulty linking sentiment to the correct entity	"This dumpster fire is going to zero"
Evolving Language	Rapidly changing slang during market events	Static models degrade over time	Event-specific memes

Innovations in Interpreting Financial Sentiment:

Table 2: Comparison of transformer-based models for financial sentiment analysis. The table summarizes the type of data used to specialize each model and cites each model's result on a relevant benchmark.

Model	Year	Domain Training Data	Key Features	Reported Performance
BERT (base)[11]	2018	General (Wikipedia, Books)	General LLM, no finance-specific tuning	High accuracy on generic sentiment (for comparison)
FinBERT[12]	2019	Pre: BERT; Fine-tuned on financial news and reports	Finance-specific vocabulary; Transformer encoder	90% accuracy on Financial PhraseBank (↑ vs. 82% by generic BERT)
FinSoSent[21]	2024	Pretrained on news; Fine-tuned on Reddit & StockTwits	Two-stage domain adaptation; Financial LLM	State-of-art on StockTwits sentiment (F1≈0.88, +5% vs prior best)
GPT-3.5[24]	2023	Trained on internet text (general domain)	175B parameters; few-shot capable	Below financially-tuned models on tasks (zero-shot, as reported in FinTral benchmark)
FinTral-DPO-T&R[24]	2024	Pretrained on finance text + tables + images; fine-tuned with human feedback	Multimodal (text,image,tables); 7B parameters + tools	Beats GPT-4 on 5/9 tasks

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Researchers are rapidly developing new modeling techniques to cope with these challenges and leverage rich data:

Domain-specific adaptation and pretraining: Financial NLP now often uses unsupervised domain adaptation and further pretraining on finance text. This is because the vast amount of data available for processing makes supervised training and data labeling extremely costly. For example, Delgadillo and team introduce FinSoSent, an LLM pre-trained on financial news and stock-related social media. FinSoSent is fine-tuned on a wide range of financial data and achieves state-of-the-art performance on sentiment analysis tasks.[21] This two-stage approach (news pretraining + social fine-tuning) shows how domain-tailored LLMs can perform better. Domain adaptation like this is crucial for out-of-distribution generalization.[7] The measurable success of this method is noted in Table 2.

Prototype-based interpretability: models that classify text by comparing it to stored "prototype" examples, which represent typical patterns associated with a label in the training data.[8] For example, a sarcastic prototype might be a Reddit post like "Oh fantastic, my portfolio is only down 80% today", while a bullish prototype could be "GME 🚀🚀 going to the moon". New input is compared against these prototypes in order to determine sentiment. This approach offers two key advantages over black-box transformers: (1) Transparency: analysts can see exactly which examples influenced the decision, increasing trust in high-stakes financial contexts,[22,23] and (2) Robustness to figurative language, because the model uses contextual patterns, it can correctly interpret sarcasm or slang that might confuse lexicon-based models.[5]

Wen & Rezapour show this method achieves both transparency and high-level sarcasm detection, making it a strong candidate for noisy financial text.[8]

Multimodal modeling: Financial sentiment often depends on non-textual cues (charts, memes, emojis). New models are now able to combine visual and textual data for processing. For instance, FinTral is a GPT-4–level multimodal LLM that processes not just text but also tables, images (charts or stock logos), and numbers.[24] Their best model "surpasses GPT-4 in five out of nine tasks" and "demonstrates an exceptional zero-shot performance." The authors highlight that FinTral excels in real-time analysis and decision-making in finance, pointing to the viability of the model in sentiment analysis of social media conversations containing memes, emojis, and charts.[24] Similarly, the Coin-Meme study constructs a dataset of memecoin investments combining images, text, and social context. They show that humor and imagery (crypto memes) crucially shape "memecoin" prices, suggesting models must blend text with vision to capture market sentiment in the Web3 era.[25]

Benchmarks and Datasets:

Building and evaluating better models requires high-quality data. The community has developed several financial sentiment corpora and benchmarks:

Financial PhraseBank: A classic dataset of ~5,000 sentences from financial news manually labeled as positive, negative, or neutral. It was used to train the original FinBERT, and it was used to show 8% more accuracy in a financial context compared to BERT, as shown in Table 2.[26] The dataset's time has passed, and it serves as a baseline comparison for all future training datasets.[21]

FinLin: A recent multi-source corpus combining StockTwits posts, financial news articles, and investor/company reports from the same time frame. FinLin covers multiple companies and provides fine-grained sentiment and relevance scores for each text. With 3,204 StockTwits messages and 394 news reports annotated, FinLin is one of the first corpora linking social posts to market context.[27]

FL_ST (FinLin StockTwits) subset: From FinLin, a team extracted a specialized subset of 3,204 StockTwits (named FL_ST), each labeled with a numeric sentiment score. They use this to fine-tune LLMs for StockTwits sentiment, illustrating how new social-media data can augment standard models.[27,28]

FinMarBa: A forthcoming dataset of news headlines annotated via market reactions rather than humans. FinMarBa automates labeling news by subsequent price moves, aiming to reduce bias in sentiment signals. The authors are releasing a large-scale news dataset with "market-based" labels and code for financial LLMs, which will provide a new public benchmark.[29]

The best current benchmarks are entity-linked, market-informed datasets like FinLin and FinMarBa, because they connect sentiment directly to specific firms and label it using or validating against real market movements.[27,29] This alignment ensures models are evaluated on signals that actually matter for trading, unlike generic polarity labels separated from economic context. Entity linking forces models to handle relevance, and market-informed labels reduce annotator bias while capturing the sentiment-return relationship.[29] Another alternative is multimodal datasets that combine multiple forms of input, as in the data used for FinTral and memecoin studies.[24,25]

Future Directions:

Future systems must withstand domain shifts and noise. This means being tough against misleading posts, like pump-and-dump schemes, and adapting to new types of data over time. Ramponi and Plank emphasize the need for NLP that can generalize under domain shift.[7] This involves continual learning: updating models with new data while avoiding catastrophic forgetting. The FinTral study already explicitly tests real-time inference, and its architecture is designed to handle "hallucinations in the financial domain."[24]

Future sentiment models will fuse text with other modalities. One could incorporate speech (earnings call audio), structured tabular data, or user-profile information on top of image data, which is currently being used. The success of FinTral and memecoin analysis suggests that multimodality can capture nuances in sentiment. Figuring out how to do this at a high level is a key next step.

Systems that let analysts interact with LLMs in the loop will be important. The Alpha-GPT line of work (and related "AI agent" approaches) shows how traders can inject hypotheses and constraints into LLM-based analysis.[30] Future models may allow users to correct sentiment labels when combined with

prototype-based models. Humans may also provide additional context or verify model interpretations on the spot. This human-in-the-loop design can help reduce risks of automated sentiment tools (biases or hallucinations) by keeping experts "in the loop," since the stakes at which some of these AI tools operate are high.

Finally, building trust in financial NLP means transparent models. Prototype-based or example-driven explanations (as in Wen & Rezapour's sarcasm model) can be incorporated in most forms of financial sentiment analysis. Research into model interpretability (generating rationales, highlighting evidence in text, or detecting when a post is likely sarcastic) will help users gauge confidence.

The highest-impact direction is streaming, domain-adaptive sentiment analysis. This will produce systems that continuously learn from new slang, memes, and market events while producing real-time sentiment feeds.[7,24] Since the application of this data is most seen in intraday movement, real-time sentiment analysis will benefit investors to the fullest. FinTral's real-time capabilities show this is feasible, and continual adaptation prevents a loss of accuracy as the language of online investors changes.[24]

From a comparative perspective, domain adaptation currently appears to be the most practical and scalable solution, as it directly addresses the dominant issue of interpreting challenging language. Multimodal modeling is likely to yield the greatest long-term gains as investor communication becomes increasingly visual, but its utilization is highly dependent on how investor conversation evolves moving forward. Human-in-the-loop approaches, while less scalable, offer critical safeguards for real-world financial use and may play a central role in regulatory or decision-support contexts. This form of modeling will likely be used in conjunction with domain adaptation in financial sentiment analysis moving forward. Ultimately, the most effective future systems are likely to combine these approaches, integrating adaptive training, multimodal inputs, and human feedback into a unified sentiment analysis pipeline.

In short, combining powerful new models with rich social-finance data is opening exciting possibilities. The field is moving toward LLM-based platforms that handle messy social chatter, fuse multiple data streams, and update continuously. By using domain adaptation, multimodal fusion, and human oversight, future financial sentiment systems promise to be far more robust, accurate, and actionable than today's tools.

Limitations of Review:

Despite the large body of recent research in this domain, notable limitations should be acknowledged.

First, limited heterogeneity across datasets and a lack of standard metrics limit the ways in which methods of financial sentiment analysis can be compared across studies. While theoretical conclusions can be drawn by using data from multiple studies, it is difficult to quantitatively make comparisons in precision and accuracy between models. This review, therefore, emphasized qualitative trends and methodological patterns.

Second, domain shift poses persistent challenges that are not fully resolved by current methods. Most models are trained on fixed datasets and idealized conditions, which overestimate real-world output.

Finally, the scope of this review is necessarily selective. The pace of research in this domain is very rapid, and it is possible that relevant studies may have been overlooked or omitted. Also, corporations have a financial incentive to keep new research private, which reduces the extent of knowledge available to discuss. This review also focuses on transformer-based text models and does not extensively cover non-textual financial signals beyond their interaction with sentiment analysis.

Taken together, these limits highlight the need for standardized benchmarks to effectively compare the results of relevant studies. They also underscore that reported advances in financial sentiment analysis should be interpreted cautiously, particularly when applying results from a controlled environment to real-world applications.

Conclusion

While social media sentiment has proven to be predictive of market movement, current NLP models face challenges in analyzing this online chatter accurately in real time. Traditional models such as FinBERT excel at analyzing structured data such as financial news and reports, but struggle with social media data that is riddled with slang, sarcasm, emojis, and images.

The content and style of writing in online investor forums create a linguistic barrier for most transformer-based models. While these models are great at interpreting context, the variability in social media language is considerably more challenging. This issue arises from the fact that these models are trained on structured data that reads as it is written. It does not contain humor, modern slang, or vague language. Models such as FinBERT struggle because of the domain shift, since the social media text data it is being tested with is vastly different from its training data. There is also a scarcity of high-quality, labeled social-finance corpora for pre-training. A new dataset known as FinMarBa is promising, however.

FinSoSent is a model that is pre-trained and then fine-tuned on social-finance data, and has achieved excellent results. FinTral is a multimodal model that combines not only text data, but imagery and audio to interpret sentiment, though it is not fine-tuned for financial text. Another approach being used is prototype-based interpretability. This form of model development allows researchers to shape the training of the model and is more transparent.

The most promising solutions are domain adaptation, multimodal models, and prototype-based interpretability. Of these solutions, domain adaptation is the most research-ready as it draws on existing datasets and can achieve results quickly. Multimodal modeling and prototype modeling both require more sophisticated datasets, which aren't currently available. Also, multimodal data has not yet proven to be significant enough to be pursued.

The goal of this research is to describe a model that retrieves and interprets social media data in real time. The model must be adaptive and perform self-supervised learning to adapt to

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modern slang and trends. The high-stakes nature of such a model will require transparency and will benefit from a human-in-the-loop framework to give users confidence in the model's predictions. Improved sentiment analysis could transform trading strategies, risk modeling, credit scoring, and policy decisions.

The review shows that financial sentiment analysis is far from successful yet has great potential. A successful model for interpreting financial sentiment must be able to interpret multiple forms of data, including text from various sources, intelligently revise definitions, and pattern recognitio, asd investor conversation evolves. Markets are increasingly shaped by online investor conversation, so future NLP breakthroughs have the potential to yield great results for investors.

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I attest that the ideas, graphics, and writing in this paper are entirely my own.

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